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Imperfect information and the wage-gap for South African men

Statistical discrimination and employer learning

Kholekile Malindi
Stellenbosch University

Abstract

The employer-employee relationship is often characterised by imperfect information and uncertainty. Employers are imperfectly informed about the skills set and potential productivity of job-seekers. Job-seekers are in turn imperfectly informed about the availability of job vacancies that require the skills set they possess. The resulting uncertainty leads to inefficiencies in job search and matching (Schoer and Rankin, 2011) and may directly contribute to unemployment in the presence of high dismissal costs (Levinsohn, 2007). Faced with limited information about the skills set and expected productivity of job-seekers, employers may rely on easily observable characteristics to statistically discriminate among workers when these characteristics are correlated to productivity. This paper investigates the impact of imperfect information on the wage gap between black and white men and provides empirical evidence demonstrating statistical discrimination by South African employers on the basis of race, age and level of education.

A theoretical model of worker productivity uncertainty and employer learning is constructed for the South African labour market. The model combines insights from statistical discrimination and learning models to produce testable predictions regarding the impact of imperfect information on wage differentials. The structural parameters of the model are estimated with maximum likelihood estimation using South African household labour market data. The estimation of the theory model is preceded by a descriptive analysis that exploits group variation of within-firm wage growth due to the accumulation of the first year of tenure as an indirect measure of worker uncertainty and employer learning.

The maximum likelihood and OLS results provide strong evidence in support of the hypothesis that South African employers engage in statistical discrimination on the basis of race, age and educational attainment when making employment and wage decisions. Black, young and men

with just matric qualifications (i.e. 12 years of schooling – completed high school) were found to have greater *ex ante* uncertainty around their expected productivity and thus benefitted more from employer learning. The greater uncertainty, it is argued, is driven by low and variable quality of pre-tertiary education that has reduced the potency of the matric certificate as a signal of worker's expected productivity.

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1. Introduction

The employer-employee relationship is often characterised by imperfect information. Employers are imperfectly informed about the skills set and ability of job-seekers. Job-seekers are in turn imperfectly informed about the availability of job vacancies requiring the skills they possess. The resulting uncertainty has important consequences for the functioning of the labour market and for the outcomes achieved by labour market participants. Imperfect information and its impact on the assessment of worker productivity is a subject of many theoretical models in the labour economics literature. The statistical discrimination model, for example, suggests that when faced with imperfect information regarding the skills set and expected productivity of job-seekers, employers will rely on easily observable characteristics like education and race to distinguish among workers when these characteristics are correlated to productivity. When employers exhibit such behaviour they are said to be engaging in statistical discrimination. The statistical discrimination model was pioneered by Phelps (1972) and Arrow (1973) and further developed by Aigner and Cain (1977) and Lundberg and Startz (1983).This paper incorporates the employer learning hypothesis into an Aigner and Cain (1977) style statistical discrimination model and investigates imperfect information and uncertainty regarding worker productivity in a developing country context.

A great deal of uncertainty driven by imperfect information exists in South Africa regarding the quality of workers entering the labour market. “There is ample evidence both of considerable quality variation and of a poor range of signals, associated with South African human capital” (Duff & Fryer, 2005:7). The evidence referred to by these authors is contained in a large body of literature that documents the large variation in learner performance and differential school quality received by South Africans. This has resulted in employers not trusting schooling qualification as a credible signal of expected productivity. The labour market effects of the worker quality uncertainty have, however, been only studied in the context of the returns to schooling and in the measurement of the racial discrimination component in earnings and employment regressions. Missing from these studies is the process or mechanism through which differential school quality, performance, and the resulting uncertainty regarding worker ability affect labour market outcomes. This paper fills this void in the literature by studying the role played by imperfect information in the assessment of worker productivity and on its impact on the wage gap between black and white South African men. The paper provides empirical evidence demonstrating statistical discrimination by South African employers based on race, education and age a decade after the transition into democracy.

DRAFT

We construct a theoretical model of worker uncertainty that allows the uncertainty to be resolved over the employment spell with the current employer. The model combines insights from statistical discrimination and employer learning models to produce testable predictions regarding the impact of imperfect information on wage differentials. The structural parameters of the model are estimated with maximum likelihood estimation using South African nationally representative household labour market data. The estimation of the of the structural parameters is preceded by a descriptive analysis based on ordinary least squares (OLS) estimation that exploits group variation of with-in wage growth due to the accumulation of the first year of tenure as an indirect measure of worker uncertainty and employer learning. The OLS results are interpretable within the context of statistical discrimination that takes the form of rational stereotyping. While the results of the structural model are interpretable within the context of statistical discrimination that stems from differential reliability of the signal of productivity.

2. Background and context: South African literature

This paper investigates the role played by imperfect information in the assessment of worker productivity, and on its impact on group differences in average wages in South Africa. The paper argues that difficulties or uncertainty in assessing worker productivity is driven by low and variable quality of pre-tertiary schooling that has reduced the potency of school certificates as credible signals of expected productivity. The uncertainty in worker productivity, it is argued, systematically differs by race and age. This is because of the strong correlation between the variation in learner performance and variable school quality on the one hand, and race and age on the other hand. This section tasked with providing a background and context for the paper by summarising and reviewing the literature that documents the large variation in learner performance and differential school quality received by South Africans.

The socio-economic conditions faced by black and white South Africans differ greatly. The difference is so stark and contrasting that former president Thabo Mbeki claimed that “South Africa is a country of two nations . . . the one black and the other white” (Thabo Mbeki, 1998:). Education was one of the key areas that the former president identified as distinguishing the two nations from one another. This is because under the Apartheid government “the schooling system was divided along racial lines” with “unequal educational funding, support and management” (Branson and Leibbrandt, 2013:7). Enrolment rates into secondary high school for blacks also lagged those of whites and were coupled with a lowering of school quality that is yet to significantly improve (Branson, Ardington, Lam and Leibbrandt, 2013).

Branson and Leibbrandt (2013) identify three ways that school quality may affect an individual's labour market outcomes. Firstly, they note a link between an individual's educational attainment and school quality. The suggestion is that the lower the quality of schooling attended, the lower is educational attainment with all else held constant. Secondly, the authors argue that an individual's employment likelihood is reduced by attending a low quality school. Lastly, an individual's earnings capacity may be undermined by the low quality of schooling by its influence on the individual's expected quality or ability.

The evidence of the effect of school quality on labour market outcomes is scarce due to limitations of available data and econometric challenges/issues (Branson and Leibbrandt, 2013). However, a few studies have attempted to, empirically, study the effect of school quality on labour market outcomes in South Africa. These studies largely involve incorporating some measure or proxy of schooling quality in the estimation of, firstly, the wage and employment premiums to educational attainment while attempting to partial out the effect of school quality. Secondly, the other group of studies estimate the unexplained component of the wage gap that 'represents' labour market discrimination while attempting to control for the confounding effect of school quality.

Branson et al (2013) study changes in educational attainment and the effect of those changes on employment and earnings using a birth cohort analysis. The authors find that the educational attainment gap between blacks and whites has improved markedly. Work by van der Berg (2007) using census and household survey data provides a similar picture. The improvement in educational attainment is particularly evident for the younger cohorts as the younger generations have enjoyed higher enrolment rates into secondary schooling. Educational attainment as measured by years of schooling completed, however, overestimates the gains made in education. Chamberlain and van der Berg (2002), van der Berg (2007), Burger and van der Berg (2011) and Branson et al (2013) have expressed concerns regarding the effective level of learning and cognitive gains achieved due to the high variance in learner performance and the low and variable quality of schooling received by mainly black learners. Learner performance in mainly black schools is poor and highly variable even when compared to other African and developing countries that dedicate fewer resources to education (van der Berg, 2007). Furthermore, black learners also have higher grade repetition rates compared to their white counterparts (Lam, Leibbrandt and Mlatsheni, 2007) and this also undermines the gains achieved in educational attainment.

Branson et al (2013) also provide evidence of relatively poor labour market outcomes (employment and earnings) accompanying the increases in educational attainment for the younger cohorts. This too is evidence consistent with increased variation in schooling quality (Branson et al, 2013).

Concerns surrounding variable school quality have prompted some researchers to incorporate measures and proxies of school quality directly into employment and earnings regressions. Chamberlain and van der Berg (2002) proxy for school quality with literacy and numeracy test scores, Burger and van der Berg (2011) use matric test scores, while Branson and Leibbrandt (20130 use pupil-teacher ratios together with the proportion of matric pupils within the same school that pass with matric exemption – requirement for acceptance into university.

Chamberlain and van Berg (2002) demonstrate that the component of the wage gap ascribed to labour market discrimination is significantly reduced when one control for school quality. This finding is echoed by Burger and van der Berg (2011) but with a different proxy for school quality and different methodology. Branson and Leibbrandt (2013) on the other hand, demonstrate a positive relationship between earnings and school quality. The relationship between employment and school quality is however found to be very weak. This leads the authors to conclude, "the difference in school quality is differentiating workers skills in ways that are not immediately evident to an employer, but materialise once the individual is employed" (Branson and Leibbrandt, 2013:26). This indeed forms part of the motivation that has prompted us to incorporate the employer learning hypothesis into a statistical discrimination model and investigate the impact of worker uncertainty on the wage gap for South African workers.

3. International literature review

This section of the paper provides a brief review of the theoretical and empirical literature on statistical discrimination.

Statistical discrimination: theory

Aigner and Cain (1977), building on earlier work by Phelps (1972), developed a statistical model of labour market discrimination. This model has served as a key point of departure for later theoretical and empirical models of statistical discrimination. In the Aigner and Cain model, worker productivity (ability) is unobservable. Employers observe and base their employment decision on a noisy signal of worker productivity. Employers are also able to observe the group (e.g. black or white, male or female) that a worker belongs to. A key assumption is that the productivity signal that employers receive at the hiring stage is less informative for one group (usually blacks – minority groups more generally) relative to the other group. Productivity for all workers, however, is assumed to be drawn from the same distribution for both groups.

Aigner and Cain (1977) showed that a model with only the above features does not generate differences in average wages between groups that it purports to explain. The authors therefore extended the model by assuming that employers are risk averse. With this additional assumption, average wages are now a function of not only the expected productivity conditional on the productivity signal but also a negative function of the conditional variance of productivity conditional on the productivity signal. Consequently, the extended model generates group differences in average wages, with the group with nosier signal (higher variance around their productivity) earning lower relative wages.

The standard statistical discrimination model has over the years been subjected to further extensions that incorporate insights from other labour market models. Lundberg and Startz (1983) incorporated a human capital investment option into the statistical discrimination model. The investment is costly, unobservable and is undertaken prior to entering the labour market. Minority groups (e.g. blacks) are still assumed to have a less informative productivity signal. The higher signal-noise ratio for minority groups coupled with investments in human capital being unobservable means that minority groups have less of an incentive to invest human capital. With minorities investing less in human capital and having a less informative productivity signal, the model predicts that they will earn lower average wages relative to their counterparts because of lower investment in human capital.

Oettinger (1996) extended the model further by introducing a dynamic structure to the model that allows for uncertainty around the productivity of workers to be resolved through employers' observations of the workers' output. This extension improves on the static nature of the previous models and introduces new (and empirically testable) predictions about the wage gap between black and white workers. The empirical contributions of the model by Oettinger (1996) are considered in the next subsection together with other key empirical studies of statistical discrimination.

DRAFT

Statistical discrimination: empirical evidence

In a seminal study, Altonji and Pierret (2001) devised an empirical test for statistical discrimination that relies on employers' ability to learn about the true productivity of their workers by observing their output. As employers learn about the true productivity of their workers, the coefficients on the easy to observe correlates of productivity in wage regression should fall while the coefficients on the hard to observe correlates should rise. Using U.S. data on young people, Altonji and Pierret (2001) find evidence of young workers being statistically discriminated against on the basis of education. Interestingly, the authors find no evidence of statistical discrimination on the basis of race even though race is a good candidate for an easy to observe correlate of productivity.

Pinkston (2006) uses the framework developed by Altonji and Pierret (2001) and demonstrates that black men in the US have less credible labour market signals compared their white counterparts when these workers enter the labour market. Strobl (2003) apply this framework to a developing country. The author uses matched employer-employee data from Ghana and provides evidence in support of the statistical discrimination model.

Oettinger (1996) and Lewis and Terrell (2001) developed alternative frameworks for testing for statistical discrimination. These tests rely on differential returns to tenure, labour market experience and job mobility. According to these authors, groups that are statistically discriminated against should have lower estimated wage returns to labour market experience and job mobility, and higher estimated wage returns to tenure compared to groups that suffer no statistical discrimination. Oettinger (1996), Lewis and Terrel (2001) and Goldsmith, Hamilton and Darity (2006) use this framework to demonstrate evidence of statistical discrimination against black workers in the US.

4. Theoretical model

One of the key contributions of this paper is a development of a statistical discrimination model that incorporates learning by employers for a developing country. The type of statistical discrimination modelled takes the form of screening discrimination. The crucial assumption underlying screening discrimination is that employers are less able to accurately assess the expected productivity of individuals from the minority group compared to individuals from the majority group. This is due to members of the minority group having less accurate and reliable signals of worker productivity. We allow for the resulting uncertainty regarding worker productivity to be resolved as employers learn about the true productivity of workers by observing the worker's output on the job. The model developed here embodies the key features of statistical discrimination models and largely follows the formulation in Aigner and Cain (1997).

Model setup

Suppose individual worker productivity, y, is determined as:

$$y = \alpha + \boldsymbol{\theta s} + u\sigma_u \qquad (1)$$

where α is a constant, $\boldsymbol{s}$ is a vector of observable determinants of worker productivity, $\boldsymbol{\theta}$ is a vector of parameters capturing the effect of $\boldsymbol{s}$ on worker productivity. Worker productivity is also a function of other factors that are assumed to be unobservable and thus captured by the model error term, u. As in Aigner and Cain (1977), y is assumed to be normally distributed with zero mean and a standard deviation of σ_u.

Productivity as determined by equations (1) is unobservable by employers. Employers instead observe, in every period, a noisy signal of worker productivity, $\hat{y}_t$:

$$\hat{y}_t = y + e_t\sigma_e \qquad (2)$$

e_t captures the noise or error in employers' assessment of worker productivity. $e_t$is assumed to be normally distributed with zero mean and a standard deviation of σ_e. Firms can observe $\boldsymbol{s}$ but not u. $\boldsymbol{s}$ can be gauged from information contained in résumés and job application forms. At period t, the firm can observe all the signals $(\hat{y}_0, \dots, \hat{y}_t)$ and forms an expectation regarding the worker's productivity, $E(y|\boldsymbol{s}, \hat{y}_0, \dots, \hat{y}_t)$, conditional on the information received. We further assume that firms are risk-averse as they may care and dislike the uncertainty that results from variation in worker productivity. To incorporate risk-aversion by employers, we follow Aigner and Cain (1977) by allowing the firm's profit function and hiring decision to be a function of not only the worker's conditional expected productivity but also the conditional variance y, written as $Var(y|\boldsymbol{s}, \hat{y}_0, \dots, \hat{y}_t)$.

Assuming firms to be risk averse and to care and dislike uncertainty resulting from variation in worker productivity is a reasonable characterisation of the South African labour marker. It was argued in section two that the majority of South African workers receive low and variable quality of pre-tertiary schooling. This has had the effect of reducing the accuracy of schooling qualifications as a signal of worker quality. The prevailing labour market environment and conditions amplify the potential costs of uncertainty regarding worker quality to employers. There is prevailing perception by firms that dismissal costs and other labour market rigidities are very high in South Africa (Levinsohn, 2007, Schoer and Rankin, 2011 and Leibbrandt, Woolard, McEwen and Koep, xxx). The other labour market rigidities include adherence to minimum wage and affirmative action legislation, and bargaining council agreements (Leibbrandt et al, xxx). We therefore assume firms in our model to be risk-averse, not only for modelling convenience but also because it is a reasonable depiction of the South African labour market.

The firm's wage offer to at period t to a worker with observables $(\boldsymbol{s}, \hat{y}_0, \ldots, \hat{y}_t)$ is given by

$$w_t = E(y|\boldsymbol{s}, \hat{y}_0, \ldots, \hat{y}_t) - \delta Var(y|\boldsymbol{s}, \hat{y}_0, \ldots, \hat{y}_t) \qquad (3).$$

δ is a parameter that captures the importance of worker uncertainty on the firms wage offer. According to equation (3), wages are a negative function of the conditional variance of productivity. Thus, high variance workers incur a wage penalty and the importance of that penalty depends on δ.

This means that in period 0 the worker will earn

$$w_0 = E(y|\boldsymbol{s}, \hat{y}_0) - \delta Var(y|\boldsymbol{s}, \hat{y}_0) \qquad (4),$$

and solves to

$$w_0 = \alpha + \boldsymbol{\theta s} + \left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_e^2}\right)(\hat{y}_0 - \alpha - \boldsymbol{\theta s}) - \delta\left\{\sigma_u^2\left(\frac{\sigma_e^2}{\sigma_u^2+\sigma_e^2}\right)^2 + \sigma_e^2\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_e^2}\right)^2\right\} \qquad (5),$$

and in period t

$$w_t = \alpha + \boldsymbol{\theta s} + \left(\frac{{\sigma_u}^2}{{\sigma_u}^2+\left(\frac{1}{t+1}\right){\sigma_e}^2}\right)\left[\left(\frac{1}{t+1}\right)(\hat{y}_0 + \cdots + \hat{y}_t) - \alpha - \boldsymbol{\theta s}\right] - \delta\left\{\left(\frac{\left(\frac{1}{t+1}\right){\sigma_e}^2}{{\sigma_u}^2+\left(\frac{1}{t+1}\right){\sigma_e}^2}\right)^2 {\sigma_u}^2 + \left(\frac{{\sigma_u}^2}{{\sigma_u}^2+\left(\frac{1}{t+1}\right){\sigma_e}^2}\right)^2\left(\frac{1}{t+1}\right){\sigma_e}^2\right\} \quad (6)$$

The right-hand side of equation (6) comprises of the conditional expectation of productivity and the conditional expectation of the variance of productivity. Wages are therefore a function of the observable determinants of productivity, $\boldsymbol{\theta s}$, plus a constant. The next term represents the additional information, $(\hat{y}_0 + \cdots + \hat{y}_t) - \alpha - \boldsymbol{\theta s}$, that employers receive via interviews and evaluations of the worker's productivity weighted by the variances of worker productivity, σ_u^2 and noise in employers assessment of worker productivity, σ_e^2. This additional information becomes less important as the worker's tenure increases. This reflects the finding by Lange

(2007) that employer learning regarding worker's productivity is front-loaded and revealed early in an employment spell.

The last term in equation (6) captures the conditional variance of worker productivity. This term tends to zero, since with each successive period that an employee is evaluated the variance around the firm's prediction of the productivity of the employee gets smaller and smaller and tends to zero when t (tenure) tends to infinity.

Equation (6) locates the sources of individual wage growth in two places. Firstly, wages grow as the firm acquires new information,$(\hat{y}_0 + \cdots + \hat{y}_t) - \alpha - \boldsymbol{\theta s}$, and this additional information allows it to more accurately assess the worker's productivity. Secondly, the additional information removes the uncertainty regarding the worker's productivity and thus the penalty attached to the uncertainty gets smaller and allows the wages to converge on the worker's expected productivity.

Model predictions

To demonstrate discrimination, we follow Aigner and Cain (1977) who arge and show that discrimination results from differences in earnings across groups that is not related to differences in average ability between the groups. As such, consider two groups of workers (group 1 and group 2) with equal average productivity, expressed as $E(y_1) = E(y_2) = \mu$. To distinguish group 1 workers from group 2 workers, we further assume that the former has a larger conditional variance of productivity, $\sigma_{u1}^2 > \sigma_{u2}^2$, given the signal of productivity, $\hat{y}_t$. This is the key assumption in models of statistical discrimination and it determines the direction of discrimination (Aigner and Cain, 1977). In accordance with these models, group 1is considered the minority group, whom we will attempt to demonstrate discrimination against. Consequently, we also assume that group 1 workers have a nosier signal of worker productivity. This implies $\sigma_{e1}^2 > \sigma_{e2}^2$.

From equation (5), which depicts initial wages, we can locate two sources of lower initial average wages for group 1 workers relative to group 2 workers. Firstly, conditional on $\boldsymbol{s}$ – observable determinants of worker productivity, group 2 initial wages are larger because employers are able to extract more information, $(\hat{y}_0 - \alpha - \boldsymbol{\theta s})$, from group 2 workers at the hiring stage. This is implied by the assumption of more precision in the signal of worker productivity, $\hat{y}_0$, for group 2 workers.

DRAFT

Secondly, the last term of in equation (5) indicates that group 1 workers are penalised for greater dispersion around their productivity. With $\sigma_{u1}^2 > \sigma_{u2}^2$, uncertainty is larger for group 1 workers and this leads to lower initial average wages because initial wages are a negative function of the worker uncertainty component of equation (5). Putting these two sources together, our model, therefore, predicts lower initial average wages for group 1 workers compared to group 2 workers. The lower initial average wages for group 1 workers is not related to average productivity differences between the two groups and therefore constitutes statistical discrimination.

Given the greater *ex ante* uncertainty regarding the expected productivity of group 1 workers, the employer learning hypothesis predicts greater subsequent relative wage growth for these workers. The uncertainty gets resolved as the employer views the worker's output on the job and then updates the initial assessment of the worker's productivity. From equation (6), $(\hat{y}_0 + \cdots + \hat{y}_t) - \alpha - \boldsymbol{\theta s}$ locates the source of wage growth for these workers. Employer learning matters less for group 2 workers since the initial signal ($\hat{y}_0$) of worker productivity was more informative. As the uncertainty gets resolved, the wage penalty associated with the uncertainty falls. This is a standard result of employer learning models and suggests that changes in wages result from the arrival of new information regarding worker productivity (Kahn and Lange, 2014, and Sicilian, xxxx).

In section two, we argued that blacks, young men and men with only complete secondary schooling (matric) face a larger degree of *ex ante* uncertainty regarding their expected productivity. This is because these groups of workers, relative to their respective counterparts, rely heavily on school certificates to signal their ability to potential employers. However, we further argued that the low and variable quality of pre-tertiary schooling received by these workers has reduced the potency of pre-tertiary schooling certificates as credible signals of worker productivity. These workers are also not able to rely on previous work experience as a signal because these workers disproportionally make up the bulk of those classified as (long-term) unemployed. We, therefore, consider blacks, youth and those matric or less to be type 1 workers, while whites, older men and those with tertiary school qualifications to be the respective type 2 workers. The model's predictions discussed above therefore apply accordingly.

5. Data

The empirical analysis in the next section makes use of the panel version of the Labour Force Surveys (LFS) conducted by Statistics South Africa (Stats SA). The LFS are nationally representative cross-sectional household surveys that are designed to monitor developments in the South African labour market. The surveys were conducted twice yearly – March and September – from September 2000 to September 2007 when they were replaced by the Quarterly Labour Force Surveys. The LFS were designed as a rotating panel of dwelling units with 20% of these units dropped in subsequent waves and replaced with new dwelling units (Stats SA, 2006). The rotations were designed in such a way that a total sample of 30 000 households was maintained in each wave.

Stats SA's Labour Force Survey Panel (LFSP) is the first nationally representative panel dataset of the South African labour market (Banerjee et al, 2008). It was constructed from the LFS cross-sectional surveys running from September 2001 to March 2004 after the collection, processing and release of the individual LFS waves (Stats SA, 2006). The LFPS was constructed afterwards because the original LFS were only initially intended as a rotating panel of dwelling units and not of individuals or households (Stats SA, 2006).

Panel data is necessary for our empirical analysis because our estimation relies heavily on the tenure variable and panel data offers a unique opportunity to deal with inconsistencies in the tenure variable. We therefore use the version of the LFSP used in Burger (2016). The author implements a cleaning algorithm that addresses concerns regarding the consistency of the tenure variable.

The estimation sample is restricted to black and white 18 to 60 year old males working in formal and private sector jobs. Workers in subsistence agriculture and those reporting to be self-employed were also excluded from the analysis.

6. Empirical analysis

Part A

This section discusses presents the results of our descriptive analysis and parameter estimation of our statistical discrimination model. The descriptive analysis is based on Ordinary Least Squares estimation and relies on group variation in the average wage gain due to the accumulation of the first year of tenure as a 'measure' of employer learning. The estimated employer learning is then used to infer about the productivity signalling of our two groups (black and white men). Assuming that employers set wages equal to expected productivity conditional on a worker productivity signal, initial average wages for a minority (discriminated) worker will be lower relative to his 'true' productivity. This is due to the greater difficulty of predicting this worker's productivity. The lower initial wage relative to 'true' productivity can also be interpreted as the cost or compensation that a risk-averse employer will have to receive to incentivise the hiring of a worker whose productivity is more uncertain.

This suggests a larger gap between initial wages and 'true' productivity for minority workers (i.e. black men, youth and matriculants). If employers continue to equate wages to expected productivity in each period then as the uncertainty around the worker's productivity is revealed by observing the worker's output, then actual wages should converge to true productivity. Therefore, there should be more rapid wage growth for these workers since employers were assumed to be more uncertain about the productivity of these workers. Since employer learning occurs early in an employment spell (Lange, 2007), a noisy initial productivity signal should imply a steeper wage tenure profile. This is indeed the prediction made and empirically tested by Oettinger (1996), Lewis and Terrell (2001), and Goldsmith et al (2006) for the U.S.

To operationalise the above, I estimate a (pooled) OLS wage (expressed as the natural logarithm of hourly wage rate) regression controlling for variables that proxy for human capital, demographic characteristics and labour market characteristics. I then add a dummy variable ('*oneyear'*) equal to one if tenure is larger or equal to one, and zero otherwise. Adding this dummy variable in our hourly log wage regression ensures that the average wage gain due to the accumulation of the first year of tenure is not restricted by the quadratic specification of tenure (Altonji and Shakotko, 1987). 'o*neyear'* is then interacted with race, age, and education.

Table 1 presents pooled OLS wage regressions but only reports coefficients for our key variables of interest. Other variables that are controlled for but not shown in Table 1 include province, firm size, wave fixed effects, household head status, and geo type (i.e. rural vs urban), occupation and industry dummies.

In Table 1, we specify schooling as a spline with knots at 7 years of schooling (*primary* – completed primary schooling), 11 years of schooling (*secondary* – incomplete secondary schooling), 12 years of schooling (*matric* – completed secondary schooling), and then the last knot represents those with more than 12 years of schooling (*tertiary*). We specify a separate dummy variable for individuals with 12 years of schooling plus diploma or certificate not obtained from a university (*diploma + certificate*).

Table 1: Log hourly wage regression, pooled OLS

Variables	1	2	3	4
Primary	0.0307 (0.0023)***	0.0306 (0.0023)***	0.0307 (0.0023)***	0.0307 (0.0023)***
Secondary	0.0740 (0.0037)***	0.0743 (0.0037)***	0.0744 (0.0037)***	0.0739 (0.0037)***
Matric	0.1573 (0.0124)***	0.1577 (0.0124)***	0.1576 (0.0124)***	0.1272 (0.0197)***
Diploma+Certificate	0.2094 (0.0202)***	0.2091 (0.0202)***	0.2094 (0.0202)***	0.2322 (0.0417)***
Tertiary	0.1481 (0.0090)***	0.1483 (0.0090)***	0.1485 (0.0090)***	0.1820 (0.0157)***
Black	-0.7190 (0.0131)***	-0.7744 (0.0237)***	-0.7186 (0.0131)***	-0.7187 (0.0131)***
Tenure	0.0288 (0.0019)***	0.0287 (0.0019)***	0.0291 (0.0019)***	0.0290 (0.0019)***
Tenure^^{2}	-0.0006 (0.0001)***	-0.0006 (0.0001)***	-0.0006 (0.0001)***	-0.0006 (0.0001)***
Potential Experience	0.0239 (0.0015)***	0.0242 (0.0015)***	0.0245 (0.0017)***	0.0238 (0.0015)***
Potential Experience^^{2}	-0.0003 (0.00003)***	-0.0003 (0.00003)***	-0.0003 (0.00003)***	-0.0003 (0.00003)***
Oneyear	0.0464 (0.0120)***	-0.0160 (0.0251)	0.0404 (0.0152)***	-0.0660 (0.0536)
Oneyear*Black		0.0731 (0.0254)***		
Oneyear*Young			0.0190 (0.0286)	
Oneyear*NoMatric				0.1054 (0.0541)*
Oneyear*Matric				0.1474 (0.0554)***
Oneyear*Diploma+Certificate				0.0702 (0.0677)
Intercept	1.4232 (0.0510)***	1.4700 (0.0538)***	1.4142 (0.0530)***	1.4293 (0.0511)***
R^2	0.6429	0.6430	0.6429	0.6430
N	30,001	30,001	30,001	30,001
Other controls	Yes	Yes	Yes	Yes

Other control variables: occupation, industry, rural/urban classification, province of residence, household head status, firm size, and wave dummies.
Robust standard errors are contained in parentheses.
** p<0.1; ** p<0.05; *** p<0.01*

We observe from column 1 that the return to incomplete secondary schooling (0.0740) is more than double that of primary schooling (0.0307). Completing secondary schooling (matric) brings about a further doubling of the returns to schooling (0.1573). A year of tertiary schooling increases the returns by a further 0.1481. While a post-secondary diploma or certificate is worth 0.2094 regardless of how long an individual took to complete it.

The negative and very large coefficient (-0.7190) on the black dummy variable indicates substantially lower average wages for black men compared to white men. On the other hand, South African men receive roughly equal returns to tenure and (potential) labour market experience. However, the coefficient on *oneyear* seems to suggest that a sizeable proportion of the wage returns to tenure accrue within the first year of an employment spell. Column 2 to 4 tries to determine whether the wage gain due to the accumulation of the first year of tenure differs by race, age and level of schooling completed.

In column 2, the coefficient on the *oneyear* variable interacted with black is large and statistically significant. This suggests that, with everything else held constant, black men enjoy much rapid average wage growth within the first year of an employment spell relative to white men. Turning attention to age in column 3, the interaction term is small and statistically insignificant. This suggests that there is no difference in the wage gain in the first year of an employment spell by age.

In column 4, instead of interacting the schooling splines with *oneyear,* we instead specify schooling dummy variables and interact these with *oneyear*. *NoMatric* takes on a value of one for individuals with 11 years or less of schooling, and zero otherwise. *Matric* takes on a value of one for individuals with 12 years of schooling, and zero otherwise. *Diploma + Certificates* is specified the same way as above. Individuals with tertiary schooling act as the comparison (omitted) group. The results in column 4 indicate that men with 12 years of schooling and less enjoy more rapid wage growth relative to men with post-secondary schooling. Interestingly, men with exactly 12 years of schooling (complete secondary schooling – matric) experience the most rapid wage growth in the first year of an employment spell. Moreover, those with diplomas and certificates have wage growth that is similar to those with bachelors.

The overwhelming picture painted by Table 1 is that black men and those who are less educated appear to enjoy much greater wage growth in the first year of an employment spell. We interpret this evidence consistent with greater *ex ante* uncertainty about the productivity of these workers, driven mainly by these workers having less informative productivity signals. Consequently, they benefit the most from ‘employer learning’ and uncertainty being resolved.

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In Table 1, we implicitly assumed that employer learning or the resolving of worker uncertainty takes place within the first year of an employment spell. To test the robustness of our results, we repeated the exercise[1] performed in Table 1 but focusing on the wage gain due to the accumulation of the first two years of an employment spell. This change in specification did not alter the overall pattern of the results presented in Table 1.

A further robustness check performed is correction for sample selection bias that arises in wage regressions based on South African labour data. With high unemployment and likelihood of obtaining employment varying by race, level of schooling and age, wage earners are very likely to be a non-random sample of the working-age population. We address this issue by running a Heckman sample selection model. This too does not alter the general pattern of the results presented in Table 1.

In Table 2, we explore alternative channels through which employer learning and the resolving of worker uncertainty can work through. Faced with uncertainty about the potential productivity of a worker, a potential scenario that may arise is for the firm to hire that worker on a contract or on non-permanent basis. If the worker proves to be a good hire, the firm could then award that worker with a written contract or permanent employment.

In Table 2a, we estimate the same regression as in Table 1 but with a dummy variable (*contract*) that takes on a value of one if an individual has written contract of employment, zero otherwise, as the dependent variable. In Table 2b, the dependent variable is a dummy variable (*permanent*) that takes on a value of one if an individual's employment is on a permanent basis and zero if it is casual, fixed-term, or seasonal. The results obtained from these tables seem to support the earlier results. Firstly, black and less educated men are more likely to be hired without a written contract and on a non-permanent basis due to more uncertainty about their expected productivity. Secondly, these workers then enjoy a greater likelihood of being offered a written contract and transitioning into permanent employment in the first year of an employment spell relative to their respective counterparts.

These first set of results have illustrated that black and less educated men face lower initial labour market conditions. These workers have lower wage returns, and are less likely to have written contracts of employment and to be employed on permanent basis. We hypothesised that this may partly be due to these workers having greater *ex ante* uncertainty regarding their

[1] Results are available but not yet reported in this version of the draft.

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Table 2a: Contract likelihood regression, pooled OLS

Contract (yes=1; no=0)	1	2	3	4
Oneyear	0.0750 (0.0079)***	-0.0030 (0.0135)	0.0812 (0.0099)***	-0.0348 (0.0218)
Oneyear*Black		0.0938 (0.0139)***		
Oneyear*Young			-0.0194 (0.0192)	
Oneyear*NoMatric				0.1410 (0.0226)***
Oneyear*Matric				0.0804 (0.0235)***
Oneyear*Diploma+Certificate				-0.0186 (0.0300)
R^2	0.20	0.20	0.20	0.20
N	31,279	31,279	31,279	31,279
Other controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes

Table 2b: Permanent employment likelihood, pooled OLS

Permanent (yes=1; other=0)	1	2	3	4
Oneyear	0.1797 (0.0077)***	0.0005 (0.0123)	0.1752 (0.0094)***	0.0290 (0.0248)
Oneyear*Black		0.2155 (0.0132)***		
Oneyear*Young			0.0139 (0.0180)	
Oneyear*NoMatric				0.1922 (0.0255)***
Oneyear*Matric				0.1074 (0.0261)***
Oneyear*Diploma+Certificate				0.0087 (0.0327)
R^2	0.24	0.25	0.24	0.24
N	31,665	31,665	31,665	31,665
Other controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes

Other control variables: race dummy, schooling spline, tenure, tenure-squared, potential experience, potential experience-squared, occupation, industry, rural/urban classification, province of residence, household head status, firm size, and wave dummies.
Robust standard errors are contained in parentheses.
** p<0.1; ** p<0.05; *** p<0.01*

expected productivity. Employer learning therefore matters more for these workers. Consistent with this hypothesis, these workers were shown to have more rapid wage growth and greater likelihood of receiving contracts of employment and permanent employment in first year of an employment spell. This is evidence in support of the predictions of our theory model. We now turn to direct estimation of the structural parameters of the theory model.

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Part B

The structural parameters of the theory model are estimated using maximum likelihood estimation. The estimable equation is given by equation (7) below and represents expected log hourly wage conditional on $\boldsymbol{s}$ and t:

$$E(w_t|\boldsymbol{s},t) = \alpha + \boldsymbol{\theta s} - \delta \left\{ \sigma_u^2 \left(\frac{\left(\frac{1}{t+1}\right) \quad \sigma_e^2}{\sigma_u^2 + \left(\frac{1}{t+1}\right) \quad \sigma_e^2} \right)^2 + \left(\frac{\sigma_u^2}{\sigma_u^2 + \left(\frac{1}{t+1}\right) \quad \sigma_e^2} \right)^2 \left(\frac{1}{t+1}\right) \quad \sigma_e^2 \right\} \qquad (7)$$

And we specify our observable determinants of worker productivity as $\boldsymbol{s} = f(schooling, labour\ market\ experience, black, tenure)$. We then allow the variance of worker productivity to be determined by this function $\sigma_u^2 = \exp(\rho + \boldsymbol{\lambda z})$, with $\boldsymbol{z} = f(schooling\ dummies, age, black)$.

For purposes of identification, we normalize σ_e^2 to 1. (We experimented with different normalization values and the parameter estimates were not substantially different.) We then restrict the estimation sample to individuals with a tenure value that is equal to or less than 20 years.

In Table 3, we present results for the restricted and unrestricted model. The restricted model is essentially a Mncerian wage regression estimated by maximum likelihood. The unrestricted model is defined by equation (7) and estimates both wages and the dispersion in wages. The top panle of Table 4 shows that the parameter estimates are very similar across the two models. The one exception though is the coefficients on the tenure and tenure-squared terms. The unrestricted model shows a much smaller estimated wage return that is linear and not concave – the tenure-squared coefficient is statistically insignificant and cannot be distinguished from zero. This points to part of the wage return tenure in the restricted model representing the effects of employer learning as uncertainty is resolved. Accounting for the dispersion in wages as we do in the unrestricted model makes the tenure wage profile linear as depicted by figure 1 below. In the context of our theoretical model, the non-linearity in the wage tenure profile is driven by or accounted for by the non-linearity in the rate of employer learning.

Because the restricted model is nested within the unrestricted model, we can perform a likelihood ratio test of the two models. The likelihood ratio test static is 3404.88 and leads us to strongly reject the null hypothesis and thus to prefer the unrestricted model.

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Table 3: Estimation of theoretical model, maximum likelihood estimation

	Unrestricted	Restricted
Log hourly wage		
Primary	0.0761	0.0763
	(0.0030)**	(0.0041)**
Secondary	0.1358	0.1395
	(0.0044)**	(0.0059)**
Matric	0.2353	0.2362
	(0.0145)**	(0.0196)**
Diploma+Certificate	0.2839	0.2937
	(0.0235)**	(0.0301)**
Tertiary	0.2631	0.2619
	(0.0084)**	(0.0102)**
Potential experience	0.0480	0.0492
	(0.0017)**	(0.0023)**
Potential experience^^{2}	-0.0006	-0.0006
	(0.00004)**	(0.00005)**
Black	-0.9360	-0.9091
	(0.0139)**	(0.0187)**
Tenure	0.0208	0.0490
	(0.0070)**	(0.0037)**
Tenure^^{2}	0.0001	-0.0010
	(0.0003)	(0.0002)**
Intercept	1.1312	0.8919
	(0.0551)**	(0.0408)**
Variance		
No Matric dummy	-0.1271	
	(0.0193)**	
Matric dummy	-0.0946	
	(0.0196)**	
Diploma + Certificate	-0.0670	
	(0.0236)**	
Age	-0.0240	
	(0.0025)**	
Age^^{2}	0.0003	
	(0.00003)**	
Black	0.0705	
	(0.0099)**	
Intercept	0.3808	
	(0.0491)**	
Delta	0.5099	
	(0.1131)**	
LR chi2(8)	3404.88	
N	28,138	28,138

* *p*<0.05; ** *p*<0.01

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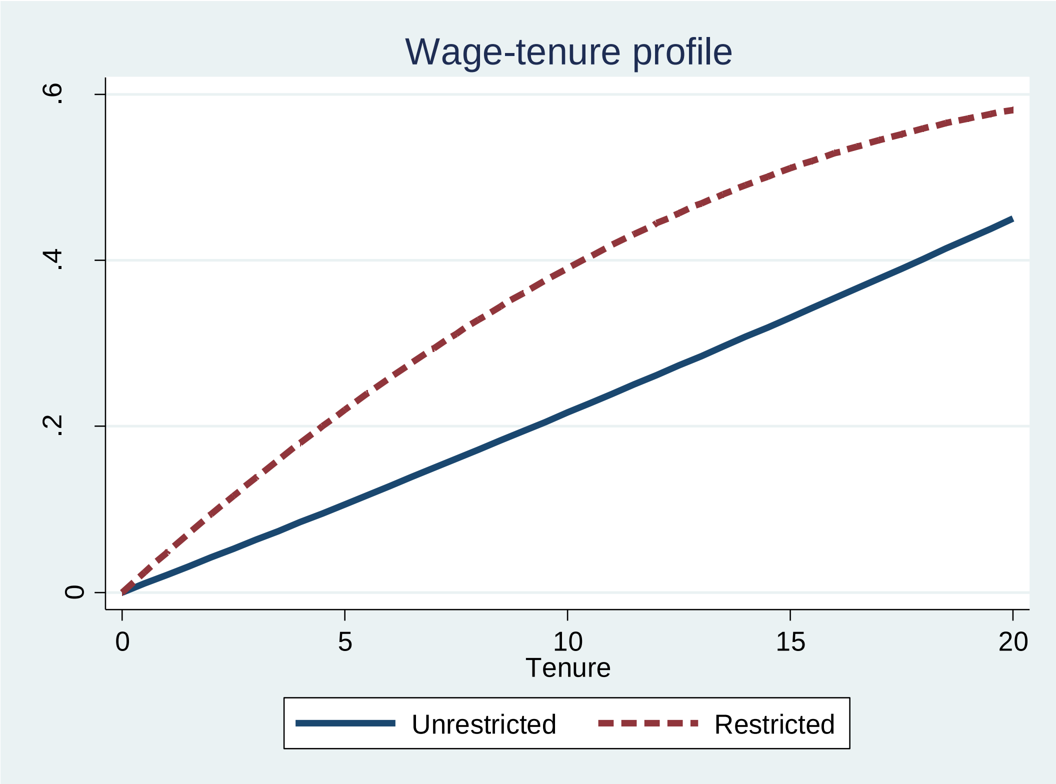

Figure 1

The bottom panel of Table 3 reports the results for the wage variance estimation from the unrestricted model. We specify the same schooling dummies as in Table 1 and 2. The results suggests that, relative to men with tertiary schooling, there is less wage dispersion for those with lower years of schooling. This could reflect the nature of jobs (occupation and industries, more generally) that the least educated self-select themselves into. Another possibility is that schooling qualifications generates less or imprecise information regarding the expected productivity of these workers and consequently everyone is paid a similar wage. Whereas with tertiary schooling qualifications, employers are able to use information about the quality of the tertiary institution or degree to distinguish among workers.

The coefficients on the age variables suggests that the wage dispersion decreases with age non-linearly. This results is a bit surprising as it points to lower dispersion for older workers. The pure employer learning model predicts that wages dispersion increases with age as employers acquire additional information that allows them to further distinguish among workers (Kahn and Lange, 2014). This result therefore needs further investigation.

The large and statistically significant coefficient on black (0.0705) indicates that there is greater wage dispersion for blacks relative to whites. This provides evidence of our hypothesis of more uncertainty regarding the ability of black workers. Worker ability for blacks is more uncertain because of low and variable school performance. In our model, the importance of worker uncertainty is determined by delta (δ). This parameter is estimated as 0.5099 and suggests workers with greater uncertainty are penalised.

In the bottom panel of Table 4 below, we rely on our alternative measure of age – i.e. young. We then interact our variables of interest together. We see that wage dispersion (i.e. uncertainty regarding worker ability) is larger if a worker is black, young and has 12 years of schooling (matric). Matric certificate is associated with greater wage dispersion for younger workers (see interaction of young and matric in column 4). This is in line with school quality being more variable and of less quality for younger birth cohorts. We further observe in column 2 that young black men have larger wage dispersion because of their youthfulness, race and the interaction of these two attributes.

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Table 4: Estimation of theoretical model, maximum likelihood estimation

	1	2	3	4
Log hourly wage				
Primary	0.0755	0.0755	0.0755	0.0755
	(0.0030)***	(0.0030)***	(0.0030)***	(0.0030)***
Secondary	0.1356	0.1355	0.1357	0.1357
	(0.0044)***	(0.0044)***	(0.0044)***	(0.0044)***
Matric	0.2350	0.2346	0.2337	0.2355
	(0.0146)***	(0.0146)***	(0.0146)***	(0.0146)***
Diploma+Certificate	0.2846	0.2845	0.2835	0.2848
	(0.0235)***	(0.0235)***	(0.0234)***	(0.0235)***
Tertiary	0.2618	0.2625	0.2607	0.2620
	(0.0084)***	(0.0084)***	(0.0085)***	(0.0084)***
Potential experience	0.0487	0.0487	0.0486	0.0487
	(0.0017)***	(0.0017)***	(0.0017)***	(0.0017)***
Potential experience^^{2}	-0.0006	-0.0006	-0.0006	-0.0006
	(0.00003)***	(0.00003)***	(0.00003)***	(0.00003)***
Black	-0.9308	-0.9312	-0.9317	-0.9311
	(0.0139)***	(0.0138)***	(0.0139)***	(0.0139)***
Tenure	0.0217	0.0210	0.0225	0.0219
	(0.0071)***	(0.0071)***	(0.0071)***	(0.0071)***
Tenure^^{2}	0.0001	0.0001	0.0000	0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Intercept	1.1190	1.1244	1.1162	1.1175
	(0.0553)***	(0.0550)***	(0.0553)***	(0.0553)***
Variance				
No Matric dummy	-0.1215	-0.1192	-0.1289	-0.1212
	(0.0193)***	(0.0194)***	(0.0199)***	(0.0193)***
Matric dummy	-0.0955	-0.0938	-0.0780	-0.1077
	(0.0196)***	(0.0196)***	(0.0226)***	(0.0208)***
Diploma+Certificate	-0.0699	-0.0682	-0.0727	-0.0691
	(0.0236)***	(0.0236)***	(0.0237)***	(0.0236)***
Black	0.0630	0.0515	0.0774	0.0619
	(0.0098)***	(0.0121)***	(0.0134)***	(0.0099)***
Young	0.0984	0.0576	0.0990	0.0851
	(0.0123)***	(0.0271)**	(0.0123)***	(0.0144)***
Black*Young		0.0505		
		(0.0301)*		
Black*Matric			-0.0307	
			(0.0197)	
Young*Matric				0.0456
				(0.0268)*
Intercept	-0.0802	-0.0730	-0.0863	-0.0769
	(0.0189)***	(0.0194)***	(0.0193)***	(0.0190)***
Delta	0.4888	0.5021	0.4773	0.4857
	(0.1137)***	(0.1139)***	(0.1138)***	(0.1137)***
N	28,138	28,138	28,138	28,138

7. Conclusion

This paper investigates the impact of imperfect information between employees and employers and its impact on the average wages of black and white South African men. The paper develops a theory model that incorporates uncertainty about workers' productivity and learning by employers in a developing country characterised by high unemployment and other labour market features that are strongly correlated to race. The theory model was tested both directly and indirectly. The indirect testing involved an OLS descriptive analysis that exploits group variation in the tenure profile. The direct testing involved maximum likelihood estimation of the structural parameters of the theory model. The results provide evidence of imperfect information contributing to the wage-gap between black and white South African men.

8. References

Abraham, K.G. and Farber, H.S. (1987) Job duration, seniority, and earnings. *American Economic Review*, 77(3): 278-297.

Aigner, D.J. and Cain, G.G. (1977) Statistical theories of discrimination in labor markets. *Industrial and Labor Relations Review,* 30(2): 195-187.

Altonji, J.G. and Blank, R.M. (1999) Race and gender in the labor market. In Ashenfelter, O. and Card, D. (eds.), Handbook of Labor Economics, 3C: 3143-3259. Amsterdam: Elsevier Science.

Altonji, J.G. and Pierret, C.R. (2001) Employer learning and statistical discrimination. *The Quarterly Journal of Economics*, 116(1): 313-350.

Altonji, J.G. and Shakotko, R.A. (1987) Do wages rise with job seniority? *Review of Economic Studies*, 54: 437-459.

Arrow, K. (1973) The theory of discrimination. In Ashenfelter, O.A. and Rees, A. (eds.), *Discrimination in labor markets,* 3-33. New Jersey: Princeton University Press.

Becker, G.S. (1962) Investment in human capital: A theoretical analysis. *Journal of Political Economy*, 70(5): 9-49.

Ben-Porath, Y. (1967) The production of human capital and the life cycle of earnings. *Journal of Political Economy*, 75(4): 352-365.

Branson, N., Ardington, C., Lam, D. and Leibbrandt, M. (2013) Changes in education, employment and earnings in South Africa – A cohort analysis. University of Cape Town, *SALDRU Working Paper*, 105.

Branson, N., Garlick, J., Lam, D. and Leibbrandt, M. (2012) Education and inequality: The South African case. University of Cape Town, *SALDRU Working Paper*, 75.

Branson, N. and Leibbrandt, M. (2013) Education quality and labour market outcomes in South Africa. *OECD Economics Department Working Papers*, 1021.

Bratsberg, B. and Terrell, D. (1998) Experience, tenure, and wage growth of young black and white men. *The Journal of Human Resources*, 33(3): 658-682.

Burger, R.P. and Teal, F.J. (2014) The effect of schooling on worker productivity: Evidence from a South African industry panel. *Stellenbosch Economic University, Department of Economics Working Papers,* 04/14.

Burger, R.P. and Jafta, R. (2006) Returns to race: Labour market discrimination in post-apartheid South Africa. *Stellenbosch University, Department of Economics Working Papers,* 04/2006.

Duff, P. and Fryer, D. (2005) Market failure, human capital, and job search dynamics in South Africa: The case of Duncan village. *DPRU Working Paper,* 05/98.

Erichsen, G. and Wakeford, J. (2001) Racial wage discrimination in SA before and after the first democratic election. University of Cape Town, University of Cape Town, *DPRU Working Papers*, 01/49.

Garen, J.E. (1989) Job-match quality as an error component and the wage-tenure profile: A comparison and test of alternative estimators. *Journal of Business & Economic Statistics*, 7(2): 245-252.

Harris, M. and Holstrom, B. (1982) A theory of wage dynamics. *Review of Economic Studies*, 49(3): 315-333.

Jovanovic, B. (1979) Job matching and the theory of turnover. *Journal of Political Economy*, 87(5): 972-990.

Kerr, A. and Teal, F.J. (2015) The determinants of earnings inequalities: Panel data evidence from KwaZulu-Natal, South Africa. *Journal of African Economies,* 1-29.

Keswell, M. and Poswell, L. (2004) Returns to education in South Africa: A retrospective sensitivity analysis of the available evidence. *South African Journal of Economics*, 72 (4):834-860.

Lange, F. (2007) The speed of employer learning. *Journal of Labor Economics*, 25(1): 1-35.

Lazear, E.P. (1981) Agency, earnings profiles, productivity, and hours restrictions. *American Economic Review*, 71(4): 606-620.

Leibbrandt, M., Finn, A., and Woolard, I. (2012) Describing and decomposing post-apartheid income inequality in South Africa. *Development Southern Africa*, 29(1): 19-34.

Leibbrandt, M., Woolard, I., Finn, A., and Argent, J. (2010) Trends in South African income distribution and poverty since the fall of apartheid. *OECD Social, Employment and Migration Working Papers*, 101.

Levinsohn, J. (2007) *Two policies to alleviate unemployment in South Africa*. Mimeo. University of Michigan.

Lewis, D. and Terrell, D. (2001) Experience, tenure, and the perceptions of employers. *Southern Economic Journal*, 67(3): 578-597.

Light, A. (1998) Estimating returns to schooling: When does the career begin? *Economics of Education Review*, 17(1): 31–45.

Light, A. and Ureta, M. (1995) Early-career work experience and gender wage differentials. *Journal of Labor Economics*, 13(1): 121-154.

Lundberg, S.J. and Startz, R. (1983) Private discrimination and social intervention in competitive labor markets. *American Economic Review*, 73: 340-347.

Mincer, J. (1974) *Schooling, experience, and earnings*. New York: Columbia University Press.

Mincer, J. and Jovanovic, B. (1981) Labor mobility and wages. In Sherwin Rosen (ed.), *Studies in Labor Markets*, 21-64. Chicago: University of Chicago Press.

Mwabu, G. and Schultz, T.P. (2000) Wage premiums for education and location of South African workers, by gender and race. *Economic Development and Cultural Change*, 48(2): 307-334.

Ntuli, M. and Kwenda, P. (2014) Labour unions and wage inequality among African men in South Africa. *Development Southern Africa*, 31(2): 322-346.

Oettinger, G. (1996) Statistical discrimination and the early career evolution of the black-white wage gap. *Journal of Labor Economics*, 14(1): 52-78.

Phelps, E.S. (1972) The Statistical Theory of Racism and Sexism. *American Economic Review*, 62(4): 659-661;

Rospabe, S. (2002) How did labour market racial discrimination evolve after the end of apartheid? *The South African Journal of Economics*, 70(1): 185-217.

Salop, J. and Salop, S (1976) Self-selection and turnover in the labor market. *Quarterly Journal of Economics*, 90(4): 619-627.

Schoer, V., Rankin, N., and Roberts, G. (2014) Accessing the first job in a slack labour market: Job matching in South Africa. *Journal of International Development*, 26: 1-22.

Statistics South Africa (2006). *The South African Labour Force Panel Survey methodology document*. National Statistics System Division, Pretoria

Szelewicki, M. and Tyrowicz, J. (2009) Labour market racial discrimination in South Africa revisited. *University of Warsaw Faculty of Economic Sciences, Working Paper*, 08/2009.

Topel, R. (1991) Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of Political Economy*, 99(1): 145-176.

Van der Berg, S. (2014) Inequality, poverty and prospects for redistribution. *Development Southern Africa*, 31(2): 197-218.

Williams, N. (1991) Seniority, experience, and wages in the UK. *Labour Economics*, 16: 272–283.