An investigation of the labour market determinants of income dynamics for a highly unequal society: The South African case

by

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Declaration

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my original work, that I am the authorship owner thereof (unless to the extent explicitly otherwise stated) and that I have not previously in its entirety or part submitted it for obtaining any qualification.

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Abstract

South Africa ranks as the country with the highest income inequality in the world. Inequality of labour market outcomes drives most of this inequality. Labour market success (or failure) is a crucial determinant of where an individual or household is positioned on the income distribution. Furthermore, labour market outcomes in South Africa are characterised by a strong racial and gender hierarchy. Black women are on many levels the most disadvantaged with the lowest average earnings, highest unemployment, lower level of skill attainment, etc. They are consequently located at the bottom of this hierarchy regarding labour market outcomes. White men, on the other hand, are the most advantaged and are thus located at the top of this hierarchy.

Differences in labour market outcomes in South Africa have spawned a large body of literature that identifies pre-labour and labour market differences in the accumulation of and returns to human capital as the key determinants of labour market inequality. A smaller strand of the literature points to labour market discrimination and barriers to entry into wage employment as contributing factors to the inequality of labour market outcomes in South Africa. This dissertation contributes to both strands of the literature. It contributes to the first strand of the literature by investigating the two critical components of the dynamic structure of wages. This includes the wage returns to labour market experience and job tenure for different demographic groups. On-the-job training as a means of human capital investment and a source of inequality is mostly ignored in the South African literature on differences in labour market outcomes. The dissertation adds theoretical and empirical evidence of the importance of information asymmetry and statistical discrimination in the barriers to entry and labour market discrimination literature, respectively.

The empirical evidence presented in this dissertation is based on rigorous implementation and adaption of micro-econometric techniques to a nationally representative household South African panel dataset. The overall result points to better labour market outcomes for black workers regarding higher wage growth. This is due to the accumulation of on-the-job training and subsequent resolving of uncertainty regarding their expected productivity. This result is contrary to the stereotypical racial and gender hierarchy that sees black workers having inferior labour market outcomes. Additionally, this motivates the observed decline in inter-racial income inequality and the rise in intra-racial income inequality, especially amongst the black population.

Opsomming

Suid-Afrika word beskou as die land met die hoogste inkomste-ongelykheid ter wêreld. Meeste van hierdie ongelykheid word deur ongelykheid in terme van uitkomste in die arbeidsmark gedryf. Sukses (of mislukking) in die arbeidsmark is ’n sleutel determinant van waar ’n individueel of huishouding in die inkomste verspreiding geplaas word. Daarbenewens, word arbeidsmark uitkomste deur sterk ras- en geslag hiërargies gekenmerk. Swart vroumense is op baie vlakke die meeste benadeel (met die laagste gemiddelde inkomstes, hoogste werkloosheid, en die laagste verkryging-van-vaardighede vlakke), en is dus aan die laagste end van hierdie hiërargie in terme van arbeidsmark uitkomste. Blanke mans, aan die ander kant, is die meeste bevoordeel en is dus aan die boonste end van hierdie hiërargie.

Verskille in arbeidsmark uitkomste in Suid-Afrika het ’n groot liggaam literatuur geïnspireer wat verskille in die akkumulasie en opbrengs van menslike kapitaal (voor- en binne die arbeidsmark) as die sleutel determinante van arbeidsmark-ongelykheid identifiseer. ’n Kleiner deel van die literatuur wys na arbeidsmark diskriminasie en hindernesse tot toetrede as faktore wat bydra tot ongelykheid van arbeidsmark uitkomste in Suid-Afrika. Hierdie dissertasie dra by tot beide dele van die literatuur. Dit dra by tot die eerste deel van die literatuur deur die ondersoek van die twee sleutel komponente van die dinamiese struktuur van lone – die loonopbrengs verbonde aan arbeidsmark ondervinding en posbekleding vir verskillende demografiese groepe. Op-die-werk opleiding as ’n vorm van menslike kapitaal investering en as ’n bron van ongelykheid is grotendeels in die Suid-Afrikaanse literatuur oor verskille in arbeidsmark uitkomste geïgnoreer. Die dissertasie dra teoretiese en empiriese bewyse by oor die belangrikheid van inligting asimmetrie en statistiese diskriminasie in die hindernisse tot toetrede- en arbeidsmark diskriminasie literatuur.

Die empiriese bewyse wat in hierdie dissertasie aangebied word, is gebaseer op streng implementasie en aanpassing van mikro-ekonometriese tegnieke op ’n nasionaal–verteenwoordigende Suid-Afrikaanse stel paneeldata op die huishoudelike vlak. Die algehele resultaat wys na beter arbeidsmark uitkomste vir swart werkers in terme van hoër loongroei, as gevolg van akkumulasie van op-die-werk opleiding en opeenvolgende oplossing van onsekerheid rondom hul verwagte produktiwiteit. Hierdie resultaat is in teenstelling met die stereotipiese ras- en geslagshiërargie waar swart werkers minderwaardige arbeidsmark uitkomste ervaar. Daarbenewens, gee dit ’n motivering vir die waargeneemde afname in inter-ras inkomste ongelykheid en toename in intra-ras inkomste ongelykheid, veral onder die swart bevolking.

Table of Contents

CHAPTER 1

INTRODUCTION

1. BACKGROUND AND CONTEXT OF THE STUDY

Labour market success (or failure) is a crucial determinant of where an individual or household is positioned on the income distribution. The importance of the labour market for income distribution is perhaps more acute in the South African case where inequality of labour market earnings has been estimated to account for as much as 85% of overall income inequality[1] (Leibbrandt, Woolard, Finn & Argent, 2010). This reflected the high inequality among those in wage employment as measured by a Gini coefficient of 0.60 (van der Berg, 2014). Also, post-Apartheid data showed an increase in income inequality in the two decades following the political transition into democracy in 1994 (Leibbrandt, Finn & Woolard, 2012; and van der Berg, 2014). Consequently, income inequality remains a crucial challenge facing South Africa.

The South African labour market is not only the key contributor to the rising trend in income inequality; but the labour market failed in its role of reducing poverty. Leibbrandt, Woolard, McEwen & Koep (2009) identified the government's expansion of social support grants and not the performance of the labour market as the main driving force behind falling poverty in the post-Apartheid era.

A large body of literature investigated the determinants of labour market inequality among South African workers. Pre-labour market determinants are well understood and mainly relate to schooling outcomes for previously disadvantaged groups, regarding both quantity and quality (van der Berg, 2008). The labour market determinants identified in the literature are much broader. The determinants that have been studied most extensively are the returns to schooling (Branson, Garlick, Lam & Leibbrandt, 2012; and van der Berg, 2008 and 2014), and labour market discrimination (Burger & Jafta, 2006; Erichsen & Wakeford, 2001; Kingdon & Knight, 2004; Mlatsheni & Rospabe, 2002; Rospabe, 2002; and Szelewick & Tyrowicz, 2009). Other commonly identified determinants include (i) segmentation into union versus non-union (Ntuli

[1] The sources of income inequality in South Africa are broad and, *inter alia*, include returns to wealth and investments, access to financial capital, and ownership of immovable property. Leibbrandt, Woolard, Finn and Argent (2010) use survey data to decompose measured income inequality into its different sources within the constraints of the available data. The decomposition exercise highlights the importance of income earned from labour market activities in contributing to overall income inequality. This should however be interpreted with caution as the data does not permit measurement of all sources of income and those that are measured often suffer from measurement error.

& Kwenda, 2014; and Kerr & Teal, 2015), (ii) public versus private and formal versus informal (Kerr & Teal, 2015); and (iii) unproductive job search strategies (Duff & Fryer, 2005; and Schoer, Rankin, & Roberts, 2014, and Abel, Burger, Carranza & Piraino, 2017).

Part of the challenge for the performance of the labour market is that the economy underwent a structural shift in the 1970s from primary sectors to services sectors. This coincided with technological advancements that induced more skills-biased production methods (Bhorat, 2004; and Burger & Woolard, 2005). These trends resulted in growing demand for skilled workers, and a widening gap between high-skilled and low-skilled workers. Against this backdrop, this dissertation investigates the dynamic structure of individual wages for South African workers. To do this, we focus on the wage returns to labour market experience and job tenure, and how employer learning and productivity uncertainty shape these returns. Certain models (most notably the human capital model) interpret these wage effects as the consequence of skill accumulation within a given job and across different jobs. It is however, true that this is not the only interpretation of the relationship between wages on the one hand, and labour market experience and job tenure on the other hand. Nevertheless, the wage returns to labour market experience and job tenure are two key components of the dynamic structure wages and may indeed offer some insight into wage growth between individual workers.

By addressing issues of endogeneity and measurement error in the tenure and experience wage profiles, the dissertation brings us closer to being able to accurately measure the wage effects of 1) skill accumulation and 2) how much of these skills are transferrable between jobs (i.e. experience) and how much is not (i.e. tenure).

Labour market outcomes in South Africa exhibit a strong racial hierarchy that is most strikingly evident in the outcomes of black and white workers. For this reason, this dissertation will focus on black and white workers. This narrowed focus allows us to compare the outcomes of the most advantaged to the most disadvantaged groups. This hierarchy also has a gender dimension: black women are on many levels the most disadvantaged (e.g. lowest average earnings, highest unemployment, and lower level of skill attainment) and as such are located at the bottom of this hierarchy in terms of labour market outcomes. White men on the other hand are the most advantaged and are thus located at the top this hierarchy[2].

In terms of wage inequality, Leibbrandt et al. (2009) report that whites earned 5.1 times more than blacks in 1993 and this figure marginally improved to 4.4 times in 2008. Leibbrandt et al.

[2] More often than not, the experiences and outcomes for other groups (including coloureds and Indians) are located somewhere in the middle. The outcomes of coloureds are closer to the outcomes of blacks, while Indian's outcomes are closer to those of whites.

(2012) and van der Berg (2014) pointed out that rising aggregate income inequality is driven by rising within group as opposed to between-group income inequality. For this reason, the study also analyses gender differences within each racial group.

The empirical results presented in this study are based on the Labour Force Surveys (LFSs) and Labour Force Survey Panel (LFSP) collected by Statistics South Africa (Stats SA). The LFSs are nationally representative cross-sectional household surveys that were designed to monitor developments in the South African labour market. The surveys were conducted twice yearly in March and September, and from September 2000 to September 2007, when the Quarterly Labour Force Surveys replaced them. The LFS's 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.

The individual cross-sectional surveys running from September 2001 to March 2004 were pooled together for the analysis. These waves correspond to Stats SA's LFSP that is also used for the analysis. The LFSP is the first nationally representative panel data set on the South African labour market and tracks individuals over a four-year period in the latter years of the first decade into democracy. Much of the analysis would also have been possible with the National Income Dynamics Study (NIDS) data set, which covers a more recent period, contains a richer set of covariates and has more thoroughly documented sampling methodology and variable pre-processing. However, the NIDS data consists of fewer waves and substantially fewer observations per wave than the LFSP, which is why the latter was preferred for the analyses in this thesis. It is however, prudent and advisable to exercise a great deal of caution when interpreting the conclusions drawn with the LFS and LFSP datasets because of attrition and the data being somewhat dated.

2. THE CONTRIBUTION OF THIS STUDY TO OUR KNOWLEDGE

The wage returns to labour market experience and job tenure are two critical components of the dynamic structure of wages (Williams, 1991). Consequently, they are fundamental in understanding the dynamic aspects of wage inequality identified as the primary source of South Africa's income inequality. Most empirical studies of South African wage determinants treat labour market experience and job tenure as control variables that are included to ameliorate omitted variable bias. No direct causal interpretation is afforded to these variables. The regression coefficients for experience and job tenure are affected by various confounding factors, including measurement error, omitted variable bias, simultaneity and specification errors. Addressing these issues adds to our understanding of the role played by the labour market in terms of how experience within and across firms is rewarded and how the wage gaps between groups evolve over individuals' working careers.

Differences in the wage returns to labour market experience is an important determinant of between-group differences in wage growth, and the analysis in the thesis allows us to better understand these trends. For example, the thesis demonstrates that part of the reason of why black women are at the bottom of the income distribution is because their labour market experience is not rewarded at the same rate as other demographic groups. Accurate estimates of the returns to experience and tenure are important for other reasons as well, including an improved understanding of the costs of unemployment and high worker turnover, and the merits of the labour market interventions designed to address these problems.

This thesis attempts to address this shortcoming in the literature by studying the returns to labour market experience and job tenure. Chapter two explicitly acknowledges the measurement error inherent in using potential experience as a proxy for actual accumulated labour market experience, and proposes alternative measures that are likely to produce less biased estimates. Chapter three uses the panel component of the data to account for unobserved worker heterogeneity and match quality, factors that would otherwise bias the effect of job tenure on wages. Chapter four uses insights from economic theory and a non-linear systems estimator to separately identify the effects of employer learning and specific skills accumulation on the tenure-wage profile.

Another contribution of this thesis is that it adds evidence from a developing country to the debates regarding the measurement of tenure and experience effects. Theoretical, methodological and empirical advancements in labour economics and other sub-branches of economics usually occur with a focus on developed labour markets and institutions. However, these tools and insights may not necessarily be applicable to a developing country context. Empirical evidence from analyses of developed country data guides our understanding of labour market phenomena in developing countries and is often used to set policies in developing countries. Moreover, where there is empirical evidence based on developing country data, such evidence is sometimes derived using methodologies that make assumptions that are inappropriate for developing country setting. This thesis attempts to develop approaches to studying the returns to labour market experience and tenure that are more appropriate and cognisant of the unique features of the South African labour market.

Chapter two of this study explores a different methodology for constructing a proxy variable for labour market experience. This is relevant for any country in which long periods of non-employment is a common feature of the labour force, and where surveys that ask comprehensive retrospective questions on all previous unemployment spells are unavailable. This methodology pays specific attention to labour market features that are prevalent in developing country setting like high incidence of grade repetition at school. Chapter two scrutinises the validity of the potential experience proxy variable in the context of a high unemployment labour market. We find that the frequently used measure provides highly misleading estimates of the returns to labour market experience and inter-group wage profiles.

Chapter three is the first study, to our knowledge, to apply several techniques – which have produced diverging estimates of the returns to job tenure in developed labour markets – to developing country data. We show that South Africa conforms to the stylised facts found in the international literature: once we account for differences in worker heterogeneity and match quality the effect of job tenure on wages is small on average, but larger for disadvantaged groups.

Chapter four constructs a theoretical model that captures essential features of the South African labour market and schooling system, and that are also relevant to many other developing country labour markets. We show that worker groups that find it difficult to credibly signal their productivity to firms are penalised by a reduced likelihood of employment and low entry-level wages. This penalty is gradually reduced as the employer receives more information about the workers' true productivity.

CHAPTER 2

NOT REACHING YOUR POTENTIAL? ADJUSTING POTENTIAL EXPERIENCE FOR SOUTH AFRICAN WORKERS

ABSTRACT

On-the-job training is an important part of human capital accumulation, which allows workers to command higher earnings as they gain work experience. Mincer's (1974) suggestion to use years of potential experience as a measure of on-the-job training works well in contexts where labour market attachment is continuous and begins immediately after finishing school, but may be the source of substantial measurement error and estimation bias for women and other disadvantaged groups. We provide evidence of this bias in wage regressions for workers in a developing country characterised by high unemployment. Consequently, the chapter explores Elsby and Shapiro's (2011) method that uses the employment profile to address the measurement error in potential experience. Furthermore, the chapter provides an extension to this method that allows for the construction of a new proxy variable for labour market experience. These methods are relevant for any country in which long periods of non-employment is a common feature of the labour force, and where surveys that ask comprehensive retrospective questions on all previous unemployment spells are unavailable. These methods pay specific attention to labour market features that are prevalent in developing country setting like high unemployment and incidence of grade repetition at school. Our results suggest that the negative wage "effects" of gender and race are substantially smaller when replacing Mincer's measure of potential experience with alternative measures that allow heterogeneity in time spent outside of the labour market. In contrast to the results from traditional Mincerian regressions, different groups of South African workers earn roughly similar wage returns to actual labour market experience.

1. INTRODUCTION

Economic models have made important contributions towards our understanding of the distribution of individual earnings. Polachek (2007:5) points out that this understanding "gets at the very core of social science because it answers questions regarding the very foundations behind human well-being". One important determinant of individual earnings is the returns to on-the-job investment in human capital that accrues to individuals as they gain work experience. By incorporating on-the-job investment into a model of school investment and earnings, Mincer (1974) pioneered, what would become the most frequently used empirical tool in the analysis of individual earnings.[3] Mincer's model assumes that on the-job investment is a deterministic function of labour market experience, which he proposed measuring as years of potential experience: age minus years of schooling minus six. Accordingly, potential experience would be identical to and would serve as a good measure for labour market experience in the absence of direct measures if workers are (1) continuously attached to the labour market, and (2) they begin their working careers directly after completing schooling (Mincer, 1974). A third assumption, not explicitly stated in Mincer's original work, is that there should be no grade repetition, and that all learners start their schooling at age 6.

When Mincer developed his model, most survey questionnaires asked questions on age and schooling, but not for a complete work history of respondents – the responses to which could be used to construct direct measures of labour market experience. This data limitation necessitated the use of potential experience in the absence of a direct measure of actual labour market experience. It also meant that Mincer's model could be estimated on most labour market data sets and with simple regression techniques, which facilitated its widespread use. However, since the 1970s, many developed countries have seen the occasional addition of survey modules that ask probing questions about work history. Given the time cost involved in such modules, they are still rare in developing countries. Unfortunately, it is in these countries where work and school interruptions and long periods of non-employment are most common, and hence where Mincer's potential experience proxy will be a less accurate measure of actual work experience. Fertility rates and household sizes are higher as well in developing countries, which further contributes to the high rates of non-participation and employment interruptions. These features of developing country labour markets and inherent data limitations cast doubt over the appropriateness of using potential experience as a proxy for actual labour market experience.

[3] Others have described Mincer's earnings model as "the most widely accepted empirical specification in economics" (Murphy & Welch, 1990:202), and "the 'workhorse' of empirical research on earnings determination" (Lemieux, 2006:128).

This chapter investigates the effects of using potential experience in Mincerian earnings regression in the context of a labour market where deviations between potential and actual work experience is the norm rather than the exception. South Africa is characterised by high unemployment, frequent work interruptions and lengthy unemployment spells, and high rates of grade repetition. Our empirical analysis will demonstrate that Mincer's (1974) pre-conditions for the validity of potential experience as a 'good' proxy measure for labour market experience are violated in the sample of South African workers. The developed country literature (for example Filer, 1993; Miller, 1993; Light & Ureta, 1995; Regan & Oaxaca, 2009; and Blau & Kahn, 2013) has documented that such violations render the estimates from traditional and augmented Mincerian earnings functions unreliable. More precisely, the estimated wage return to labour market experience is understated, the wage returns to schooling is overstated, and the racial and gender wage gaps due to employment interruptions is incorrectly attributed to wage discrimination.

The existing literature on the shortcomings of using potential experience is almost entirely restricted to developed country labour markets, and has usually focussed on violations of Mincer's first pre-condition (due to interruptions in labour force attachment of women). A notable exception that looks at the violation of Mincer's second pre-condition is D'Amico and Maxwell (1994), who study the effects of unemployment during the school-to-work transition for young men in the United States. This chapter will extend this literature by investigating the effects of using potential experience in a developing country that is characterised by violations of both of Mincer's preconditions. Other related studies in the literature have focused on the misspecification bias due to the quadratic specification of potential experience and omission of higher order terms (for example Murphy & Welch, 1990 and Lemieux, 2006).

Unlike much of the developed country studies, our data does not include direct measures of actual labour market experience. However, we can investigate the sensitivity of results obtained from using alternative measures for actual labour market experience that explicitly acknowledge deviations from Mincer's conditions. Specifically, we propose using an extension of Elsby and Shapiro's (2011) method of adjusting the wage-experience profile by the employment rate. This extension best understood as a data-constrained approximation of Light and Ureta's (1995) proposed method of adjusting potential experience by the fraction of time worked by an individual since the beginning of their career.

The empirical analysis provides evidence of specific biases that arise due to the use of potential experience in a context where the assumptions motivating this variable are violated. We find that using Mincer's potential experience proxy causes the wage-experience profiles of women and black men to appear significantly flatter than is actually the case. These effects are most pronounced for black women, since the gap between actual and potential experience is largest for this group. Using Mincer's potential experience proxy also tends to inflate the conditional racial and gender wage gaps, and the estimated between-group differences in the wage return to labour market experience in particular. This is not to say that between-group wage gaps are not very large or problematic; rather it points to a lack of continued access to employment, as opposed to wage discrimination in the rewarding of labour market experience, as the main determinant of such differences.

2. LITERATURE REVIEW

Several theoretical models predict that earnings rise with labour market experience. These models, however, offer different explanations for this prediction. Underlying the differences in these models is the role assigned to individual worker productivity growth as the key driving force behind the observed pattern of rising earnings with labour market experience. The human capital model asserts that earnings reflect a worker's productivity, from which it follows that earnings growth over the life-cycle reflects productivity-enhancing investments in human capital (see for example Becker, 1962; Ben-Porath, 1967; and Mincer, 1974). Other models base their prediction of rising earnings with labour market experience on the importance of imperfect information, implicit contracts, signalling, sorting, aging and principal-agent considerations over the worker's life-cycle[4].

In this section, we provide a brief background on the Mincerian earnings function and a review of the empirical strategies suggested in the literature for addressing the bias in the use of potential experience. A summary of the related evidence is also provided.

2.1 Mincerian earnings function: A background

Systematic differences in the acquisition of human capital is a key factor that explains the inferior labour market outcomes of women and blacks. Mincer's model distinguishes between human capital acquired through schooling and through on-the-job investment. Schooling usually precedes on-the-job investment and according to Mincer (1962:50), it should be viewed as a "general and preparatory stage" that "is neither an exclusive nor a sufficient method of training the labor force". On-the-job investment, on the other hand, is more specialized. It involves learning new market skills, and adapting and enhancing skills learned while at school (Becker, 1962). This is achieved through learning-by-doing and from experience, apprentice and internship programs, and other forms of workplace training programs (Mincer, 1962). Our

[4] A more detailed review of this literature can be found in the next chapter.

focus in this paper is on the second stage of human capital acquisition and specifically on-the-job investment that improves workers' productivity through learning-by doing and from experience.

Women and blacks accumulate less work experience, and by implication, undertake less on-the-job investment. For women, this is because of frequent employment interruptions during the first two decades of the working career due to childbirth and rearing and other household responsibilities (Munasinghe, Reif & Henriques, 2008). Blacks, on the other hand, experience high rates of unemployment and endure long periods of unsuccessful job search (D'Amico and Maxwell, 1994). These factors systematically hinder the process of acquiring labour market experience. As such, the use of potential experience as a proxy for labour market experience will systematically overstate the amount of labour market experience acquired by these groups. Nonetheless, the use of potential experience is very entrenched in the Mincerian earnings literature, perhaps due to the perception that the data limitations preclude the use of more accurate alternative measures. The resulting econometric issues have largely been ignored in the South African and developing country literature.

When Mincer (1974) first suggested potential experience as a proxy for labour market experience in the absence of direct measures, he noted two preconditions for its use. Potential experience serves as a good proxy if workers are (1) continuously attached to the labour market and (2) they begin their working careers directly after completing schooling. A third precondition is implied by the way the potential experience variable was constructed: there should be no grade repetition, and that all learners start their schooling at age 6. Women's lower labour market attachment and black's high incidence of unemployment and lengthy periods of unsuccessful job search violate the first two preconditions. This has implications for the statistical properties and interpretation of regression estimates produced using potential experience as a proxy for labour market experience in earnings functions based on Mincer's (1974) specification. Specifically, this practice has been shown to bias downwardly the estimated wage return to labour market experience, to bias upwardly the wage returns to schooling, as well as producing misleading estimates of the channels of racial and gender wage discrimination (Filer, 1993; Miller, 1993; Light & Ureta, 1995; Weichselbaumer & Winter-Ebmer, 2005; Regan & Oaxaca, 2009; and Blau & Kahn, 2013). This is because time out of the labour market together with time spent searching for a job limit on-the-job investment (Miller, 1993; D'Amico and Maxwell, 1994; and Regan & Oaxaca, 2009).

2.2 Empirical strategies and evidence

In the United States (US), the 1979 National Longitudinal Survey of Youth (NLS) and the Panel Survey of Income Dynamics (PSID) are two datasets that contain information on the work histories of individuals. These datasets permit researchers to measure the amount of actual experience accumulated by individuals. Unfortunately, these datasets are sometimes not appropriate, as they are unrepresentative of the US population and small in size (Regan & Oaxaca, 2009; and Blau & Kahn, 2013). As a result, a literature has emerged that investigates alternative methods of measuring labour market experience in datasets where data on the work histories of individuals is not present.

The dominant method in this literature involves the use of datasets containing individuals' work histories and then estimating equations that predict actual experience. The coefficients from these equations are then used to construct a measure of predicted experience in datasets that lack data on individuals' work histories. The NLS and PSID contain information that allow the researcher to measure an individual's cumulative actual experience based on hours or weeks worked for a given years (Regan & Oaxaca, 2009; and Blau & Kahn, 2013). Therefore, these datasets are typically used for the estimation of the equations that predict actual experience.

Filer (1993) follows the method described above in analysing the labour market outcomes of women in the US. The equations that predict actual experience in Filer's study are occupation-specific. The author finds that the predicted experience measure has a greater correlation with women's wages than potential experience. Furthermore, controlling for predicted experience as opposed to potential experience leads to a reduction in the estimated wage return to schooling.

Regan and Oaxaca (2009) build on the work of Filer (1993) and others and suggest three extensions to the method of predicting experience from actual experience equations. Firstly, the authors use all hours worked instead of weeks worked. This allows the authors to capture the effects of multiple jobs, part- and over-time on the accumulation of actual experience. Secondly, the authors use a semi-log specification for the predicted experience model as opposed to Filer's (1993) linear model. The motivation for the semi-log specification is based on the fact that actual experience cannot take on values below zero, and also needs to be bound away from zero (Regan & Oaxaca, 2009). Lastly, the authors allow for a more flexible and general specification of the equations predicting actual experience. This is achieved by not restricting these equations to be occupation-specific as in Filer (1993).

After applying the above extension, Regan and Oaxaca (2009) confirm the results found by Filer (1993). Namely, the estimated wage effect of labour market experience is significantly larger when using predicted experience in place of potential experience. In addition, the use of potential experience biases upwards the wage effects of schooling. Regan and Oaxaca (2009) also perform a decomposition of the gender wage gap. They find that the explained component of the gender wage gap is larger when using predicted experience in place of potential experience.

The method of using measures of actual experience to predict experience in datasets lacking such measures has attracted criticism. At the heart of the criticism is the appropriateness of the measures of actual experience. Light and Ureta (1995) argue that two individuals with the same amount of cumulative actual experience at a given point in time could have taken totally different paths in accumulating that given amount of actual experience. The two individuals could have experienced employment interruptions at different ages that lasted different lengths. Additionally, the two individuals could also differ in the frequency of their employment interruptions. Yet, it is possible that, notwithstanding these differences, the two individuals could at a given point in time have the exact amount of accumulated actual experience. The differences in the paths followed in accumulating a given amount of actual experience can in turn affect earnings and the relationship between earnings and labour market experience (Light & Ureta, 1995).

In light of the above criticism, Light and Ureta (1995) proposed replacing actual experience – measured from data on weeks or hours worked – with a combination of variables that better capture the work histories of individuals. The authors suggest using data on the "fraction of time worked last year, 2 years ago, 3 years ago, and so forth, back to the beginning of the career" (Light & Ureta, 1995:129-130). These variables are combined with other variables that address the issues that arise when an individual reports a zero for the fraction of time worked for a given year. Using these more comprehensive measures of experience in place of actual or potential experience, the authors find larger wage returns to labour market experience and smaller wage returns to firm tenure for white men and women.

The data requirements for the above methods are very burdensome. Datasets available for the analysis of labour market outcomes in South Africa and other developing countries lack even the basic measures needed to construct the cumulative actual experience variable that Light and Ureta (1995) criticise. It is worth pointing out also that retrospective questions about individual's work histories are likely to be less accurate than schooling and age responses, and hence also an imperfect solution to the data requirement.

Elsby and Shapiro (2011) propose an alternative method that is not as data intensive as the above methods. Instead of constructing a variable that better measures labour market experience, the authors propose a method of adjusting the potential experience-wage profile. They argue that in steady state and with employment assumed to be an identically and independently distributed (i.i.d) Bernoulli distribution across workers and time, the product of potential experience and the employment rate is equal to actual experience for a given worker. However, evidence that employment tends to be persistent rather uncorrelated over time implies that this measure is likely to be biased. A worker's actual experience can be expected to lie between the adjusted experience measure and the potential experience measure (which implicitly assumes complete persistence in employment), so these values can be viewed as upper and lower bounds for actual experience. In the next section, we extend this method and apply it to a South African household dataset.

3. CHALLENGES OF POTENTIAL EXPERIENCE IN THE SOUTH AFRICAN CONTEXT

In this section, we highlight three important challenges within the South African context that are likely to drive a wedge between potential and actual labour market experience. These challenges include high and unevenly distributed unemployment, grade repetition and schooling outcomes, and pre-labour market work experience. We begin by focusing on unemployment.

3.1 Unemployment

The first issue to highlight is South Africa's high and unevenly distributed unemployment. Race, gender, age and school attainment correlate strongly with unemployment. This is evident from the significantly higher unemployment rate for blacks, women, youth and those with low levels of school attainment. In 2005, roughly 40% of those who were unemployed were without work for more than three years, and 60% of these work-seekers had never held a job at all (Lam, Leibbrandt & Mlatsheni, 2007; and Banerjee, Galiani, Levinsohn, McLaren & Woolard, 2008; and Kingdon & Knight, 2004).

Part of the problem is the unsuccessful job search strategies of young black workers (Schoer, Rankin & Roberts, 2014, and Banerjee et al., 2008). Figure 2.1 below confirms that young black workers, especially black women, face a much lower probability of finding employment compared to their white counterparts. For example, according to our sample the probability of employment at the age of 40 differs greatly: white men have a 90% chance of being employed, compared to a probability of 70% for white women and black men, and 55% for black women. The speed of labour market absorption also varies: white men and women reach their maximum employment rate in their thirties, whereas black men and women only reach that point in their forties. This suggests that there are long periods of unsuccessful job search for black workers before they are absorbed into the labour market.

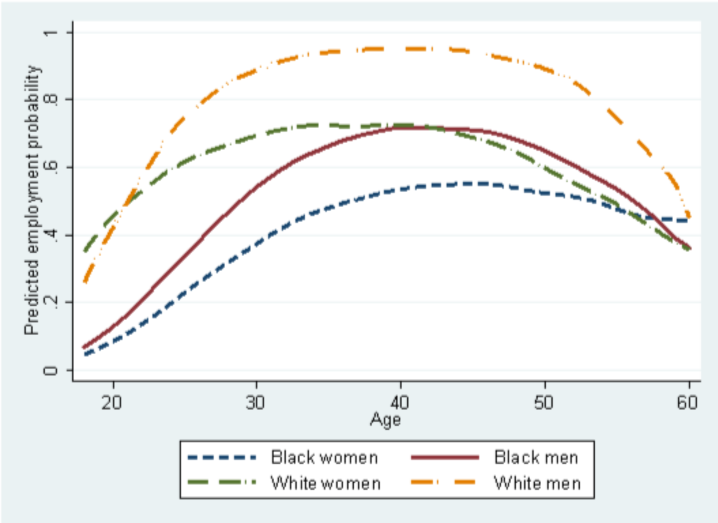


Figure 2.1: Employment probability by race and gender

Note: These age-empoyment profiles are estimated from kernel-weighted local polynomial regressions of employment on age, using the Epanechnikov kernel function and bandwidth chosen by the rule-of-thumb method.

A large proportion of these work-seekers end up being discouraged and joining the ranks of the economically inactive (Yu, 2013). While discouraged or unemployed, these individuals are not accumulating human capital and improving their productivity at the same rate as those in employment. This has direct consequences for the labour market experience they accumulate. The potential experience measure, which fails to distinguish between these labour market states, will therefore be a biased proxy for labour market experience, and the magnitude of this bias will be a function of race and gender (Regan & Oaxaca, 2009).

3.2 Grade repetition and schooling outcomes

South Africa's racially skewed distribution of school outcomes is another area of concern when considering the use of potential experience as a proxy for labour market experience. Lam et al. (2007) provide evidence of higher rates of grade repetition amongst black learners compared to white learners. Pugatch (2012) also provides evidence of re-enrolment in school after an initial period of dropout being a non-trivial feature of the school-to-work transition in South Africa. These differences are largely due to racial disparities in the quality of schools attended by South African learners and contributes to the lower levels of school attainment for blacks relative to their white counterparts. Many scholars have expressed concern regarding the effective level of learning and cognitive gains achieved on the one hand, and grade advancement on the other hand in black schools (Ardington, Branson, Lam & Leibbrandt, 2011; Lam, Ardington & Leibbrandt, 2011; van der Berg, Wood & le Roux, 2002; van der Berg, 2007).

Apart from contributing to racial inequality in the labour market, the differential rates of grade repetition and school interruptions also presents complications for the use of potential experience as a proxy for labour market experience. Potential experience "assumes that all individuals with S years of schooling begin their careers at the same age" (Light & Ureta, 1995: 131). In the South African case, many individuals will reach S years of schooling at ages later than $S + 6$, so potential experience will systematically overstate labour market experience. This problem is expected to be most severe amongst black workers than for white workers.

3.3 Pre-labour market work experience

There is also growing evidence of racial differences in the accumulation of work experience prior to entering the labour market. Lam et al. (2007) report that in the Cape Town metropolitan area, 45% of white 17-year-old male learners indicate that they have accumulated some form of work experience while still at school. This figure is roughly 5% for black 17-year-old male learners. This is in line with Light's (1998) finding for the US, that pre-labour market work experience is more significant for whites.

4. EMPIRICAL STRATEGY

Labour market experience is an important determinant of post-school investment in human capital, but no direct measures of actual labour market experience exist in most developing country datasets (including South Africa). Although it has become standard practice to use potential experience as a proxy measure for labour market experience in the absence of direct measures, this measure requires many assumptions that are hard to reconcile with observed labour market behaviour of many individuals.

It is worth pointing out that in the South African literature some scholars have attempted to address the challenges associated with the use of potential experience by using age as a proxy of labour market experience (for example Keswell and Poswell, 2004; and Grun, 2004). Mincer (1974) considered the use of age as a proxy for labour market experience, but dismissed it and instead recommended the use of potential experience over age. He pointed out that the age profile of individual earnings capture other factors other than the productivity-enhancing investments made by individuals over the life cycle. The age-earnings profile reflects investment behaviour together with other factors such as "elements of chance, changing market opportunities, and bio-psychological developments" (Mincer, 1974:65). Furthermore, Mincer (1974) showed that the use of age in an earnings function biases the schooling coefficient and complicates its interpretation. Therefore, in the absence of direct measures of labour market experience, Mincer (1974:80) concluded that potential experience is "a much more powerful determinant of earnings than age".

We follow two strategies to correct for the shortcomings in potential experience. The first is a direct application of the Elsby and Shapiro (2011) method discussed in section 2. The second strategy extends this method to reflect more comprehensively the very different life-cycle profiles of labour absorption between the demographic groups. Light and Ureta (1995) perform a similar adjustment by using reported work histories to construct a measure of cumulative work experience based on the fraction of time worked each year since the beginning of the career. In the absence of these work histories, we instead use non-parametric techniques to estimate the group-specific age-employment profiles that reflect the very different schooling outcomes and job search experiences of members of the different groups. The cumulative function of this profile is then used to estimate the fraction of time members of different groups are expected to have worked since the beginning of their career.

4.1 Adjusted experience: Elsby and Shapiro (2011)

Elsby and Shapiro (2011) suggested adjusting the wage-experience profile by the employment rate. Under steady state conditions and under the assumption of employment being an i.i.d process across workers, the product of the employment rate and potential experience is equal to actual experience for a given worker. To implement this, we first calculate the group-specific employment rates in our sample. This estimate is then used to rescale potential experience for each individual by a common group-specific factor. This gives an upper bound for actual labour market experience since employment tends to be persistent rather uncorrelated over time. In this study we define groups by race and gender, giving us four groups: black men and women, and white men and women. We will refer to this new rescaled worker experience variable as "adjusted experience".

4.2 Predicted experience: Extending Elsby and Shapiro (2011)

Adjusted experience assumes all individuals in the same group face the same employment profile. In reality, individuals within groups will vary in their likelihood of finding employment, since this likelihood is affected by factors other than race and gender. Our second approach acknowledges this shortcoming, and uses the information from the different age-employment profiles faced by individuals to refine the adjustment of potential experience. Specifically, we estimate a probit employment regression separately by race and gender. These probit regressions control for schooling[5] and age (specified as a quadratic). We then use the coefficients from these regressions to predict the employment likelihood at each age from the

[5] Specified as a spline with knots at 7 years (completed primary), 12 years (completed secondary) and tertiary which is more than 12 years of schooling. We further specify a separate dummy variable that takes on a value of one for individuals with 12 years of schooling plus diploma or certificate not obtained from a university, and zero otherwise.

age of 18 to 60. The predicted employment probabilities are then added from the age of 18 until their present age to create a predicted number of years of employed. We will refer to this new cumulative work experience variable as "predicted experience".

This predicted experience measure can be thought of as an approximation to Light and Ureta's (1995) fraction of time worked each year measure. Our measure captures the sum of the employment probabilities at each age and expresses it in terms of the number years up until the individual's present age. Light and Ureta (1995) are in the enviable position of having data on individual's work histories. Because of data limitations, we use the employment probit to predict the likelihood that an individual was employed each year since the age of 18 (earliest starting age of the career in our sample) until their current age. We rely on group-specific information, which assume within-group homogeneity in the effects of schooling and age on the employment likelihood.

The use of predicted experience in OLS wage regressions will induce bias in our estimates and affect our statistical inferences because predicted experience is a generated regressor and is susceptible to sampling error. To address this issue we implement bootstrapping techniques that generates anew our predicted experience variable and run the regressions controlling for this variable in the same bootstrapped sample. This process is repeated 1000 times and yields bootstrapped standard errors that are used for statistical inference.

It is worth pointing out that our proposed adjustments only address the challenges associated with potential experience that arise from non-employment. Our strategies are silent on the effects of discontinuities in labour force attachment. This is indeed a shortcoming of our strategies. This shortcoming, however, does not negate the contribution of this chapter. The existing literature on the challenges of potential experience is predominantly focused on the issue surrounding discontinuities in labour force attachment for women and the effect thereof on labour market experience and other labour market outcomes. With the recent trend of rising unemployment globally, the wedge between actual and potential experience accounted for by non-employment is becoming more prominent even in developed countries.

5. DATA AND DESCRIPTIVE ANALYSIS

The descriptive and empirical analysis in this study makes use of the individual cross-sectional waves of the Labour Force Surveys (LFS) together with the panel version – Labour Force Survey Panel (LFSP) collected by Statistics South Africa (Stats SA). The LFSs 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 approximately 30 000 households was maintained in each wave.

Stats SA's LFSP is the first nationally representative panel dataset of the South African labour market. It was constructed from the LFS cross-sectional surveys running from September 2001 to March 2004 (Stats SA, 2006). Individuals were only linked after the collection and release of the surveys, since the surveys were designed as a rotating panel of dwelling units rather than individuals (Stats SA, 2006).

The estimation sample is restricted to black and white men and women between the ages of 18 to 60 working in formal, private sector firms. Workers in subsistence agriculture and those reporting to be self-employed were also excluded from the analysis.

Table 2.1 below provides summary statistics (the means and standard deviations – in parentheses) of hourly real wages, age, schooling, potential experience, predicted experience and adjusted experience, by demographic group. Black workers have lower average wages compared to white workers, while women earn lower average wages compared to their male counterparts. The racial wage gap, however, is much more pronounced than the gender wage gap. One possible explanation for this could be that blacks accumulate fewer years of labour market experience and this in turn, *ceteris paribus*, contributes to their lower average wages.

In the literature of the determinants of wages, age has been used directly and indirectly to measure labour market experience. As a direct measure, age is used to proxy for labour market experience in wage regressions. Researchers that prefer the use of potential experience as a proxy for labour market experience use age to construct the potential experience variable. From Table 2.1 we see that black women on average are the youngest demographic group, followed by black men and white women who are more than a full year older on average. White men are the oldest group on average with a mean age of roughly 38 years. Consequently, the age variable suggests that black women in our sample have accumulated the least amount of labour market experience, while white men have the highest accumulated labour market experience. However, as discussed above, there are serious objections to the use of age (both directly and in indirectly) as a measure of labour market experience.

Table 2.1: Summary statistics of key variables, by demographic group

	Hourly Wage	Age	Completed Schooling	Potential Experience	Predicted Experience	Adjusted Experience
Black women	6.87	35.27	9.24	19.87	4.94	6.69
	(9.52)	(9.00)	(3.57)	(10.55)	(4.01)	(3.55)
Black men	8.66	36.53	8.24	21.99	8.04	9.97
	(11.69)	(9.04)	(3.70)	(10.88)	(5.51)	(4.93)
White women	25.2	36.96	12.24	18.66	11.94	11.04
	(25.05)	(10.51)	(1.55)	(10.86)	(7.16)	(6.43)
White men	38.86	38.51	12.27	20.37	16.42	16.38
	(45.85)	(10.57)	(1.78)	(10.90)	(9.53)	(8.76)

Notes: Own calculations. Standard deviations in parentheses.

The last three columns of Table 1.1 report mean values for the three measures of labour market experience. According to potential experience, men have more years of experience compared to women. Within each gender, Table 2.1 indicates that black workers have higher accumulated potential experience compared to their white counterparts. The racial comparison of potential experience is contrary to the pattern we would expect to see for actual experience. Given the greater incidence of unemployment and slower absorption rate into employment for black workers, the expectation would have been for black workers to accumulate fewer years of experience. The unexpected racial pattern in the mean years of potential experience reflects the large racial differences in years of completed schooling. By simple arithmetic, it is easy to see that the potential experience measure will make it seem like black workers have accumulated more years of potential experience since potential experience is constructed as age minus years of schooling completed minus six. Therefore, potential experience delivers a distorted picture of the labour market experience accumulated by the different demographic groups.

The predicted and adjusted experience measures reverse this trend: white males have the highest levels of experience, followed by white women, black men, and black women. This relative ranking between the groups depicts a racial and gender hierarchy that is commonly observed for many labour market outcomes in South Africa, where black women are the most disadvantaged and white men are the most advantaged. The large racial gap in labour market experience accumulated is consistent with the evidence of the South African labour market discussed in section 2. The predicted and actual experience measures provide roughly similar estimates for the mean and standard deviations of labour market experience accumulated by the four demographic. The main distinction is that adjusted experience suggests a mean experience level that is roughly two years more than predicted experience for black men and women.

Table 2.1 allows for a comparison of the three measures of labour market experience based on the means. However, we may also be interested in comparing the entire distribution. Figure 2.2 below, provides kernel densities by demographic groups. These graphs depict density distributions based on our three measures of labour market experience and estimated with nonparametric techniques.[6] Figure 2.2 echoes the observations drawn in the previous paragraph that based on the comparison of mean values for the three labour market experience measures. The density distributions based on potential experience lie on top of each other without any clear racial or gender differences in the distributions. Figure 2.2 b) and c) provide a totally different and contrasting picture that reflects a clear role for race and gender in the comparison of density distributions. Black workers have higher and concentrated densities at earlier at lower values of experience. White men, and to lesser extent white women, are much more evenly distributed.

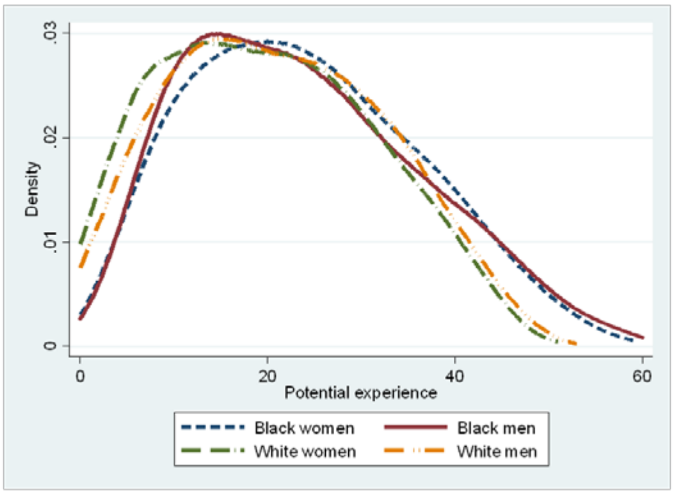


Figure 2.2b): Kernel densities by demographic groups, predicted experience

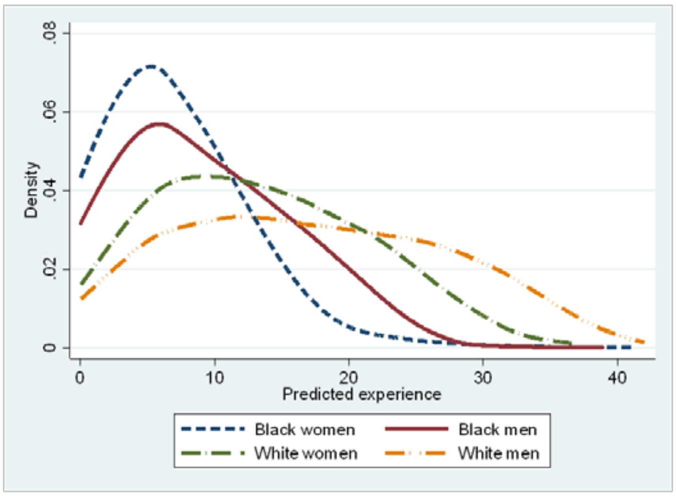


Figure 2.2b): Kernel densities by demographic groups, predicted experience

[6] The Epanechnikov kernel function was used in estimating the densities and the bandwidth was chosen based on the rule-of-thumb method.

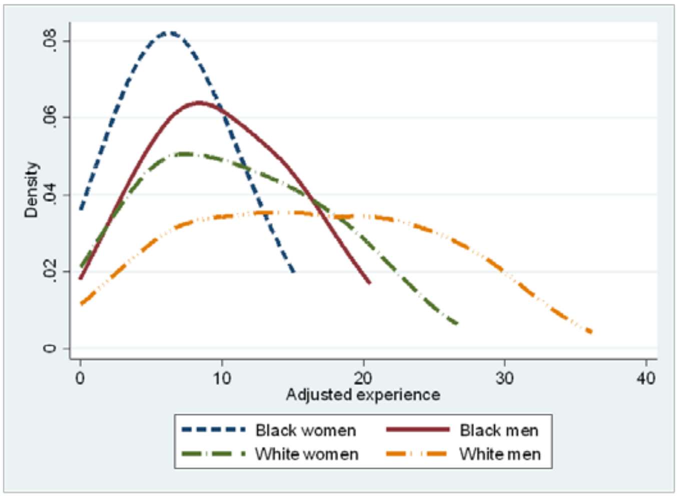


Figure 2.2c): Kernel densities by demographic groups, adjusted experience

The three figures below provide age-experience profiles for our three measures of labour market experience. Depending on the measure of labour market experience considered, different conclusions are reached regarding the relative ranking of the profiles by race and gender. Figure 2.3 uses potential experience as the proxy for labour market experience. A racial gap for experience accumulated at each age is revealed in Figure 2.3. At all ages, black workers have more years of labour market experience accumulated than white workers have. Within each race, the age-experience profiles lie on top of one another suggesting that there is no systematic differences in the accumulation of work experience by gender. The racial gap in these profiles is due to differences in educational attainment depicted in Table 2.1.

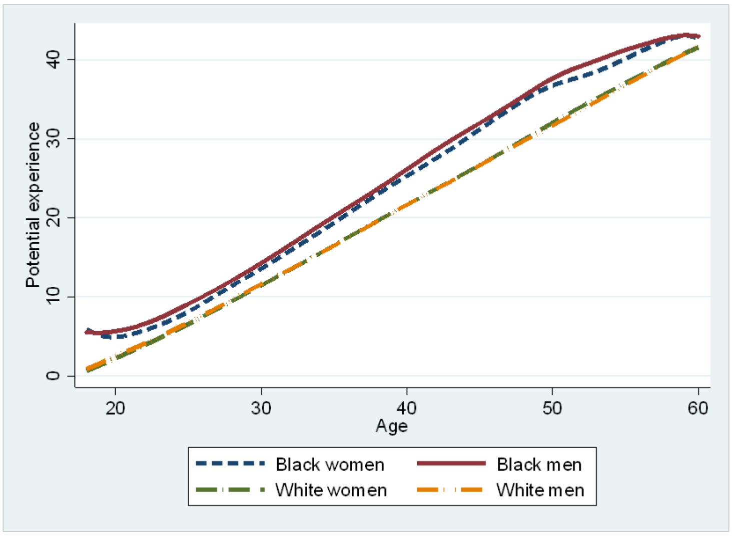


Figure 2.3: Age-experience profiles by demographic group, potential experience

Note: These age-experience profiles are estimated from kernel-weighted local polynomial regressions of potential experience on age, using the Epanechnikov kernel function and bandwidth chosen by the rule-of-thumb method.

In Figure 2.4 below, a very different picture emerges when changing the proxy of work experience to adjusted experience. The age-experience profile for white men lies above all the other profiles, and black women's profile is the flattest. This depicts the divergent employment outcomes of white men and black women that is usually observed in the South African labour market. The age-experience profiles of black men and white women lie roughly on top of one another and in between those of white men and black women. Although the expected racial gap and gender gaps in experience are observed at most ages, this pattern does not emerge clearly at young ages. This is because black men and women are more likely to exit the schooling system at younger ages, at which point they start accumulating potential experience. The fact that the adjusted experience measure is scaled by age-invariant employment rates means that the very slow absorption of black men and women at young ages is not reflected in this measure. This paints an unrealistically optimistic picture of the early-life labour market experiences of black workers relative to their white counterparts.

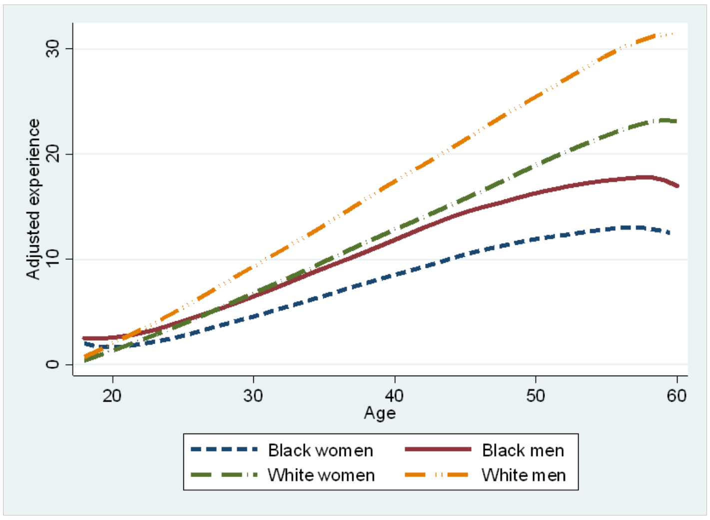


Figure 2.4: Age-experience profiles by demographic group, adjusted experience

Note: These age-experience profiles are estimated from kernel-weighted local polynomial regressions of adjusted experience on age, using the Epanechnikov kernel function and bandwidth chosen by the rule-of-thumb method.

Figure 2.5 uses predicted experience as the proxy measure of labour market experience when constructing the age-experience profiles. We now observe both racial and gender gaps in the age-experience profile, albeit at different ages. A clear racial gap in favour of white workers is now clearly revealed: at every age, white workers are expected to have accumulated more years of work experience compared to black workers. The gender gap on the other hand, only emerges beyond the age of 30, from which point it continues to widen. The use of more information in the construction of the predicted experience variable allows for more flexibility in the age-experience profiles. Specifically, the additional information about the difficulties experienced by young black men and women to find employment allows the predicted experience profile to accurately reflect these disadvantages in the accumulation of work experience. It is, therefore, our contention that the age-experience profiles based on the predicted experience proxy provides a better approximation of the true underlying relationship between labour market experience and age. In the next section, we use the three measures of predicted experience to estimate the raw wage and gender gap, and the wage returns to labour market experience for each demographic group.

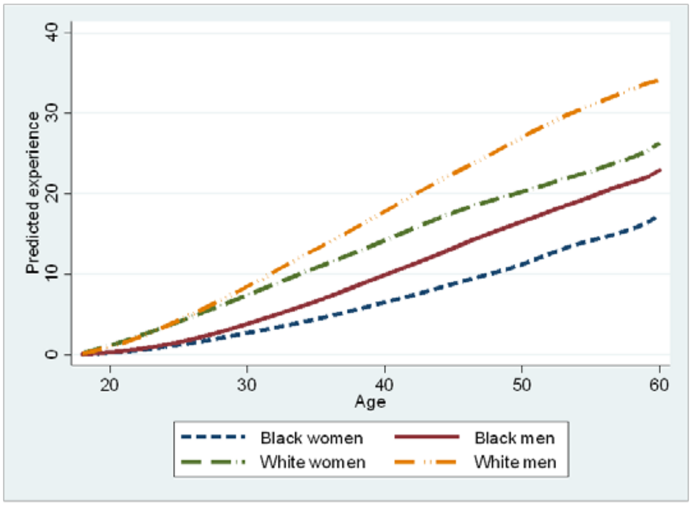


Figure 2.5: Age-experience profiles by demographic group, predicted experience

Note: These age-experience profiles are estimated from kernel-weighted local polynomial regressions of predicted experience on age, using the Epanechnikov kernel function and bandwidth chosen by the rule-of-thumb method.

6. EMPIRICAL APPLICATION

The literature review in section two revealed that potential experience biases the wage return to labour market experience and the racial and gender wage gaps. However, the empirical evidence in this regard is drawn from studies on developed country labour markets. In this section, we add to this literature by providing empirical evidence from the South African labour market. Section 6.1 provides estimates of the wage return to labour market experience. In section 6.2, we discuss the results for the estimates of the gender and racial wage gaps using the three measures of labour market experience. Section 6.3 provides a summary of the results.

6.1 Wage return to labour market experience

The wage returns to labour market experience are a key component of the dynamic structure of wages (Williams, 1991). How individual wages grow over the working career therefore depend on the rate of return of labour market experience accumulated over the working career. Table 2.2 below provides evidence of the bias in the estimated wage return to labour market experience. The bias arises because potential experience is a poor proxy for labour market experience. In Table 2.2, we estimate log hourly wage regressions by OLS separately for each race and gender. For each demographic group, we run three regressions with each regression having a different measure for labour market experience. In all regressions, we control for a wide range of individual, household and labour market characteristics, but only report the coefficient estimates on the measures of labour market experience.[7]

Table 2.2: Wage returns to labour market experience, by demographic groups

	Black women	Black men	White women	White men
Panel A:				
Potential Experience	0.0130	0.0193	0.0364	0.0306
	(0.0041)***	(0.0031)***	(0.0059)***	(0.0065)***
Potential Experience^2	-0.0001	-0.0002	-0.0008	-0.0007
	(0.0001)	(0.0001)***	(0.0001)***	(0.0001)***
	Ratio of smallest to largest: 0.37			
Panel B:				
Predicted Experience	0.0274	0.0307	0.0575	0.0334
	(0.0061)***	(0.0036)***	(0.00096)***	(0.0062)***
Predicted Experience^2	-0.0009	-0.0007	-0.0019	-0.0009
	(0.0004)***	(0.0002)***	(0.0004)***	(0.0002)***
	Ratio of smallest to largest: 0.65			
Panel C:				
Adjusted Experience	0.0387	0.0425	0.0616	0.0380
	(0.0122)***	(0.0069)***	(0.0100)***	(0.0081)***
Adjusted Experience^2	-0.0010	-0.0008	-0.0021	-0.0011
	(0.0007)	(0.0003)***	(0.0004)***	(0.0002)***
	Ratio of smallest to largest: 0.62			

Notes: These regressions control for schooling[8], tenure; province, rural/urban status, household head, marital status, firm size, union status, wave fixed effects, number of children, industry classification, and occupational classification. The standard errors in Panel B were obtained by bootstrapping with 1000 replications to account for the effects of a generated regressor.

In Panel A, we proxy for labour market experience by potential experience. The estimated coefficients on potential experience and potential experience squared are reported for all four demographic groups. The estimated coefficients on the linear potential experience term are statistically significant for all four groups. However, there magnitudes differ with black women having the lowest estimated coefficient at around 0.01 and white women the largest estimated coefficient at around 0.04. These positive and statistically significant coefficients on the linear potential experience terms indicate positive wage returns. However, to quantify the full wage returns to labour market experience (according to our potential experience measure) we need to also consider the estimated coefficient on the quadratic term. For black women, the estimated coefficient is statistically insignificant, meaning that it cannot be distinguished from zero. This suggests that the wage-experience profile for black women is, approximately, a positive linear function that depends on the estimated coefficient on the linear term.

[7] The full regression output can be found in the Appendix in Tables A1 and A2.
[8] Specified as a spline with knots at 7 years (completed primary), 12 years (completed secondary) and tertiary which is more than 12 years of schooling. We further specify a separate dummy variable that takes on a value of one for individuals with 12 years of schooling plus diploma or certificate not obtained from a university, and zero otherwise.

For the remaining three groups, the estimated coefficient on the quadratic term is negative and statistically significant. This suggests that wages increases at a decreasing rate with potential experience for these workers. However, the wage returns to potential experience decrease at a much faster rate for white workers compared to black men since the latter's estimated coefficient is 4 times larger than the estimated coefficient for black men. Figure 2.6 below, uses the estimated coefficients on the potential experience variables to construct wage-experience profiles for the four groups. The profiles depict a clear ranking by race with white workers' profiles lying substantially above those of black workers for the zero to 20 years range of potential experience. The larger estimated coefficients on the quadratic term in Table 2.2 for white workers means that their profiles start declining while the profiles of black workers continue to rise. At 20 years of potential experience, black men reach the same level of expected log hourly wages as white men. At 30 years of potential experience, black men reach the same level of expected log hourly wages as white women and black women reach the same level as white women.

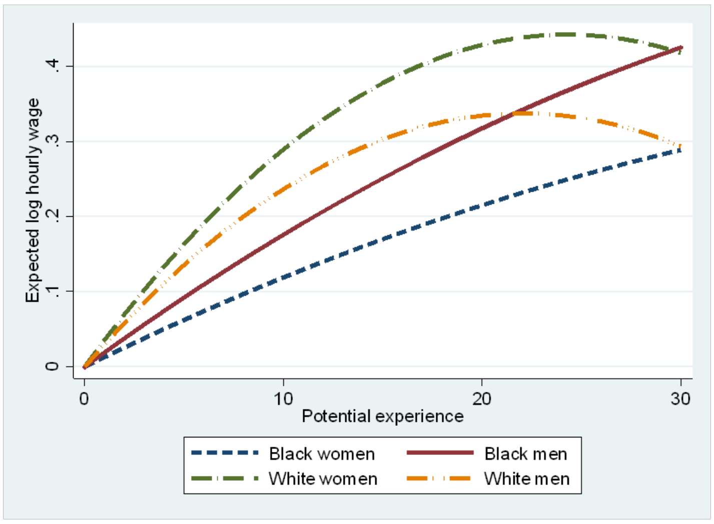


Figure 2.6: Wage-experience profiles by demographic groups, potential experience

Table 2.1 above, indicated that the four demographic groups accumulate roughly equal years of potential experience. However, the combination of evidence presented in Panel A of Table 2.2 and Figure 2.6 leads to the inference that the wage returns to labour market experience black workers are significantly smaller than those for white workers, especially at low years of potential experience. No clear gender dimension is evident from the results presented.

In preceding sections, we argued that potential experience is a poor proxy for labour market experience. Potential experience is particularly poor in measuring labour market experience for black women. This could be one reason for the lower wage returns for black women. In Panel

B and C, we therefore re-estimate the log hourly wage regressions using the different measures of labour market experience suggested above in section 4 – predicted and adjusted experience.

Replacing potential experience with predicted experience changes the estimated coefficients very dramatically for black women. The linear coefficients from Panel A to B changes by over 100%. The coefficient on the quadratic term in Panel B is 10 times larger in magnitude and is now statistically significant. Using the predicted experience measure also has a sizeable effect on the estimated coefficients of black men and white women. The linear coefficients for these workers increase by roughly 60%. While the coefficient on the quadratic term is three times larger for black men and double for white women in absolute terms. Switching from between the experience measures produces a much more muted effect on the estimated wage effects of experience for white men.

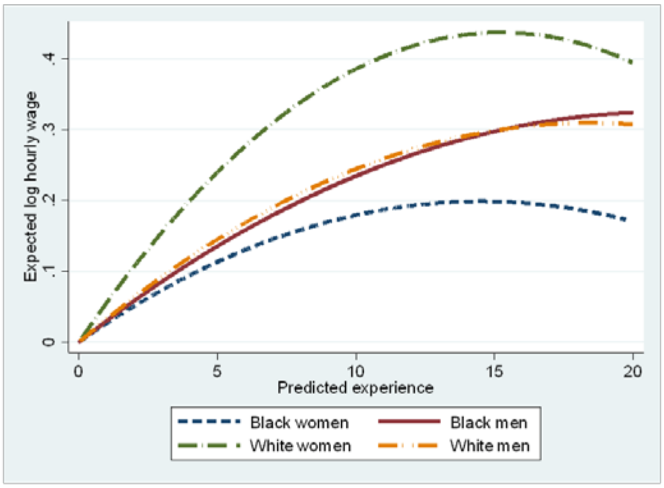


Figure 2.7: Wage-experience profiles by demographic groups, predicted experience

Figure 2.7 above illustrates the wage-experience profiles based on the estimated coefficients in Panel B. The evidence presented by Figure 2.7 does not support the ranking of the profiles by race evident in Figure 2.6. The use of a measure that better captures the cumulative labour market experience of disadvantaged groups has brought the profiles much closer to each other. The profiles for men, specifically, lie directly on top of each other. Nevertheless, Figure 2.7 indicates that black women benefit the least from accumulating labour market experience.

The effects of replacing potential experience with adjusted experience goes in the same direction as the effects of using predicted experience. However, these effects are much larger and more pronounced for all demographic groups. Figure 2.8 below summarises these effects by depicting wage-experience profiles. A clear ranking by gender, as opposed to race, is now evident. The profiles for women now lie above those for men. The profile for men again lie on top of one another. However, a racial gap within the profiles for women, in favour of white workers, now emerges.

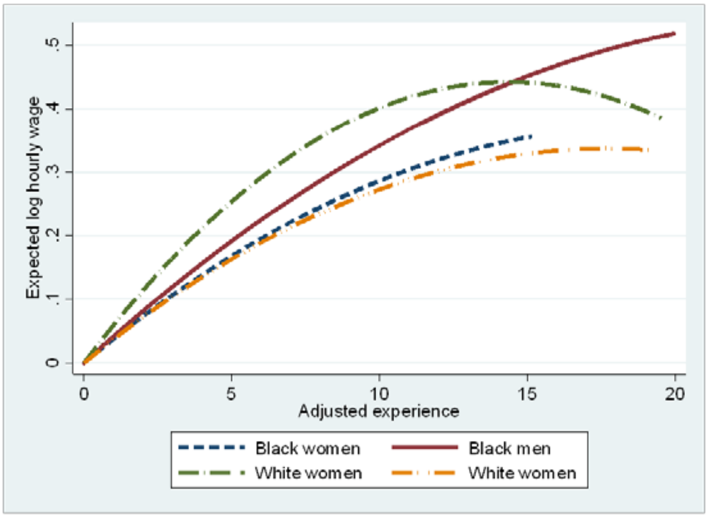


Figure 2.8: Wage-experience profiles by demographic groups, adjusted experience

The three figures above depicting the wage-experience profiles have been in the Appendix with 95% confidence intervals. The confidence intervals around the predictions are wide and suggest that the differences between the profiles may not be statistically significant. We however, contend that the differences in the trajectory of the profiles do carry economic significance.

In Table 2.3 below, we use the estimated coefficients reported in Table 2.2 to calculate the cumulative wage growth due to 5, 10 and 15 years. The cumulative wage growth due to 5 years of work experience for black women is only 6% if potential experience is used to proxy for labour market experience. Using predicted and adjusted experience, this cumulative wage return is 16% and 19%, respectively. The cumulative wag returns for white workers are roughly similar when replacing potential experience with predicted experience. For all demographic groups, the estimated cumulative wage returns are largest when adjusted experience is used to proxy for labour market experience.

Table 2.3: Cumulative wage returns to experience, by demographic groups

	Black women	Black men	White women	White men
		Potential Experience		
5 years	6%	9%	17%	14%
10 years	13%	19%	30%	23%
15 years	19%	27%	37%	27%
		Predicted Experience		
5 years	16%	18%	23%	15%
10 years	28%	32%	36%	26%
15 years	35%	41%	37%	31%
		Adjusted Experience		
5 years	19%	21%	30%	18%
10 years	34%	39%	52%	32%
15 years	43%	52%	62%	41%

6.2 Gender and racial wage gaps

Measurement error in the proxy for labour market experience has consequences beyond biasing the wage return to labour market experience. The gender and racial wage gaps may also be biased. Table 2.4 below provides evidence of this bias for the South African labour market. We estimate log hourly wage regressions by ordinary least squares (OLS) with three different measures of labour market experience.

In Model 1, we estimate the raw gender and racial wage gaps by controlling for gender and race dummy variables together with an interaction of these two variables. With just these explanatory variables, we are able to explain about 35% of the variation in log hourly wages in our sample. This highlights the salience of race and gender for the determination of individual wages in South Africa.

Table 2.4: Gender and racial gaps in log hourly wages with different measures of experience[9]

	Model 1	Model 2	Model 3	Model 4
Women	-0.327 (0.024)***	-0.242 (0.026)***	-0.190 (0.027)***	-0.263 (0.025)***
Black	-1.563 (0.018)***	-0.909 (0.020)***	-0.789 (0.024)***	-0.871 (0.020)***
Women*Black	0.108 (0.029)***	-0.062 (0.029)**	-0.025 (0.030)	0.046 (0.028)*
Education splines:				
Primary		0.067 (0.004)***	0.070 (0.004)***	0.054 (0.003)***
Secondary		0.141 (0.005)***	0.144 (0.005)***	0.125 (0.004)***
Matric		0.273 (0.016)***	0.273 (0.016)***	0.214 (0.014)***
Tertiary		0.280 (0.012)***	0.277 (0.012)***	0.241 (0.011)***
Diploma+Certificate dummy		0.276 (0.026)***	0.271 (0.026)***	0.240 (0.023)***
Tenure		0.051 (0.002)***	0.048 (0.002)***	0.047 (0.002)***
Tenure^2		-0.001 (0.0001)***	-0.001 (0.0001)***	-0.001 (0.0001)***
Potential Experience		0.033 (0.002)***		
Potential Experience^2		-0.0004 (0.00005)***		
Adjusted Experience			0.077 (0.003)***	
Adjusted Experience^2			-0.002 (0.0001)***	
Predicted experience				0.071 (0.002)****
Predicted experience^2				-0.002 (0.0001)***
Intercept	3.351 (0.017)***	1.163 (0.042)***	0.994 (0.044)***	1.394 (0.029)***
R^2	0.35	0.55	0.55	0.54
N	47,361	33,390	33,390	45,575

Notes: Robust standard errors in parentheses. The standard errors in Model 3 were obtained by bootstrapping with 1000 replications to account for the effects of a generated regressor. * p<0.1; ** p<0.05; *** p<0.01.

Holding race constant across workers, Model 1 reports that the average log hourly wage of a South African women is about 39%[10] less than her male counterpart. The point estimate of -

[9] Table A3 in the appendix reports similar regression output results but with a change in specification that exhaustively accounts for interactions between race and gender on the one hand and the experience proxy measures on the other hand.

[10] $(e^{0.327} - 1)*100$

0.327 (with standard error of 0.024) is large and statistically significant at the conventional levels. With regards to the race dummy, white workers are the reference category. On average, black workers earn over 300% less than their white counterparts. The point estimate on the interaction variable is 0.108 (with standard error of 0.029). This suggest that black women do not suffer the full combined disadvantage of being female and black.

In Model 2, we add education, tenure and potential experience as control variables. These additional variables serve as control variables, while the gender and race dummies together with their interaction term remain as our variables of interest. Model 2 differs from Model 3 and 4 by the choice of measure used to proxy for labour market experience. By varying the measure of labour market experience, we are able to determine the impact of the measure on the gender and racial wage gaps.

The additional control variables push up the R-squared, now indicating that we are able to account for more than 50% of the variation in log hourly wages in our sample. The additional controls also have an impact on our estimated gender and racial wage gaps. The implied gender gap decreases since the point estimate on the gender dummy increases from -0.327 to -0.242 between Model 1 and 2. In Model 3, we use adjusted experience as opposed to potential experience as the proxy for labour market experience. This leads to a further reduction in the gender gap that is due to a larger point estimate on the gender dummy from -0.242 to -0.190 between Model 2 and 3. In Model 4, the point estimate marginally decreases to -0.263 when measuring labour market experience by predicted experience. Thus, the wage gap between women and men is the smallest when using adjusted experience as the proxy for labour market experience.

The point estimate on the race dummy increases to -0.909 in Model 2 after controlling for education, tenure and potential experience. This coefficient increases to -0.789 when using adjusted experience to proxy for labour market experience. The estimated coefficient on the race dummy in Model 4 is not very different from the coefficient estimated in Model 2, when using potential experience as the proxy for labour market experience. In other words, the wage gap between black and white workers is the smallest when we proxy labour market experience by adjusted experience.

The three measures of labour market experience have contrasting effects on the interaction term. In Model 2, this coefficient is negative and statistically significant with a point estimate of -0.062. This coefficient is not statistically significant in Model 3. In Model 4, the coefficient turns positive and is almost half in magnitude compared to the estimate obtained in Model 1.

6.3 Summary and discussion

In this section, we reported results from two empirical applications that used three measures for labour market experience. The purpose of these applications was to provide empirical evidence of the bias associated with the use of potential experience as a proxy for labour market experience in the context of a developing country characterised by high unemployment. South Africa's unemployment situation is also problematic because of its highly skewed distribution. Our alternative measures of labour market experience were constructed, therefore, to explicitly account for the skewness of the distribution of the employment profiles of different demographic groups.

We estimated the raw gender and racial wage gaps using the three measures of labour market experience. Empirical evidence from developed countries shows that the explained component of the gender wage gap is larger when replacing potential experience with better measures of labour market experience (see for example Regan and Oaxaca, 2009). Therefore, in other words, the gender wage gap should be smaller when using a proxy that more accurately measures labour market experience. Our own evidence presented in Table 2.2 is consistent with this finding. The wage penalty for women decreased considerably from 0.242 to 0.19 when replacing potential experience with adjusted experience. Our results also showed that the racial wage penalty is smaller when replacing potential experience with adjusted experience with a decrease from 0.909 to 0.789.

The difference in the estimated wage gaps was more pronounced when replacing potential experience with adjusted experience as opposed to replacing it with predicted experience. In constructing the predicted experience measure, we allowed more flexibility and information about individual's age and level of schooling to affect the rescaling of potential experience. However, this additional information was not used contemporaneously in the calculating of the cumulative work experience of individuals. Data availability only permitted the use of the information retrospectively. So for example, we used the cumulative labour market outcomes and conditions of 20 years olds with 12 years of schooling at t_1 to predict the cumulative labour market experience of 21 year olds with 12 years of schooling at t_1, etc. This is unfortunately an unavoidable feature and shortcoming of our method. This may be one possible explanation for the slightly different outcomes between predicted and adjusted experience.

Our second empirical application involved estimating the wage return to labour market experience separately for each gender and race. From our discussion in section three, we would expect potential experience to, systematically, overstate labour market experience for black workers. In a wage regression, this would lead to a downward bias of the 'true' wage effect of labour market experience (Filer, 1993). Our results in Table 2.2 showed that black workers have much lower wage returns compared to their white counterparts if potential experience is used to proxy for labour market experience. Replacing potential experience with predicted or adjusted experience changed the relative ranking of the wage returns between the four demographic groups. All groups, with the exception of white women, are estimated to earn similar wage returns to an additional year of labour market experience. The impact of replacing potential experience with our two alternative measures was the greatest for black workers. This constitute evidence in favour of potential experience being a poor proxy for labour market experience, particularly for black workers.

7. CONCLUSION

According to the human capital model, individuals acquire human capital in two ways: through schooling and with on-the-job training. In the absence of direct measures, Mincer (1974) measured the latter with labour market experience. Labour market experience was in turn measured as age minus years of schooling minus six. Under the conditions of continuous labour market attachment and working careers beginning directly after completing, then potential experience serves as a good proxy for labour market experience in the absence of direct measures (Mincer, 1974). Unfortunately, the labour market behaviour and outcomes of women and blacks are such that potential experience does a poor job at measuring these workers' labour market experience. This is because women face family and household responsibilities that make them more susceptible to frequent employment interruptions and discontinuous labour market attachment (Munasinghe et al., 2008). Blacks, on the other hand, are more likely to be unemployed and face long periods of unsuccessful job search that delay the start of their working careers.

This paper investigated the challenges related to the unavailability of direct measures of on-the-job training in the data sets used for the analysis of labour markets in developing countries. We constructed two alternative measures for labour market experience that explicitly take into account the skewed distribution of the employment profiles faced by black workers in the South African labour market. The two measures together with potential experience were used to estimate the gender and racial wage penalty, and the wage return to labour market experience for black and white workers. Our results showed that the gender and racial wage penalties were substantially smaller if we use our two preferred measures of labour market experience. Furthermore, replacing potential experience with our two alternative measures had the greatest impact on the estimated wage returns of black workers. Consequently, with our alternative measures, there appears to be no significant racial or gender difference in the wage return to labour market experience.

This paper makes strong case for government agencies tasked with the collection of labour market statistical data in developing countries to make serious efforts at gathering information that make it possible to measure labour market experience. The potential experience measure does a poor job at measuring the labour market experience of black workers and women. This casts a cloud of doubt and suspicion on many of the empirical findings derived from traditional and augmented Mincerian earnings functions that use potential experience as a proxy for labour market experience.

8. APPENDIX

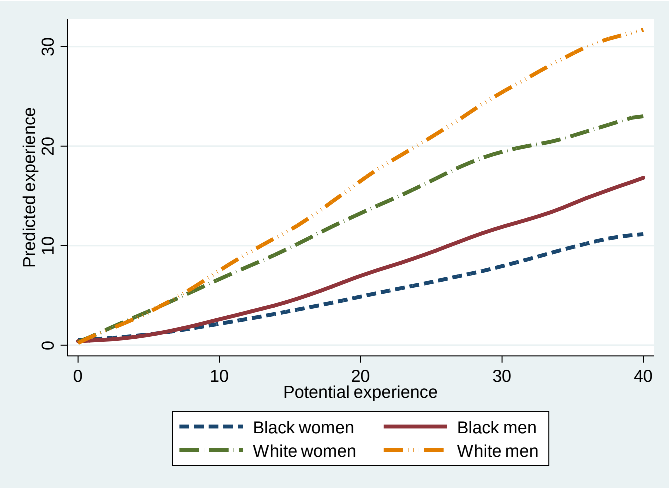


Figure A2.1: Potential experience vs predicted experience by demographic group

Note: These age-experience profiles are estimated from kernel-weighted local polynomial regressions of predicted experience on potential experience, using the Epanechnikov kernel function and bandwidth chosen by the rule-of-thumb method.

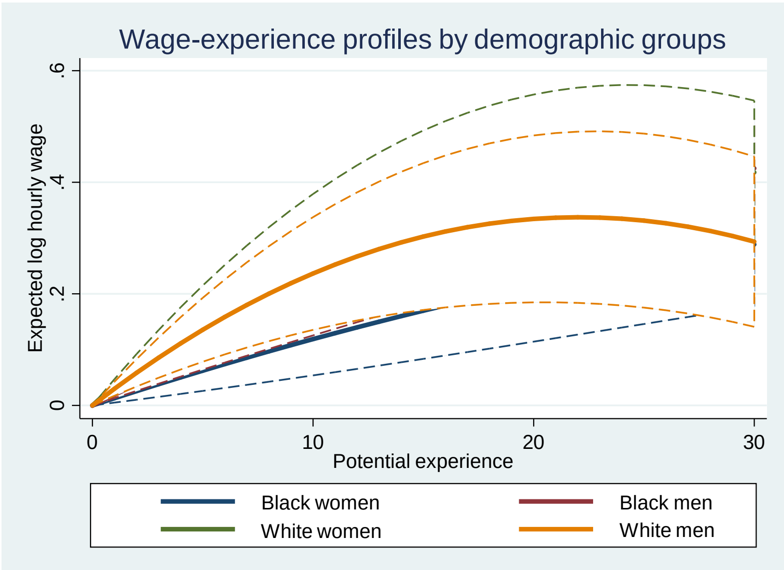


Figure A3: Wage-experience profiles by demographic groups, potential experience

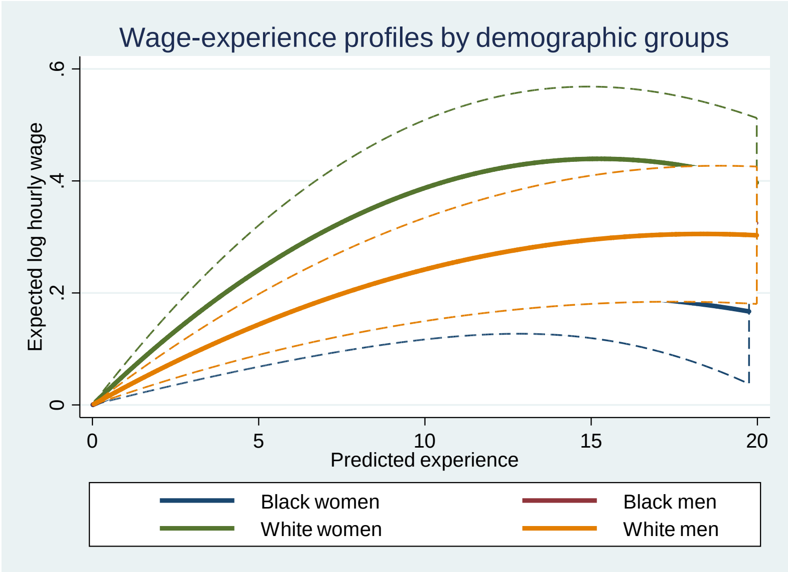


Figure A4: Wage-experience profiles by demographic groups, predicted experience

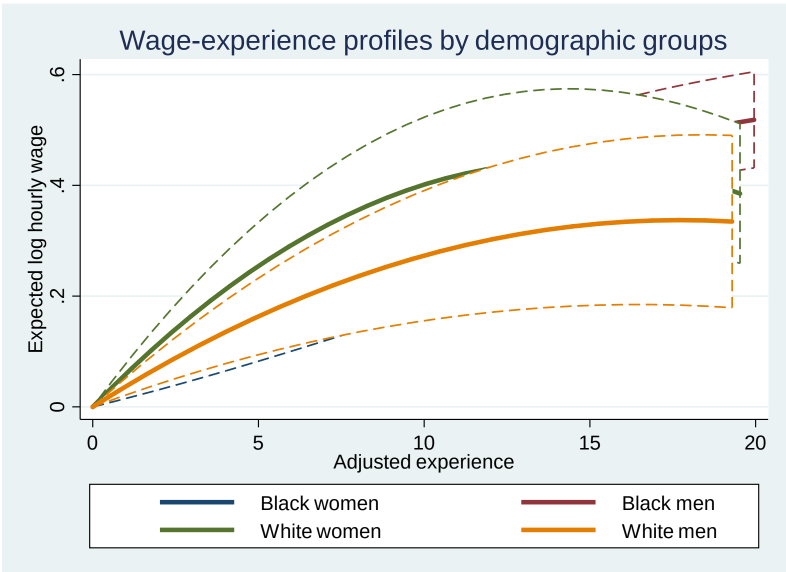


Figure A5: Wage-experience profiles by demographic groups, adjusted experience

Table A1: Wage returns to labour market experience, Panel A – potential experience

	Black women	Black men	White women	White men
Potential experience	0.0130 (0.0041)***	0.0193 (0.0031)***	0.0364 (0.0059)***	0.0306 (0.0065)***
Potential experience squared	-0.0001 (0.0001)	-0.0002 (0.0001)***	-0.0008 (0.0001)***	-0.0007 (0.0001)***
Schooling spline				
Primary	0.0192 (0.0063)***	0.0276 (0.0045)***	0.0113 (0.1170)	0.0111 (0.0357)
Secondary	0.0607 (0.0086)***	0.0717 (0.0056)***	0.0762 (0.0370)**	0.1058 (0.0290)***
Matric	0.1699 (0.0284)***	0.1529 (0.0195)***	0.1233 (0.0490)**	0.0564 (0.0426)
Tertiary	0.2444 (0.0291)***	0.2484 (0.0239)***	0.0764 (0.0266)***	0.1330 (0.0174)***
Diploma+Certificate dummy	0.2131 (0.0499)***	0.2082 (0.0482)***	0.0910 (0.0415)**	0.1260 (0.0417)***
Tenure	0.0318 (0.0042)***	0.0312 (0.0027)***	0.0224 (0.0063)***	0.0274 (0.0059)***
Tenure squared	-0.0007 (0.0002)***	-0.0007 (0.0001)***	-0.0004 (0.0002)	-0.0005 (0.0002)**
Union dummy	0.1868 (0.0256)***	0.1973 (0.0159)***	-0.0610 (0.0341)*	0.0680 (0.0350)*
Rural dummy	-0.2184 (0.0259)***	-0.1327 (0.0176)***	-0.2446 (0.0759)***	-0.1356 (0.0558)**
Province dummy 1	-0.5226 (0.0499)***	-0.2096 (0.0394)***	-0.1067 (0.0614)*	-0.2719 (0.0552)***
Province dummy 2	-0.3634 (0.0633)***	-0.1295 (0.0477)***	-0.3152 (0.0881)***	-0.2379 (0.0606)***
Province dummy 3	-0.6959 (0.0488)***	-0.3684 (0.0362)***	-0.3387 (0.0629)***	-0.2675 (0.0552)***
Province dummy 4	-0.3194 (0.0440)***	-0.0742 (0.0338)**	-0.0102 (0.0664)	-0.1435 (0.0598)**
Province dummy 5	-0.2749 (0.0467)***	-0.1381 (0.0343)***	-0.2509 (0.0653)***	-0.2095 (0.0567)***
Province dummy 6	-0.0222 (0.0472)	0.0105 (0.0332)	0.0891 (0.0587)	-0.0182 (0.0485)
Province dummy 7	-0.3561 (0.0466)***	-0.1245 (0.0356)***	-0.2626 (0.0653)***	-0.2129 (0.0572)***
Province dummy 8	-0.6001 (0.0487)***	-0.3693 (0.0390)***	-0.2805 (0.0989)***	-0.1924 (0.0790)**
House head dummy	0.0555 (0.0227)**	0.0826 (0.0191)***	0.2471 (0.0436)***	0.2681 (0.0479)***
Firm size dummy 1	0.0670 (0.0771)	0.1390 (0.0526)***	-0.1110 (0.1284)	-0.3343 (0.1891)*
Firm size dummy 2	0.1925 (0.0761)**	0.2074 (0.0511)***	-0.0112 (0.1243)	-0.2462 (0.1830)
Firm size dummy 3	0.2467 (0.0756)***	0.2638 (0.0510)***	-0.0427 (0.1276)	-0.2227 (0.1845)
Firm size dummy 4	0.2952 (0.0743)***	0.3254 (0.0504)***	0.0429 (0.1232)	-0.1010 (0.1827)
Firm size dummy 5	0.3587	0.4182	0.2164	-0.0174

	(0.0733)***	(0.0494)***	(0.1227)*	(0.1810)
Wave dummy 1	-0.0160 (0.0275)	-0.0091 (0.0192)	-0.0255 (0.0650)	0.0092 (0.0476)
Wave dummy 2	-0.0625 (0.0316)**	-0.0532 (0.0206)***	-0.0069 (0.0460)	-0.0783 (0.0567)
Wave dummy 3	-0.0345 (0.0339)	-0.0527 (0.0201)***	-0.0732 (0.0541)	-0.0455 (0.0456)
Wave dummy 4	0.0246 (0.0296)	0.0233 (0.0207)	0.0434 (0.0443)	0.0578 (0.0565)
Wave dummy 5	0.0067 (0.0312)	0.0095 (0.0212)	0.0509 (0.0457)	0.0188 (0.0484)
Marital dummy	0.1069 (0.0221)***	0.0227 (0.0158)	0.1441 (0.0433)***	0.1660 (0.0432)***
Children dummy 1	-0.0273 (0.0279)	0.0423 (0.0184)**	-0.0065 (0.0361)	-0.0318 (0.0408)
Children dummy 2	-0.0343 (0.0251)	0.0134 (0.0179)	0.0537 (0.0411)	-0.0387 (0.0463)
Children dummy 3	-0.0555 (0.0274)**	-0.0037 (0.0232)	-0.0334 (0.0642)	-0.0311 (0.0580)
Children dummy 4	-0.0788 (0.0387)**	-0.0640 (0.0303)**	-0.0644 (0.2177)	0.1842 (0.1554)
Children dummy 5	-0.2256 (0.0625)***	-0.1090 (0.0441)**	-0.3416 (0.1705)**	-0.0445 (0.0732)
Children dummy 6	-0.1832 (0.0770)**	-0.1011 (0.0847)		-0.2932 (0.1248)**
Children dummy 7	0.0824 (0.1442)	-0.2768 (0.1012)***		
Children dummy 8	0.0542 (0.3770)	0.0636 (0.1285)		
Children dummy 9	-0.3694 (0.2525)	-0.7348 (0.2523)***		
Children dummy 10	0.0263 (0.1773)	-0.0502 (0.2383)		
Children dummy 11	0.0547 (0.1622)	-0.4458 (0.2597)*		
Children dummy 12	-0.6399 (0.4180)	0.0447 (0.0446)		
Children dummy 13	-0.5449 (0.0438)***	-0.6348 (0.0350)***		
Children dummy 14	0.9946 (0.0678)***			
Occupation Dummy 1	-0.2938 (0.1308)**	-0.1034 (0.1145)	0.0458 (0.1013)	-0.1274 (0.0693)*
Occupation Dummy 2	-0.4561 (0.1008)***	-0.3083 (0.0596)***	-0.2241 (0.0551)***	-0.1470 (0.0525)***
Occupation Dummy 3	-0.6310 (0.0928)***	-0.5799 (0.0571)***	-0.4140 (0.0570)***	-0.5331 (0.0636)***
Occupation Dummy 4	-0.8269 (0.0966)***	-0.9075 (0.0568)***	-0.5545 (0.0689)***	-0.5949 (0.0717)***
Occupation Dummy 5	-0.8715 (0.1328)***	-0.6469 (0.1276)***		-0.2929 (0.1600)*
Occupation Dummy 6	-0.8946	-0.6461	-0.4972	-0.4274

	(0.0973)***	(0.0551)***	(0.1215)***	(0.0477)***
Occupation Dummy 7	-0.9009	-0.7106	-0.6250	-0.5715
	(0.0986)***	(0.0548)***	(0.1230)***	(0.0707)***
Occupation Dummy 8	-0.9682	-0.8420	-0.7415	-0.6297
	(0.0945)***	(0.0549)***	(0.1279)***	(0.0934)***
Industry Dummy 1	0.7478	0.7341	0.3036	0.3930
	(0.0804)***	(0.0267)***	(0.1534)**	(0.0950)***
Industry Dummy 2	0.3420	0.6262	0.2051	0.3410
	(0.0380)***	(0.0270)***	(0.1449)	(0.0878)***
Industry Dummy 3	0.7067	0.7357	0.0363	0.4127
	(0.1363)***	(0.0680)***	(0.1685)	(0.1164)***
Industry Dummy 4	0.4407	0.4929	0.2292	0.1504
	(0.0674)***	(0.0306)***	(0.1641)	(0.1151)
Industry Dummy 5	0.2430	0.4607	0.0977	0.2535
	(0.0357)***	(0.0274)***	(0.1469)	(0.0917)***
Industry Dummy 6	0.7125	0.6062	0.1824	0.1778
	(0.0676)***	(0.0331)***	(0.1473)	(0.1034)*
Industry Dummy 7	0.5977	0.5599	0.2463	0.3776
	(0.0394)***	(0.0337)***	(0.1475)*	(0.0924)***
Industry Dummy 8	0.4329	0.6260	0.0872	0.2152
	(0.0457)***	(0.0408)***	(0.1470)	(0.1051)**
Industry Dummy 9	0.7038	1.0078	0.6460	0.1413
	(0.2247)***	(0.1645)***	(0.1825)***	(0.2500)
Industry Dummy 10		-0.1026		
		(0.1451)		
Intercept	1.3522	0.8583	2.0338	2.1588
	(0.1365)***	(0.0931)***	(0.7803)***	(0.3014)***
R^2	0.57	0.53	0.36	0.43
N	8,353	16,889	3,359	3,990

Notes: * p<0.1; ** p<0.05; *** p<0.01

Table A2: Wage returns to labour market experience, Panel C – adjusted experience

	Black women	Black men	White women	White men
Adjusted experience	0.0387 (0.0122)***	0.0425 (0.0069)***	0.0616 (0.0100)***	0.0380 (0.0081)***
Adjusted experience squared	-0.0010 (0.0007)	-0.0008 (0.0003)***	-0.0021 (0.0004)***	-0.0011 (0.0002)***
Schooling spline				
Primary	0.0192 (0.0063)***	0.0276 (0.0045)***	0.0113 (0.1170)	0.0111 (0.0357)
Secondary	0.0607 (0.0086)***	0.0717 (0.0056)***	0.0762 (0.0370)**	0.1058 (0.0290)***
Matric	0.1699 (0.0284)***	0.1529 (0.0195)***	0.1233 (0.0490)**	0.0564 (0.0426)
Tertiary	0.2444 (0.0291)***	0.2484 (0.0239)***	0.0764 (0.0266)***	0.1330 (0.0174)***
Diploma+Certificate dummy	0.2131 (0.0499)***	0.2082 (0.0482)***	0.0910 (0.0415)**	0.1260 (0.0417)***
Tenure	0.0318 (0.0042)***	0.0312 (0.0027)***	0.0224 (0.0063)***	0.0274 (0.0059)***
Tenure squared	-0.0007 (0.0002)***	-0.0007 (0.0001)***	-0.0004 (0.0002)	-0.0005 (0.0002)**
Union dummy	0.1868 (0.0256)***	0.1973 (0.0159)***	-0.0610 (0.0341)*	0.0680 (0.0350)*
Rural dummy	-0.2184 (0.0259)***	-0.1327 (0.0176)***	-0.2446 (0.0759)***	-0.1356 (0.0558)**
Province dummy 1	-0.5226 (0.0499)***	-0.2096 (0.0394)***	-0.1067 (0.0614)*	-0.2719 (0.0552)***
Province dummy 2	-0.3634 (0.0633)***	-0.1295 (0.0477)***	-0.3152 (0.0881)***	-0.2379 (0.0606)***
Province dummy 3	-0.6959 (0.0488)***	-0.3684 (0.0362)***	-0.3387 (0.0629)***	-0.2675 (0.0552)***
Province dummy 4	-0.3194 (0.0440)***	-0.0742 (0.0338)**	-0.0102 (0.0664)	-0.1435 (0.0598)**
Province dummy 5	-0.2749 (0.0467)***	-0.1381 (0.0343)***	-0.2509 (0.0653)***	-0.2095 (0.0567)***
Province dummy 6	-0.0222 (0.0472)	0.0105 (0.0332)	0.0891 (0.0587)	-0.0182 (0.0485)
Province dummy 7	-0.3561 (0.0466)***	-0.1245 (0.0356)***	-0.2626 (0.0653)***	-0.2129 (0.0572)***
Province dummy 8	-0.6001 (0.0487)***	-0.3693 (0.0390)***	-0.2805 (0.0989)***	-0.1924 (0.0790)**
House head dummy	0.0555 (0.0227)**	0.0826 (0.0191)***	0.2471 (0.0436)***	0.2681 (0.0479)***
Firm size dummy 1	0.0670 (0.0771)	0.1390 (0.0526)***	-0.1110 (0.1284)	-0.3343 (0.1891)*
Firm size dummy 2	0.1925 (0.0761)**	0.2074 (0.0511)***	-0.0112 (0.1243)	-0.2462 (0.1830)
Firm size dummy 3	0.2467 (0.0756)***	0.2638 (0.0510)***	-0.0427 (0.1276)	-0.2227 (0.1845)
Firm size dummy 4	0.2952 (0.0743)***	0.3254 (0.0504)***	0.0429 (0.1232)	-0.1010 (0.1827)
Firm size dummy 5	0.3587	0.4182	0.2164	-0.0174

	(0.0733)***	(0.0494)***	(0.1227)*	(0.1810)
Wave dummy 1	-0.0160	-0.0091	-0.0255	0.0092
	(0.0275)	(0.0192)	(0.0650)	(0.0476)
Wave dummy 2	-0.0625	-0.0532	-0.0069	-0.0783
	(0.0316)**	(0.0206)***	(0.0460)	(0.0567)
Wave dummy 3	-0.0345	-0.0527	-0.0732	-0.0455
	(0.0339)	(0.0201)***	(0.0541)	(0.0456)
Wave dummy 4	0.0246	0.0233	0.0434	0.0578
	(0.0296)	(0.0207)	(0.0443)	(0.0565)
Wave dummy 5	0.0067	0.0095	0.0509	0.0188
	(0.0312)	(0.0212)	(0.0457)	(0.0484)
Marital dummy	0.1069	0.0227	0.1441	0.1660
	(0.0221)***	(0.0158)	(0.0433)***	(0.0432)***
Children dummy 1	-0.0273	0.0423	-0.0065	-0.0318
	(0.0279)	(0.0184)**	(0.0361)	(0.0408)
Children dummy 2	-0.0343	0.0134	0.0537	-0.0387
	(0.0251)	(0.0179)	(0.0411)	(0.0463)
Children dummy 3	-0.0555	-0.0037	-0.0334	-0.0311
	(0.0274)**	(0.0232)	(0.0642)	(0.0580)
Children dummy 4	-0.0788	-0.0640	-0.0644	0.1842
	(0.0387)**	(0.0303)**	(0.2177)	(0.1554)
Children dummy 5	-0.2256	-0.1090	-0.3416	-0.0445
	(0.0625)***	(0.0441)**	(0.1705)**	(0.0732)
Children dummy 6	-0.1832	-0.1011		-0.2932
	(0.0770)**	(0.0847)		(0.1248)**
Children dummy 7	0.0824	-0.2768		
	(0.1442)	(0.1012)***		
Children dummy 8	0.0542	0.0636		
	(0.3770)	(0.1285)		
Children dummy 9	-0.3694	-0.7348		
	(0.2525)	(0.2523)***		
Children dummy 10	0.0263	-0.0502		
	(0.1773)	(0.2383)		
Children dummy 11	0.0547	-0.4458		
	(0.1622)	(0.2597)*		
Children dummy 12	-0.6399	0.0447		
	(0.4180)	(0.0446)		
Children dummy 13	-0.5449	-0.6348		
	(0.0438)***	(0.0350)***		
Children dummy 14	0.9946			
	(0.0678)***			
Occupation Dummy 1	-0.2938	-0.1034	0.0458	-0.1274
	(0.1308)**	(0.1145)	(0.1013)	(0.0693)*
Occupation Dummy 2	-0.4561	-0.3083	-0.2241	-0.1470
	(0.1008)***	(0.0596)***	(0.0551)***	(0.0525)***
Occupation Dummy 3	-0.6310	-0.5799	-0.4140	-0.5331
	(0.0928)***	(0.0571)***	(0.0570)***	(0.0636)***
Occupation Dummy 4	-0.8269	-0.9075	-0.5545	-0.5949
	(0.0966)***	(0.0568)***	(0.0689)***	(0.0717)***
Occupation Dummy 5	-0.8715	-0.6469		-0.2929
	(0.1328)***	(0.1276)***		(0.1600)*
Occupation Dummy 6	-0.8946	-0.6461	-0.4972	-0.4274

	(0.0973)***	(0.0551)***	(0.1215)***	(0.0477)***
Occupation Dummy 7	-0.9009	-0.7106	-0.6250	-0.5715
	(0.0986)***	(0.0548)***	(0.1230)***	(0.0707)***
Occupation Dummy 8	-0.9682	-0.8420	-0.7415	-0.6297
	(0.0945)***	(0.0549)***	(0.1279)***	(0.0934)***
Industry Dummy 1	0.7478	0.7341	0.3036	0.3930
	(0.0804)***	(0.0267)***	(0.1534)**	(0.0950)***
Industry Dummy 2	0.3420	0.6262	0.2051	0.3410
	(0.0380)***	(0.0270)***	(0.1449)	(0.0878)***
Industry Dummy 3	0.7067	0.7357	0.0363	0.4127
	(0.1363)***	(0.0680)***	(0.1685)	(0.1164)***
Industry Dummy 4	0.4407	0.4929	0.2292	0.1504
	(0.0674)***	(0.0306)***	(0.1641)	(0.1151)
Industry Dummy 5	0.2430	0.4607	0.0977	0.2535
	(0.0357)***	(0.0274)***	(0.1469)	(0.0917)***
Industry Dummy 6	0.7125	0.6062	0.1824	0.1778
	(0.0676)***	(0.0331)***	(0.1473)	(0.1034)*
Industry Dummy 7	0.5977	0.5599	0.2463	0.3776
	(0.0394)***	(0.0337)***	(0.1475)*	(0.0924)***
Industry Dummy 8	0.4329	0.6260	0.0872	0.2152
	(0.0457)***	(0.0408)***	(0.1470)	(0.1051)**
Industry Dummy 9	0.7038	1.0078	0.6460	0.1413
	(0.2247)***	(0.1645)***	(0.1825)***	(0.2500)
Industry Dummy 10		-0.1026		
		(0.1451)		
Intercept	1.3522	0.8583	2.0338	2.1588
	(0.1365)***	(0.0931)***	(0.7803)***	(0.3014)***
R^2	0.57	0.53	0.36	0.43
N	8,353	16,889	3,359	3,990

Notes: * p<0.1; ** p<0.05; *** p<0.01

Table A3: Gender and racial gaps in log hourly wages with different measures of experience

	Black women	Black men	White women	White men
Panel A:				
Potential experience	0.0231	0.0423	0.0485	0.0659
	(0.0047)***	(0.0032)***	(0.0060)***	(0.0069)***
Potential experience^2	-0.0001	-0.0004	-0.0010	-0.0013
	(0.0001)	(0.0001)***	(0.0001)***	(0.0002)***
Panel B:				
Adjusted experience	0.0687	0.0933	0.0819	0.0820
	(0.0141)***	(0.0071)***	(0.0102)***	(0.0086)***
Adjusted experience^2	-0.0012	-0.0021	-0.0029	-0.0020
	(0.0009)	(0.0003)***	(0.0004)***	(0.0002)***
Panel C:				
Predicted experience	0.0697	0.0810	0.0731	0.0747
	(0.0078)***	(0.0045)***	(0.0080)***	(0.0068)***
Predicted experience^2	-0.0024	-0.0024	-0.0024	-0.0018
	(0.0005)***	(0.0002)***	(0.0003)***	(0.0002)***

Notes: These regressions control for schooling[11], tenure and tenure squared.
Robust standard errors in parentheses.
* p<0.1; ** p<0.05; *** p<0.01.

[11] Specified as a spline with knots at 7 years (completed primary), 12 years (completed secondary) and tertiary which is more than 12 years of schooling. We further specify a separate dummy variable that takes on a value of one for individuals with 12 years of schooling plus diploma or certificate not obtained from a university, and zero otherwise.

CHAPTER 3

THE TENURE-WAGE PROFILES OF DIFFERENT DEMOGRAPHIC GROUPS: THE SOUTH AFRICAN CASE

Abstract

The structure of the rewards and compensation given to labour for its services and effort in production is a central focus of many labour market models. The predictions and implications of these models have for many decades been empirically tested and explored with labour market data primarily from developed countries. The use of developing country labour market data has been very limited mainly because of lack of available good quality data. This is however changing and in this chapter, we use the panel component of the first nationally representative panel data set of the South African labour market to account for unobserved worker heterogeneity and match quality, factors that would otherwise bias the effect of job tenure on wages.

Our first set of results are based on pooled ordinary least square estimation of a wage regression separately by race and gender. These results point to the importance of controlling for occupation and industry, type of sector, features of the employment contract, type of employment and firm size when estimating the wage returns to job tenure for South African workers. The second set of results use a control function approach to implement an instrumental variables two-stage estimation procedure to address bias in our estimation. We show that South Africa conforms to the stylised facts found in the international literature: once we account for differences in worker heterogeneity and match quality the effect of job tenure on wages is small on average, but larger for disadvantaged groups. For black workers, 10 years of job tenure increases average wages by 10%. Surprisingly, our results show zero wage returns for white workers. This result deviates from the stereotypical racial hierarchy in the labour market outcomes of South African workers that commonly depicts better outcomes for white workers.

1. INTRODUCTION

How a firm compensates its workforce for its effort in production is a central focus of many labour economic models. A common prediction of these models is that wages increase with time spent working for the firm. From the perspective of the human capital model, an additional year with the firm allowed the worker to accumulate firm-specific skills that enabled the worker to be more productive (Becker, 1962). On the other hand, the information, employer learning and matching models have put forward alternative theoretical motivations for this prediction. These models emphasised imperfect information, implicit contracts and principal-agent considerations in the employer-employee relationship as the key driver of within-firm wage growth (Salop and Salop, 1976; Jovanovic, 1979; Lazear, 1981; and Harris and Holmstrom, 1982). In these models, employers use the firm's compensation structure as an incentive device to encourage optimal behaviour by workers (Lazear, 1981; and Farber, 1999).

While the theoretical motivations behind the prediction of rising wages with job tenure differ between the different models, the common finding in labour market data of a positive association between wages and job tenure backs up and gives credence to this prediction. In a seminal study, Mincer and Jovanovic (1981), for example, found that the wage returns to job tenure accounted for about one-quarter of total wage growth over the life cycle. However, in the late 1980s, an empirical debate on the wage effects of job tenure ensued. In his review of this literature, Hutchens (1989: 49) summarised the debate as one of "puzzles and doubt". The 'doubt' referred to the empirical significance of the wage effects of job tenure as more and more researchers found small or statistically insignificant wage returns to job tenure (Abraham and Farber, 1987; Altonji and Shakotko, 1987; and Marshall and Zarkin, 1987). The 'puzzles' referred to the relevance of the economic models that predicted positive wage returns to job tenure. A seminal contribution by Topel (1991) generated further debate and attention on the wage effects of job tenure from labour economists. Topel's estimates suggested that the wage return to job tenure was substantial and quantitatively similar to those found by Mincer and Jovanovic (1981) and other earlier studies (see also Garen, 1989).

At the heart of this empirical debate is the influence of unobserved heterogeneity in worker-firm match quality on the estimated wage effect of job tenure and the best econometric methodology to resolve this endogeneity. The endogeneity arises because the unobserved worker and match quality is correlated to the variable of interest, job tenure, and introduced bias in the estimation of the effects of interest (Abraham and Farber, 1987; Altonji and Shakotko, 1987; Garen, 1989; and Topel, 1991). More recent studies were unable to provide consensus and closure on this debate. For example, Altonji and Williams (2005) found statistically positive, but small, wage returns to job tenure. Subsequently, Jacobsen and Levin (2002) found large wage returns.

There are at least three reasons why the researcher should care about the wage effects of job tenure Firstly, wage returns to job tenure represent a benefit to a worker that is only realised if the worker keeps his current job. If the worker changes jobs – voluntarily or involuntarily – this benefit would be lost. Therefore, an analysis of the effects of job tenure on wages may add to and improve our assessments of the costs of unemployment and turnover in the labour market. Secondly, the returns to job tenure formed part of the dynamic structure of wages (Williams, 1991) and were thus important in understanding how workers' wages grew over time. Lastly, differences in the accumulation of and wage return to job tenure between workers has been shown to be an important determinant of the variation in wages across workers (Jacobsen & Levin, 2002). Understanding wage inequality therefore requires knowing whether these differences are driven by worker heterogeneity or the causal benefits of specific skills.

In this chapter, we extend the literature by studying the wage effects of job tenure from a developing country context. Most of the current research is based on the US labour market and recent attempts at extending the literature have focused on other developed country labour markets like the UK (e.g. Williams, 2009). Using a panel dataset of the South African labour market, we provide evidence that lends support for two important results found in the international literature. Firstly, our estimates show that the wage returns to tenure are indeed small as shown by, for example, Altonji and Williams (2005). Secondly, the ordinary least squares estimated wage returns to job tenure for black and white workers are comparable (e.g. Bratsberg & Terrell, 1998; and Lewis & Terrell, 2001). Lastly, after controlling for unobserved individual worker and worker-firm match quality, we find no wage returns for white workers while black workers receive positive but modest wage returns. This result suggests that the source of disadvantage for black workers relative to their white counterparts is primarily located at the time of entry into the job and when black workers changes jobs. Our results show that staying with the same firm for an additional year brings a higher wage return for black workers relative to white workers.

The next section discusses the relevant literature. Section three presents the methodology and data used for the empirical analysis. Section four presents and discusses the results from the empirical analysis. Section five provides a summary and concluding remarks.

2. LITERATURE REVIEW

In this section, we review the theoretical and empirical literature on the wage returns to tenure. The prediction that wages rise with job tenure is an important prediction of many theoretical models of the labour market. These models, however, differ in their explanation of why wages rises with job tenure. We will begin our review of the theoretical literature with the discussion of the human capital model, before proceeding to models with asymmetric information. The section will close with a discussion of the empirical evidence and econometric issues encountered in the estimation of the wage returns to job tenure.

2.1 Theoretical Models

An essential feature of the human capital model is that workers can raise their marginal productivity. Becker (1962) distinguished between two types of on-the-job investment in human capital that lead to increased marginal productivity. The first type, which he referred to as general training, improved the worker's marginal productivity in all firms, not only in the firm where the training took place. Specific training referred to on-the-job training that led to increases that are more substantial in marginal productivity in the firm where the training was undertaken.

Rising wages with job tenure are a consequence of workers' investment in specific training. As workers accumulate firm-specific skills, they can produce more output, and the firm earns a higher profit. Part of that increase in profit was shared with the worker in the form of higher wages (Becker, 1962). Therefore, wages will rise if both the labour and goods markets were competitive and as the worker's marginal productivity rises.

Other theoretical models have made similar predictions regarding wages and job tenure, but with different explanations. In Jovanovic's (1979) job matching model of labour turnover, the productivity of a given worker in a given job is unknown *ex ante* by both employer and employee and this gives rise to uncertainty about the quality of the worker-firm match. This uncertainty is resolved through a learning process in which the worker's output is observed by the firm over time. Firms value workers with whom they are well matched and will offer higher wages to such workers, while paying relatively lower wages to workers who are revealed to be of low productivity on a poor match with the firm. Thus, individual wages are an increasing function of job tenure because workers that are well matched will accumulate longer tenure spells while poorly matched workers move on to other firms.

Salop and Salop's (1976) model showed that firms offered wages that increased with tenure over the life cycle as a self-selection mechanism that ensured the credibility of information conveyed by job applicants. Faced with high turnover costs when employees quit, the firm would ideally like to employ those employees with lower inclinations to leave the firm prematurely. By offering initially low, but predictably increasing wages, the firm induces workers to reveal their privately held quit-propensities. Additionally, it ensures that workers with high quit-propensities self-select themselves out of jobs offering upwardly sloping wage-tenure profiles. This implies that wages may increases with tenure independently from productivity increases.

The above two models emphasise the importance and consequences of imperfect information in the employer-employee relationship. The next model demonstrates that positively sloped wage-tenure profiles may also be consistent with firms' attempts at overcoming principal-agent problems that often characterise an employer-employee relationship. In Lazear's (1981) model, paying lower wages to workers who were in the early stages of their life cycle, or paying junior workers less than their senior counterparts, showed to be an optimal strategy for a firm. This incentivises less shirking on the job and ensures that workers supply optimal levels of effort.

While the theoretical foundations of the above models differ regarding the process of within-firm wage growth for workers, they, however, make similar predictions regarding the direction of correlation between wages and job tenure. The study now reviews the evidence regarding the empirical relationship between wages and job tenure.

2.2 Empirical Evidence

The earnings function is the primary empirical tool used by labour economists to analyse data and to derive empirical evidence for their theoretical models. It naturally follows that the earnings function has featured heavily in the empirical literature that looks at the wage effects of job tenure. This literature used Mincer and Jovanovic's (1981) proposed an extension of the traditional Mincerian earnings function as a point of departure. The extension involved adding job tenure into the earnings function and interpreting the coefficient on this term as the wage effects of investment in specific human capital. The authors, however, pointed out that job tenure would capture the wage returns to specific human capital. This would be possible if the heterogeneity bias from differences in the accumulation of specific human capital among individuals, were corrected.

A further contribution by Mincer and Jovanovic (1981) was the proposal of incorporating into the earnings function information on previous job mobility of individuals as a way of addressing the heterogeneity bias. Using this econometric specification, the authors obtained large and positive wage returns to job tenure. This accounted for approximately 20-25 per cent of annual wage growth. This was interpreted as evidence in support of investment in specific human capital as the fundamental explanation for the prediction that wages rise with job tenure.

The findings by Mincer and Jovanovic (1981) were later criticised and challenged in the late 1980s. Research by Abraham and Farber (1987), Altonji and Shakotko (1987), Marshall and Zarkin (1987) and Topel (1991) pointed to the existence of additional sources of heterogeneity bias that are linked to the unobservable quality of individuals, the job and the match between the worker and the firm. These researchers argued that these unobserved heterogeneities are correlated to both the length of job tenure and individual wages. Consequently, failure to address these unobserved heterogeneities leads to biased estimates.

The correlation between worker quality and job tenure arises if more productive workers, regarding unobservable characteristics such as ability and motivation, earn more and thus tend to stay longer in their jobs and enjoy long spells of tenure. Holding workers' skills and ability constant, workers will differ in an unobservable way (or at least unobservable to the econometrician) in the degree to which their skills set (and unobservable characteristics) are well matched to their current employer. This unobservable quality of the match will correlate with both the worker's wage and the length of the worker's job tenure as predicted by Jovanovic's (1979) job matching model.

Attempts at addressing these additional sources of heterogeneity bias sparked a debate among labour economists on the wage effects of job tenure. This debate also ignited scrutiny on the relevance of the economic models that predict positive wage returns to job tenure. A big part of the debate revolved around the correct determination of the direction of the bias on the wage effects of job tenure and the correct estimators to deal with the bias.

Altonji and Shakotko (1987) and Topel (1991) proposed two of the most influential estimators in the literature. A discussion of these estimators is delayed until the next session. Estimates obtained using these estimators have produced contradicting evidence on the wage effects of job tenure. Altonji and Shakotko (1987) found that wages do not rise very much job tenure. Specifically, they found that ten years of job tenure only raised wages by 6.6%. The findings of Abraham and Farber (1987), and Marshall and Zarkin (1987), who found small wage returns to job tenure while using different estimation techniques, echoed these results.

In complete contrast to the results found by Altonji and Shakotko (1987) and others, Topel (1991) found substantial wage returns to job tenure. According to Topel's (1991) estimates, ten years of tenure raises wages by roughly 25%. Using different econometric techniques, Garen (1989) also provides evidence of large wage returns to job tenure.

Topel (1991) and Altonji and Williams (2005) provide very detailed analyses and discussion of the possible reasons for the different estimated results reported by Abraham and Farber (1987), Altonji and Shakotko (1987) on the one hand, and the results reported by Topel (1991). The authors identify differences in estimation techniques, procedures for dealing with measurement error in the job tenure variable, and procedures for de-trending the time trend. Nonetheless, studies that are more recent still report contradicting results and have not been able to provide consensus and closure on this debate. For example, Altonji and Williams (2005) find statistically positive but small wage returns to job tenure, while Jacobsen and Levin (2002) find large wage returns.

The one area where there seems to be consensus is the comparison of the between-group differences in the wage returns to job tenure. Bratsberg and Terrell (1998) use OLS, Altonji and Shakotko's (1987) IV estimator, and Topel's (1991) two-stage estimator to study the wage returns to job tenure between black and white workers. Results from all three estimators indicate that black workers earn slightly larger wage returns to job tenure compared to white workers. These results are consistent with the results found by Lewis and Terrell (2001). Wage returns to job tenure tend to be lower for women compared to men (Muniasinghe et al., 2008). Workers in union jobs have larger wage returns to job tenure compared to workers in non-union jobs (Williams, 2009).

The current literature estimates wage returns to job tenure primarily using data from the US. Estimates from developed country labour markets are overrepresented in the literature. This chapter adds the developing country perspective by estimating the wage returns to job tenure for black and white men and women in South Africa. The next section discusses the different estimators found in the literature and describes the econometric methodology used in the empirical analysis.

3. METHODOLOGY AND DATA

The previous section identified the earnings function as the key basis for much of the empirical analysis of the wage effects of job tenure. The researcher follows in this tradition and estimate the wage returns to job tenure for South African workers using the Mincerian earnings function, as extended by Mincer and Jovanovic (1981), as our point of departure in our empirical analysis. This section will describe the empirical methodology used to derive the results presented in the next section. A discussion of the data used for the empirical analysis will then follow the discussion of the methodology.

3.1 Empirical Strategy

The outcome variable is defined as the log hourly wage rate for worker i on job j at time period t, w_{ijt}. This outcome variable will be expressed as a function of job tenure – commonly measured in the literature as the amount of time a worker has spent with their current employer – Te_{ijt}, and a vector of personal and labour market characteristics like years of schooling completed and years of labour market experience, $\boldsymbol{Z}_{ijt}$. Formally, this yield:

$$w_{ijt} = \beta_0 + \beta_1 Te_{ijt} + \beta_2 Te_{ijt}^2 + \boldsymbol{\beta_3 Z}_{ijt} + \varepsilon_{ijt} \quad (1)$$

If the unobserved heterogeneity in the quality of workers and worker-firm matches are corrected for, then $\beta_1$and β_2 capture the wage returns to specific human capital. Within the human capital model, $\beta_1$is expected to have a positive sign while $\beta_2$is expected to have a negative sign indicating a concave tenure-wage profile that is a general feature of wage functions under the human capital model (Ben-Porath, 1967). ε_{ijt} is the model error term and the researcher shall have more to say about this term when the researcher consider the heterogeneity bias that taints the estimation of the wage returns to job tenure. For now, the researcher will ignore this bias and proceed with sketching the empirical strategy for the first part of our empirical analysis.

The first part of our empirical analysis will be based on the pooled ordinary least square (OLS) estimation of equation (1). Equation (1) will be estimated separately by race and gender to account for possible racial, and gender differences in the wage return to job tenure. The control variables captured by $\boldsymbol{Z}_{ijt}$ include years of schooling completed12, area of the the residency (i.e. rural versus urban), province, indication r variable for head of the the householder d status, indication r variable for marital status, potential experience13, indicator variables for survey wave fixed effects.

Our base specification for the pooled OLS regressions will have job tenure (and its squared term) as the variable interest, and the control variables will be those listed above. There is an additional list of control variables that will be added one at a time to our regressions. As part of our analysis, the researcher is interested in investigating how controlling for each of these variables affects our estimated wage effects of job tenure. These additional control variables include an alternative proxy variable for labour market experience that was suggested in the

12 Specified as a spline with knots at 7 years (completed primary), 12 years (completed secondary) and tertiary which is more than 12 years of schooling. We specify a separate dummy variable that takes on a value of one for individuals with 12 years of schooling plus diploma or certificate not obtained from a university, and zero otherwise.
13 Measured as age minus years of schooling completed minus six (Mincer, 1974).

previous chapter, occupation and industry, type of sector employment, features of the employment contract and employment type, and firm size.

The researcher now turns to the issue of the unobserved heterogeneity in the quality of workers and worker-firm matches. The bias in the wage returns to job tenure can be illustrated by decomposing the error term in equation (1) as follows (Abraham and Farber, 1987; Altonji and Shakotko, 1987; Garen, 1989; and Topel, 1991):

$$\varepsilon_{ijt} = \mu_i + \varphi_{ij} + \alpha_{ijt} (2)$$

where μ_i is an unobserved fixed individual effect, φ_{ij} is an unobserved worker-firm fixed effect that captures heterogeneity in the quality of job matches, and α_{ijt} is a random disturbance term. A common assumption imposed on equation (2) in the literature was that all terms on the right-hand side were mutually orthogonal to one another (Topel, 1991). The bias arises because the variable of interest in equation (1), job tenure, is correlated to both the individual and job match error components of equation (2). The correlation between μ_i and job tenure arises if more productive workers, in terms of unobservable characteristics such as ability and motivation, earn more and thus tend to stay longer in their jobs and enjoy longer spells of tenure. This induces an upward bias in the estimated wage return to job tenure.

The empirical debate on the wage effects of job tenure alluded to in the literature review section is based on a difference of opinion on the direction of correlation between job tenure and the worker-firm match quality, φ_{ij}. Altonji and Shakotko (1987) claim that correlation is positive and thus introduces an upward bias in the tenure-wage effect. According to the job matching model of Jovanovic (1979), workers who are well matched (higher draw of φ_{ij}) to their current firms earn higher wages and are in turn less likely to leave their jobs. This induces a positive correlation between job tenure and the worker-firm match quality component of equation (2).

Topel (1991), and more recently Stevens (2003), argued that the correlation between job tenure and the worker-firm match quality component of equation (2) was negative. Topel (1991) pointed out that individuals who changed jobs voluntarily, do so because the new job offers a higher match quality. Therefore, it is possible that workers with large values of φ_{ij} could appear in the data as having low values of job tenure. Stevens (2003) showed theoretically that low values of φ_{ij} do not necessarily cause workers to change jobs as predicted by the job matching models. Taken together, this suggest that the correlation between job tenure and the worker-firm match quality is negative.

Alltonji and Shakotko (1987) proposed an instrumental variables estimator for addressing the bias. Their empirical strategy was to instrument for the tenure variables (Te_{ijt}, and Te^2_{ijt}), with "the deviations of the tenure variables around their means for the sample observations on a given job match" as the principal instruments (Altonji and Shakotko, 1987: 439). Define $\overline{Te}_{ij}$ as the individual mean for worker i on job j over the sample. $\overline{Te}_{ij}$ can be formally expressed as follows:

$$\overline{Te}_{ij} = \frac{1}{n} \sum_{v=T\acute{e}_{ijt}}^{Te_{ijt}} Te_v \qquad (3)$$

Where the length of the sample survey is denoted as n and is measured in years, $T\acute{e}_{ijt}$ is the length of the worker's tenure when they are observed in the survey for the first time. The deviation around the mean is then given as:

$$\widehat{Te}_{ijt} = Te_{ijt} - \overline{Te}_{ij} \qquad (4)$$

Define the instrument similarly for the quadratic term as $\widehat{Te}^2_{ijt} = Te^2_{ijt} - \overline{Te}_{ij}$. By construction, "the variation in tenure over the job, in contrast to the variation in tenure across individuals and jobs, is uncorrelated with the fixed individual and job match components of the error term of the wage model" (Altonji and Shakotko, 1987: 438). The authors implement this procedure by way of two-stage least squares (2SLS) estimation and with the use of panel data.

Topel (1991) suggested an alternative method of dealing with the bias: a two-stage differencing estimation procedure. By taking the first difference of equation (1), an unbiased estimate of the with-in job wage growth is obtained for those remaining in the same job:

$$\Delta w_{ijt} = \beta_1 + \beta_2 \Delta Te^2_{ijt} + \boldsymbol{\beta_3} \Delta \mathbf{Z}_{ijt} + \Delta \alpha_{ijt} \qquad (5)$$

The differencing eliminates the unobserved fixed individual and job match specific effects. A second stage is necessary though since equation (5) does not separately identify the tenure and experience wage effects. In the second stage, Topel (1991) estimates an initial wage equation on new jobs:

$$w_{0ijt} = \beta_0 + \beta_1 Ex_{0ijt} + \beta_2 Ex^2_{0ijt} + \boldsymbol{\beta_3} \boldsymbol{Z}_{ijt} + \gamma_{ijt} \qquad (6),$$

w_{0ijt}, Ex_{0ijt}, and Ex^2_{0ijt} are the initial wage, initial (potential) labour market experience, and initial (potential) labour market experience squared, respectively. Since this is a wage equation for a worker in a new job, tenure is equal to zero and there are no concerns about any correlation of tenure with the unobserved individual and job match error components. The correlation between initial experience and the error term is a concern though. To correct for this, Topel (1991) subtracts the return to experience for workers in new jobs (i.e. β_1 in equation (6)) from the with-in job wage growth (i.e. β_1 in equation (5)) and treats this as a lower bound estimate of the return to tenure for all workers. (Quadratic terms are ignored here for ease of exposition.) This is a lower bound estimate because β_1 in equation (6) is an overestimate since initial experience is positively correlated to the error term.

The estimators proposed by both Altonji and Shakotko (1987) and Topel (1991) were widely used in the literature and produced less biased results than OLS. Nevertheless, the two estimators failed to produce completely unbiased estimates of the wage return to job tenure (Williams, 2009). The Altonji and Shakotko (1987) estimator were tainted by the correlation of labour market experience with the job match component of the error term that was predicted by the job search and matching literature. While in Topel's (1991) estimator job changes were not exogenous and were part of the optimising behaviour that informed a worker's given level of job tenure.

The literature moved to use the closure of firms as a way of generating exogenous variation in job tenure to deal with these shortcomings. Bingley and Westergaard-Nielsen (2003), and Dustmann and Meghir (2005) used this empirical strategy for the estimation of the wage returns to job tenure for workers in Denmark and Germany respectively. Unfortunately, data on firm closures and displaced workers are very hard to come by especially in scarce data places like South Africa. Consequently, the researcher will rely on the traditional estimators in the empirical analysis. It turns out that the bias that taints the Altonji and Shakotko (1987) and Topel (1991) estimators did not affect group comparisons of the wage returns to job tenure (Altonji and Blank, 1999). Bratsberg and Terrell (1998) both used these estimators together with the OLS estimation. All three estimators provided the same conclusion regarding the racial differences in the wage returns to job tenure. Munasinghe et al. (2008) provided similar evidence for differences across genders.

The researcher followed the empirical analysis in the second part of Amann and Klein's (2012) extension of Altonji and Shakotko's (1987) instrumental variables (IV) estimation procedure. Instead of implementing the IV estimation procedure by two-stage least squares, Amann and Klein (2012) used a control function approach. This involved firstly estimating, by OLS, a regression of job tenure as the dependent variable with the covariates defined as $\boldsymbol{Z}_{ijt}$ together with the instruments defined in equation (4), $\widehat{Te}_{ijt}$ and $\widehat{Te}^2_{ijt}$. The residuals from this regression were then added to equation (1) as an additional explanatory variable. Amann and Klein (2012) also included an interaction term of the first-stage residuals with job tenure as a way of allowing the wage returns to job tenure to vary by level of job tenure. A discussion follows of the data used in the study's empirical analysis in section 4.

3.2 Data

The analysis in the next section makes use of the Labour Force Surveys (LFSs) conducted by Statistics South Africa (Stats SA). The LFSs are nationally representative cross-sectional household surveys that are meant to monitor developments in the South African labour market. The surveys were conducted twice yearly in March and September and from September 2000 to September 2007. The LFSs werwassigned 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.

For the empirical analysis, the researcher pooled together the individual cross-sectional surveys running from September 2001 to March 2004. The researcher focuses on these waves because they correspond to Stats SA's Labour Force Survey Panel (LFSP) that is also used for the empirical analysis in the next section. The LFSP was constructed after the collection, processing and release of the individual LFS waves (Stats SA, 2006). The LFPS has constructed afterwards because the original LFSs were only initially intended as a rotating panel of dwelling units and not of individuals or households (Stats SA, 2006).

The estimation sample was restricted to black and white men and women between the ages of 18 and 60. Workers in subsistence agriculture and those reporting to be self-employed were excluded from the analysis. Table 3.1 below provides a summary of the descriptive statistics for some of the key variables in our analysis. From the Table we see that there is a large racial gap in real hourly wages but that such gap is smaller across genders but still significant among white workers. For instance, the average hourly wage rate for white men is roughly four times of that for black men. The racial and gender gaps in wages is a key part of the motivation for this paper. In particular, we are interested in determining how these wage gaps change as workers accumulate additional years of firm tenure.

Table 3.1: Summary statistics of key variables, by demographic group

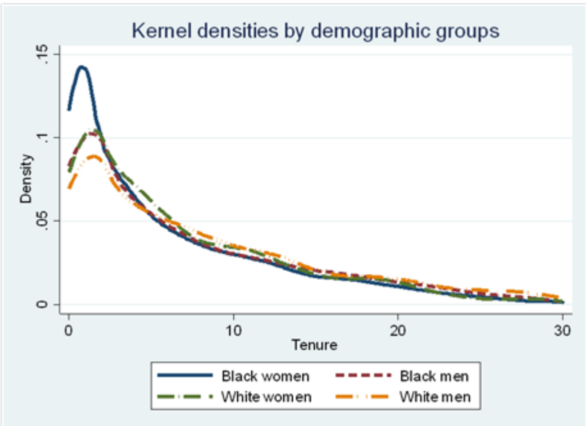
Variables	**Black women**	**Black men**	**White women**	**White men**
Real hourly wage	8.54	9.77	26.11	38.59
	(13.13)	(13.59)	(24.96)	(43.96)
Potential experience	24.00	23.74	19.93	21.19
	(12.09)	(12.37)	(11.19)	(11.22)
Years of Schooling	8.57	8.09	12.40	12.30
	(4.20)	(4.09)	(1.69)	(1.83)
Age	38.69	38.08	38.32	39.32
	(10.11)	(10.29)	(11.05)	(11.08)
Job tenure	6.60	7.58	7.02	8.58
	(7.07)	(7.81)	(7.01)	(8.37)

Notes: Own calculations. Standard deviations in parentheses.

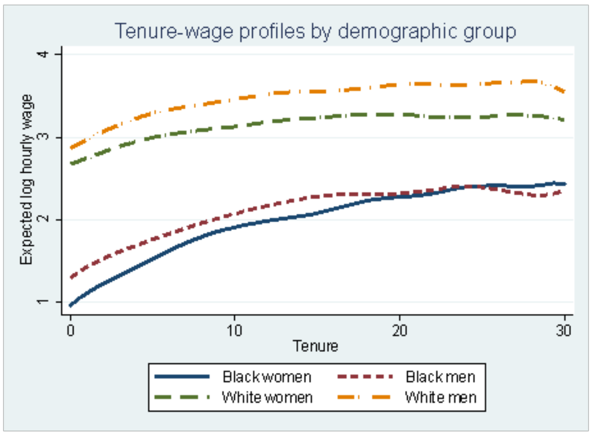
According to the measure of labour market experience, which is a combination of an individual's age and completed years of education, black workers have roughly three more years of labour market experience compared to their white counterparts. This reflects the lower average completed years of education for black workers of 9 years compared to 12 years for white workers in the sample. There are no significant differences in age.

Black women have the lowest measured average years of job tenure (at 6.6 years) while white men have the highest average years of job tenure at 8.58 years. This may suggest greater mobility for black women either within or out of the labour market.

The figure below provides kernel density plots of tenure by demographic groups. According to the figure, black women have the highest (and white men the lowest) concentration of workers with low levels of measured tenure. Besides the initial bunching at low levels of tenure, the density plots lie on top of each other. This may suggest higher degree of churning for black women that leads to low levels of observed tenure.



The next graph reports kernel-weighted local polynomial regressions of log hourly wages on tenure. The figure provides some supportive evidence for higher wage returns for black women during the first 10 years of tenure. The next section will estimate, more formally, the wage effects of job tenure for black and white South African men and women.



4. EMPIRICAL ANALYSIS

This section will present and discuss the results of the empirical analysis regarding the wage effect of job tenure on the expected average wages of black and white South African men and women. Section 4.1 below presents the first set of results estimated from pooled OLS estimation of the log hourly wage equation. The results from the control function implementation of the Altonji and Shakotko (1987) IV estimator are presented in section 4.2.

The results presented in each table below are organised in the following manner (unless otherwise indicated): Column 1 presents the results for black women followed by results for black men, white women and then white men in the last column. Consequently, a movement from the first to the last column mimics the stereotypical racial and gender hierarchy in labour market outcomes in South Africa with black women as the least advantaged and white men as the most advantaged of all groups. It will be against this backdrop that the researcher will interpret and compare the wage returns to job tenure across groups.

4.1 Part A: Pooled OLS

In this sub-section, we present results from log hourly wage regressions using pooled OLS. Separate regressions were estimated for all four groups with job tenure and its quadratic term as the variables of interest. These results are contained in Table 3.2 below. For the sake of brevity, Table 3.2 only shows point estimates for the coefficients of interest and the coefficients on the potential experience variables. The full set of results are contained in Table A1 in the appendix section.

Table 3.2: Log Hourly Wage Regression – Base specification

	Black women	Black men	White women	White men
Tenure	0.071	0.066	0.028	0.034
	(0.003)***	(0.002)***	(0.006)***	(0.005)***
Tenure squared	-0.002	-0.001	-0.0005	-0.001
	(0.000)***	(0.000)***	(0.0002)**	(0.0002)***
Potential experience	0.029	0.032	0.036	0.034
	(0.003)***	(0.003)***	(0.005)***	(0.006)***
Potential experience squared	-0.0003	-0.0004	-0.001	-0.001
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
Other controls	✓	✓	✓	✓
R^2	0.57	0.48	0.27	0.34
N	21,173	25,350	4,566	4,892

<u>Notes:</u> These regressions control for schooling (spline and dummy), province, area of residency – rural/urban status, household head dummy, marital status dummy, and wave fixed effects.
Robust standard errors are contained in parentheses.
** p<0.1; ** p<0.05; *** p<0.01*

The theoretical models discussed in section two predict a positive association between job tenure and wages. The human capital model further predicts that such returns will diminish over time. The results presented in Table 3.2 exhibit this feature of positive but diminishing wage returns to job tenure for all four groups. The coefficients on the linear terms are all positive and statistically significant, while the coefficients on the quadratic terms are negative and statistically significant.

A closer inspection of the results reveals an interesting pattern of wage returns that has a strong division along racial lines. The estimated coefficient on the linear job tenure variable for black workers is more than double the corresponding coefficient estimates for white workers. The estimated coefficients on the quadratic tenure terms indicate differences in the concavity of the wage-tenure profiles between the demographic groups. The wage returns for black women diminish at a much faster rate indicated by the larger coefficient on the quadratic term. This coefficient estimate for black women is exactly twice and four times larger than the corresponding coefficient estimates for men and white women, respectively. Our next task is to add more control variables to our base specification and investigate how controlling for these additional covariates affects our estimated wage returns to job tenure for the four groups.

Potential experience versus predicted experience

The first additional covariate of interest is an alternative proxy for labour market experience. The results obtained in the previous chapter and in Bratsberg and Terrell (1998) suggest that the use of potential experience as a proxy for labour market experience leads to biased estimates of the wage effect of labour market experience. This in turn biases the estimates of the wage returns to job tenure because of the correlation between job tenure and labour market experience. Consequently, we investigate how the use of a more accurate proxy for labour market experience affects the wage returns to job tenure for our four groups.

Table A2 in the Appendix reports the results for the log hourly wage rate equation that uses an alternative proxy for labour market experience instead of potential experience. The alternative proxy is the *predicted experience* variable proposed in the previous chapter. The results are reported in the Appendix instead of being reported in the body of this chapter simply because the results were very similar to the results presented in Table 3.2 above. In other words, replacing potential experience with a more accurate proxy for labour market experience had no impact on the wage returns to job tenure estimated with our base specification and reported in Table 3.2. The estimated wage returns to labour market experience did however change for the four groups as result of using *predicted experience* as opposed to potential experience. In going forward, all regressions will use the more accurate proxy when controlling for labour market experience.

Occupation and industry classification

We now turn our attention to occupation and industry classification for the worker's skills and type of sector of employment. Recent studies have argued against the traditional human capital model characterisation of skill accumulation as being simply firm specific or general. These studies illustrate the importance of occupation and industry experience in the accumulation of skills and determining individual worker wage growth over the life cycle (e.g. Neal, 1995; Parent, 2000; Sullivan, 2010; and Nawakitphaitoon, 2014). The omission of occupation and industry experience in the wage regression leads to inappropriate estimates of the wage returns to job tenure (Williams, 2009). Unfortunately, the data we have available for our empirical analysis does not contain measures of occupation and industry experience. Instead, we have indicator variables that classify a worker's occupation and industry by the standard classification codes. We investigate the effect of controlling for these covariates on our estimates of the wage effects of job tenure.

Table 3.3[14] and Figure 3.1 below provide descriptive evidence of systematic racial and gender differences in occupation and industry choices among South African workers. Roughly, 50% of black women in our sample are absorbed into the unskilled occupation category, and less

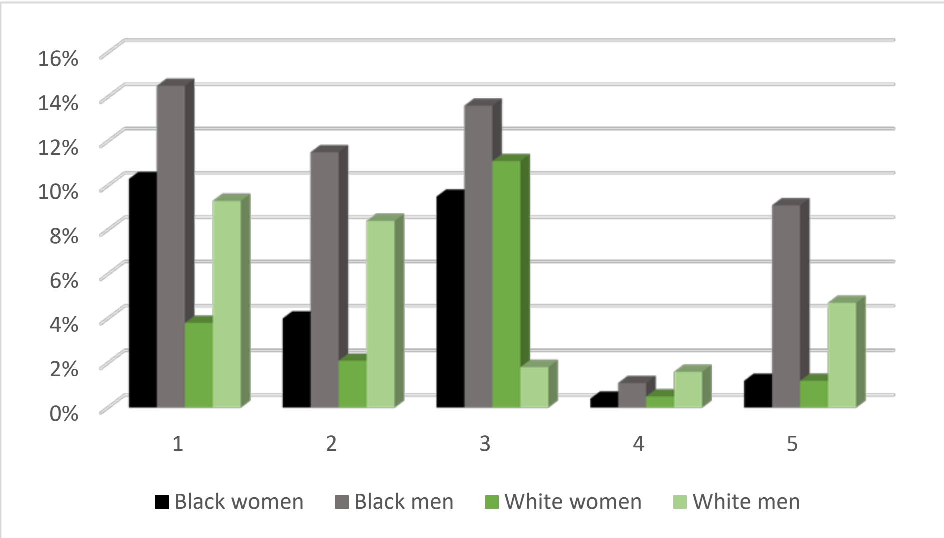
[14] This table is constructed by collapsing the standard 10 occupation categories into three skills categories and then reporting the distribution/proportions across the three skills categories by gender and race.
<u>Skilled</u>: legislators, senior officials and managers, professionals, technical and associate professionals;
<u>Semi-skilled</u>: clerks, service workers and shop and market sales workers, skilled agricultural and fishery workers, craft and related trades workers, plant and machine operators and assemblers; and
<u>Unskilled</u>: elementary occupation and domestic workers.

than 20% are in skilled occupations. This group is overrepresented in domestic services, wholesale and retail sectors. A large proportion of black men (about 60%) are absorbed into semi-skilled occupations and are evenly distributed in all industries. There is an even distribution of white workers across semi-skilled and skilled occupations with a negligible proportion found in unskilled occupations. White women are concentrated in mainly three industries[15], while there is an even distribution of white men in all industries.

Table 3.3: Occupation grouping by level of skills, percentages

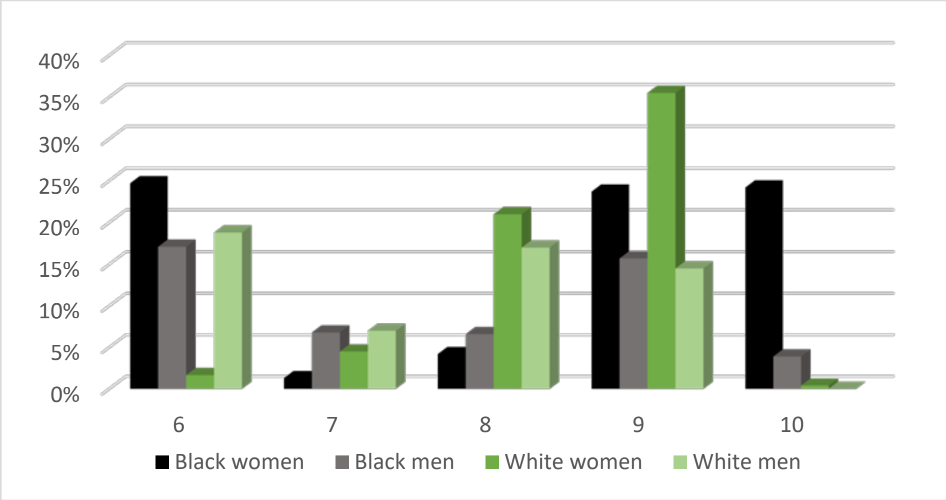
	Unskilled	Semi-skilled	Skilled	Total
Black women	50.1	33.6	16.3	100
Black men	25.0	62.4	12.6	100
White women	2.1	52.0	45.9	100
White men	3.2	43.6	53.2	100

Notes: Own calculations from Statistics SA Labour Force Surveys.



1 – Agriculture, hunting, forestry, fishing
2 – Mining & quarrying
3 – Manufacturing
4 – Electricity, gas & water supply
5 – Construction

[15] Manufacturing; financial and business services; and community, social and personal services.



6 – Wholesale & retail
7 – Transport, storage & communication
8 – Financial & business services
9 – Community, social & personal services (public sector)
10 – Private households with employed persons

Figure 3.1: Industry classification by demographic groups

These differences across groups in occupational and industry choices largely reflect differences in schooling choices and attainment, personal preferences and other constraints. The racial differences are particularly reminiscent of the racial hierarchy in occupation segregation that was engineered by the Apartheid government’s labour market policies that were designed to systematically limit the labour market opportunities of black workers.

There is a strong possibility that there may be important differences in the wage structures faced by workers in different occupations and industries that may influence the wage-tenure profiles faced by these workers. With this in mind, the regression results presented in Table 3.4 below investigate the extent to which the results presented in Table 3.2 above reflect these differences in wage structures and self-selection between the different occupations and industries.

Table 3.4: Log Hourly Wage Regression – Occupation and Industry

	Black women	Black men	White women	White men
Tenure	0.047	0.047	0.026	0.034
	(0.003)***	(0.002)***	(0.005)***	(0.005)***
Tenure squared	-0.001	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)**	(0.000)***
Occupation dummies	✓	✓	✓	✓
Industry dummies	✓	✓	✓	✓
Other controls	✓	✓	✓	✓
R^2	0.65	0.58	0.34	0.40
N	21,160	25,314	4,561	4,884

Notes: These regressions control for predicted experience, schooling (spline and dummy), province, area of residency – rural/urban status, household head dummy, marital status dummy, and wave fixed effects. Robust standard errors are contained in parentheses.
** p<0.1; ** p<0.05; *** p<0.01*

In Table 3.4, our pooled OLS hourly wage regressions controls now have occupation and industry as additional covariates. This is our attempt to control for occupation and industry effects on wages and on our variables of interest. From the regression specification in Table 3.2, we now control for 10 occupations and 10 industry dummies as additional explanatory variables. These dummy variables represent all the occupation categories and industry codes available in our dataset.

Controlling for occupation and industry has reduced the estimated coefficient on the linear job tenure variable for black workers. The coefficient on the quadratic term has reduced by a half in absolute terms for black women. For white workers, controlling for occupation and industry has only had the effect of doubling the coefficient on the quadratic term for white women. It is worth pointing out that the estimated coefficients within each racial group are remarkable similar.

The reduction in the magnitude of the estimated coefficients on the job tenure variables for black workers provides suggestive evidence of occupation and industry differences in wage structures influencing the wage-tenure profiles. Initially, what appeared to be rapid acceleration in average wages due to the accumulation of job tenure for black workers partly reflected the climbing up the occupational and industry ladders (i.e. moving into high paying occupations and industries). Furthermore, controlling for occupation and industry had no impact on the estimated wage returns for white workers because they are much more likely to be absorbed into high paying occupations and industries early on in their working careers.

In the Appendix, the analysis is extended further by estimating the regressions reported in Table 3.4 by industry. This extension provides for a more flexible and comprehensive investigation of the possibility that the wage returns to job tenure differ by industry. The Appendix reports coefficient plots and confidence intervals for tenure and tenure squared for each industry (with the exception of the electricity, gas and water supply industry that had too few observations). The regressions are specified in the same manner as in Table 3.4 but with industry omitted as a control variable. The results indicate that the wage returns to tenure do indeed differ by industry.

Formal versus informal sector, private versus public sector

The compensation structure of the efforts of labour in the production of output can also differ by the type of sector that workers plough their trade. In our sample, a larger proportion of women are found in the public sector – about 23% for both black and white women. The corresponding proportions for black men is 16% and for white men it is 15%. A further 10% of black men and 4% of black women are employed in the informal sector. The corresponding figures for white workers is just under 2% for both men and women. The rest of the workers are employed in the formal private sector. Table 3.5 below, presents the results of how the estimated wage effects of job tenure are influenced when we control for this sorting by sector type and interact it with the tenure variables in our hourly wage regressions.

Table 3.5: Log Hourly Wage Regression – Sector type

	Black women	Black men	White women	White men
Tenure wage effect:				
Private-formal sector (*base*)	0.041	0.042	0.029	0.036
	(0.003)***	(0.002)***	(0.007)***	(0.006)***
Private-formal *squared*	-0.001	-0.001	-0.001	-0.001
	(0.0001)***	(0.0001)***	(0.0003)***	(0.0002)***
Informal sector	0.036	-0.023	0.023	-0.055
	(0.014)***	(0.009)***	(0.035)	(0.054)
Informal sector *squared*	-0.001	0.001	-0.001	0.003
	(0.001)*	(0.0003)*	(0.001)	(0.002)
Public sector	-0.001	0.007	-0.022	-0.021
	(0.006)	(0.005)	(0.010)**	(0.014)
Public sector *squared*	0.0002	-0.0002	0.001	0.001
	(0.0002)	(0.0002)	(0.0004)**	(0.0004)*
Informal sector	-0.586	-0.388	-0.300	-0.129
	(0.047)***	(0.034)***	(0.160)*	(0.144)
Public sector	0.421	0.284	0.228	0.140
	(0.046)***	(0.041)***	(0.063)***	(0.094)
Other controls	✓	✓	✓	✓
R^2	0.67	0.60	0.34	0.41
N	21,160	25,314	4,561	4,884

<u>Notes:</u> These regressions control for occupation and industry dummies, predicted experience, schooling (spline and dummy), province, area of residency – rural/urban status, household head dummy, marital status dummy, and wave fixed effects.
Robust standard errors are contained in parentheses.
** p<0.1; ** p<0.05; *** p<0.01*

The regression results reported in Table 3.5 control for a set of dummy variables that indicate the type of sector workers are absorbed in. The wage effect of job tenure is approximated by interacting the tenure variables separately with each type of sector. Private formal sector is designated as the reference group. Formal private sector workers drive the pattern of tenure wage effects uncovered in the previous specifications of our wage regressions. For black workers, the wage returns for workers employed in the formal private and public sector are similar. While informal sector workers have a higher wage return. The equality of tenure wage returns between the formal private and public sectors also holds for black men. However, black men in the informal sector have a smaller estimated wage return to job tenure that is almost half of what private and public sector workers enjoy. The estimated wage return for white women in the formal private sector is roughly 3% and zero for a given additional year of job tenure for those employed in the public sector. The estimated wage returns for white men in the private formal and public sector are roughly equal at 3.6% for a given additional year of job tenure.

Firm size

In our last specification, we control for the size of the firm, features of the employment contract (i.e. is there a written contract in place or not) and type of employment (i.e. permanent, casual, fixed term and seasonal). However, we will only present results of the interaction between job tenure and firm size[16]. The size of the firm variable is constructed from an individual's response to survey questions relating to the number of employees hired at the individual's firm. From this, we created a dummy variable that equals one if the firm has 50 or more workers, zero otherwise, and referred to these as large firms.

Table 3.6: Log Hourly Wage Regression – Firm size[17]

	Black women	Black men	White women	White men
Tenure wage effect:				
Small firm (*base*)	0.035	0.026	0.020	0.033
	(0.003)***	(0.003)***	(0.007)***	(0.007)***
Small firm *squared*	-0.001	-0.001	-0.0004	-0.001
	(0.0001)***	(0.0001)***	(0.0004)	(0.0002)***
Large firm	-0.015	-0.000	-0.008	-0.012
	(0.005)***	(0.004)	(0.011)	(0.009)
Large firm *squared*	0.0004	0.0001	0.0001	0.0005
	(0.0002)**	(0.0001)	(0.0004)	(0.0003)
Large firm	0.168	0.170	0.237	0.201
	(0.028)***	(0.019)***	(0.055)***	(0.053)***
Other controls	✓	✓	✓	✓
R^2	0.68	0.62	0.35	0.42
N	20,731	24,777	4,524	4,833

*<u>Notes:</u> These regressions control for type of sector, features of the employment contract, type of employment, occupation and industry dummies, predicted experience, schooling (spline and dummy), province, area of residency – rural/urban status, household head dummy, marital status dummy, and wave fixed effects. Robust standard errors are contained in parentheses. * p<0.1; ** p<0.05; *** p<0.01*

[16] Results from the interaction of job tenure with the features of the employment contract and type of employment can be found in Table A6 in the appendix.
[17] The full set of regression coefficients can be found in Table A7 in the appendix.

The additional covariates controlled for have had a larger effect on the estimated wage effect of job tenure for black workers. The wage effects of job tenure in small firms appear to be roughly similar for all workers. The size of the firm seems not to matter for the wage returns to job tenure for all groups except black women. For all three groups, the estimated coefficients for the wage returns for large firms is close to zero and statistically insignificant. For black women, the linear coefficient is negative, statistically significant and indicates lower wage returns to job tenure for black women in large firms. The quadratic term is positive, statistically significant and indicates that the wage effects of job tenure increase at an increasing rate. While the returns may be smaller, they never diminish, and in fact, they continue to rise thus indicating a convex wage-tenure profile for black women in large firms.

Table 3.7 below shows the estimated coefficients for the tenure variables from our most preferred specification that includes all the covariates discussed above but without the interaction terms. The lower panel of Table 3.7 provides cumulative wage growth due to 5 and 10 years of job tenure calculated from the point estimates of the tenure variables. The wage returns presented in Table 3.2 showed a strong racial divide with black workers earning substantially higher wage returns compared to white workers. The role for gender did not come out very clearly since black women had the highest estimated wage return and white women had the lowest. After controlling for additional covariates, Table 3.7 depicts nearly identical wage returns for men. While black women have the largest estimated returns that are double those enjoyed by white women. For example, 5 years of job tenure increases the average wages of black women by 15%. It takes white women 10 years to achieve that same level of cumulative wage growth.

Table 3.7: Log Hourly Wage Regression – Final specification

	Black women	Black men	White women	White men
Tenure	0.0319	0.0255	0.0166	0.0251
	(0.0026)***	(0.0022)***	(0.0054)***	(0.0053)***
Tenure squared	-0.0007	-0.0005	-0.0003	-0.0004
	(0.0001)***	(0.0001)***	(0.0002)	(0.0002)**
R^2	0.68	0.63	0.35	0.42
N	20,485	24,289	4,451	4,719
	Cumulative individual wage growth due to job tenure			
5 years	15%	12%	8%	12%
10 years	28%	23%	15%	23%

Notes: These regressions control for, firm size, type of sector, features of the employment contract, type of employment, occupation and industry dummies, predicted experience, schooling (spline and dummy), province, area of residency – rural/urban status, household head dummy, marital status dummy, and wave fixed effects.
Robust standard errors are contained in parentheses.
** p<0.1; ** p<0.05; *** p<0.01*

The results presented thus far have painted a very insightful view of the role played by job tenure in wage growth for South African workers. Unfortunately, there are serious concerns regarding unobserved heterogeneity affecting the variables of interest and leading to unbiased estimates. Part two of the empirical analysis addresses this source of endogeneity and attempts to get estimates that moves us closer to the casual interpretation of the effects of job tenure on wages for South African workers.

4.2 Part B: A Control Function

According to Jovanovic's (1979) job matching model of labour turnover, the productivity of a given worker in a given job is unknown *ex ante* by both employer and employee and this gives rise to uncertainty about the quality of the worker-firm match. The uncertainty is resolved through a learning process through which the employer observes the worker's output while on the job. Consequently, workers differ in an unobservable way (from the perspective of the econometrician) in the degree to which they (or their skills set) are well matched to their current employer. This quality of the worker-firm match is therefore correlated to a worker's wage but also to the length of the worker's tenure spell.

We implement a control function approach to Altonji and Shakotko's (1987) instrumental variables estimator. This approach, which entails interacting the residuals from the IV first stage with job tenure as a way of allowing for heterogeneous returns by level of job tenure, is an extension suggested by Amann and Klein (2012). Table 3.8 below reports the results for the variables of interest.[18] The lower panel reports the cumulative wage growth due to the accumulation of job tenure.

[18] The first stage IV results can be found in Table A9 in the appendix. The full set of regression coefficient for the second stage can be found in Table A10.

Table 3.8: Log Hourly Wage Regression – Control function[19]

	Black women	Black men	White women	White men
Tenure	0.0171	0.0167	-0.0026	0.0089
	(0.0062)***	(0.0051)***	(0.0110)	(0.0121)
Tenure squared	-0.0008	-0.0005	-0.0008	-0.0002
	(0.0002)***	(0.0002)***	(0.0005)	(0.0004)
1st stage residuals	0.0214	0.0112	0.0310	0.0191
	(0.0059)***	(0.0047)**	(0.0095)***	(0.0113)*
Tenure*residuals	-0.0009	-0.0001	-0.0004	-0.0012
	(0.0004)**	(0.0004)	(0.0009)	(0.0008)
Tenure squared*residuals	0.0000	0.0000	0.0000	0.0000
	(0.0000)**	(0.0000)	(0.0000)	(0.0000)
1st stage F-stat for IVs	688	791	221	147
R^2	0.68	0.63	0.36	0.42
N	20,485	24,289	4,451	4,719
	Cumulative individual wage growth due to job tenure			
5 years	7%	7%	-3%	4%
10 years	10%	12%	-10%	7%

Notes: These regressions control for, firm size, type of sector, features of the employment contract, type of employment, occupation and industry dummies, predicted experience, schooling (spline and dummy), province, area of residency – rural/urban status, household head dummy, marital status dummy, and wave fixed effects. Robust standard errors are contained in parentheses.
** p<0.1; ** p<0.05; *** p<0.01*

There are a number of interesting and key results summarised in Table 3.8 that contrast with the results presented in Table 3.7 above. Firstly, the wage effects of job tenure for all groups are smaller when estimated using the instrumental variables strategy. For white workers the wage returns are not only smaller but they are also statistically insignificant and cannot be distinguished from zero. In other words, no additional growth in wages is gained by white workers because of an additional year of tenure, with all else held constant.

This suggests that the pooled OLS results in Table 3.7 that do not address the unobserved heterogeneity in worker-firm match quality are upwardly biased. This is in line with Altonji and Shakotko's (1987) contention that job tenure is positively correlated to the worker-firm match quality and thus introduces an upward bias in an OLS estimation of the wage effects of firm tenure. The larger returns to job tenure in Table 3.7 seem to be driven by unobserved heterogeneity in the quality of worker-firm matches that induces a spurious correlation between tenure and wages. This is also evident from the positive and statistically significant coefficients on the first stage residuals for all four groups.

[19] Figure A1 in the Appendix plots the point estimates and confidence intervals for the variables of interest (tenure and tenure squared). The figure is intended to assist the reader in assessing the statistical significance of the differences in the estimates across the different models.

Controlling for the unobserved heterogeneity in worker-firm match quality has strengthened the racial differential in the estimated wage effect of job tenure. The average wages for black workers rise by roughly 10% after spending 10 years with the same firm. Although the wage returns to an additional year job tenure for black women is similar to that of their male counterparts, the returns for black women diminish at a much quicker rate. This is consistent with greater heterogeneity in the returns for black women by level of job tenure. The negative and statistically significant coefficient on the interaction term between job tenure and the first stage residuals provide further evidence of heterogeneous returns for black women.

5. CONCLUDING REMARKS

The objective of this paper was to analyse the contributions of job tenure to wage growth for black and white South African workers. From the pooled OLS estimation, the researcher found that black workers enjoy much larger wage growth from an additional year of job tenure compared to white workers. Part of the differential in the wage returns across racial groups was accounted for by controlling for covariates that capture essential features of the type of employment and firms that these groups are absorbed in. Racial and gender differences in occupation and industry choice, type of sector, features of the employment contract, type of employment and firm size were shown to be essential covariates to control for when estimating wage returns to job tenure for South African workers.

The empirical analysis implemented estimation techniques that are widely used in the literature to address an essential source of endogeneity encountered when estimating the wage returns to job tenure. After controlling for unobserved heterogeneity in the quality of individuals and worker-firm matches, the results provided corroboration from a developing country context of the results often found in the literature. Namely, that wage returns to job tenure are modest and are more significant for black workers compared to their white counterparts. The latter result is somewhat of a surprise in the context of the South African labour market where labour market outcomes rarely deviate from the racial hierarchy that sees white workers have better labour market outcomes. Furthermore, this has significant and positive prospects for the objective of narrowing the racial gap in earnings. With the wage returns to tenure forming one component of the dynamic structure of wages and a source of wage growth, higher wage returns for black workers, *ceteris paribus*, should lead to a narrowing of the racial wage gap between members of different race groups as their tenure increases.

The literature has interpreted the racial differences in favour of black workers in the returns to job tenure as evidence that black workers accumulate firm-specific human capital at a faster rate. Another interpretation is that the wage returns for black workers include an employer-learning component that arises from greater *ex-ante* uncertainty in the expected productivity of black workers relative to white workers. The next chapter addresses the latter interpretation and provides empirical evidence from South African data.

6. APPENDIX

Table A1

	Black women	Black men	White women	White men
Tenure	0.071	0.066	0.028	0.034
	(0.003)***	(0.002)***	(0.006)***	(0.005)***
Tenure Squared	-0.002	-0.001	-0.0005	-0.001
	(0.000)***	(0.000)***	(0.0002)**	(0.0002)***
Potential Experience	0.029	0.032	0.036	0.034
	(0.003)***	(0.003)***	(0.005)***	(0.006)***
Potential Experience Squared	-0.0003	-0.0004	-0.001	-0.001
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
Education spline				
Primary	0.044	0.055	0.112	0.010
	(0.004)***	(0.004)***	(0.063)*	(0.041)
Secondary	0.157	0.131	0.187	0.182
	(0.007)***	(0.006)***	(0.034)***	(0.029)***
Matric	0.351	0.270	0.084	0.094
	(0.028)***	(0.020)***	(0.046)*	(0.041)**
Tertiary	0.372	0.370	0.148	0.184
	(0.011)***	(0.010)***	(0.014)***	(0.013)***
Diploma & Certificate	0.531	0.361	0.123	0.197
	(0.025)***	(0.025)***	(0.033)***	(0.039)***
Rural Dummy	-0.240	-0.324	-0.186	-0.217
	(0.016)***	(0.015)***	(0.067)***	(0.046)***
Province Dummy 1	-0.367	-0.239	-0.081	-0.226
	(0.033)***	(0.036)***	(0.054)	(0.048)***
Province Dummy 2	-0.292	-0.113	-0.299	-0.238
	(0.046)***	(0.045)**	(0.074)***	(0.059)***
Province Dummy 3	-0.489	-0.276	-0.296	-0.232
	(0.033)***	(0.033)***	(0.054)***	(0.049)***
Province Dummy 4	-0.271	-0.029	0.019	-0.109
	(0.031)***	(0.032)	(0.056)	(0.055)**
Province Dummy 5	-0.189	0.030	-0.277	-0.140
	(0.033)***	(0.033)	(0.062)***	(0.052)***
Province Dummy 6	0.027	0.071	0.173	0.029
	(0.032)	(0.032)**	(0.051)***	(0.044)
Province Dummy 7	-0.220	-0.011	-0.238	-0.147
	(0.033)***	(0.034)	(0.056)***	(0.051)***
Province Dummy 8	-0.379	-0.224	-0.311	-0.149
	(0.034)***	(0.036)***	(0.085)***	(0.073)**
Household Head Dummy	-0.005	0.088	0.258	0.320
	(0.017)	(0.017)***	(0.041)***	(0.047)***
Wave Dummy 1	0.009	-0.028	-0.009	0.048
	(0.021)	(0.019)	(0.058)	(0.044)
Wave Dummy 2	-0.0001	-0.067	0.021	-0.019
	(0.022)	(0.020)***	(0.044)	(0.051)
Wave Dummy 3	0.014	-0.056	-0.010	0.004
	(0.023)	(0.020)***	(0.047)	(0.046)
Wave Dummy 4	0.064	0.016	0.088	0.130
	(0.022)***	(0.019)	(0.043)**	(0.053)**
Wave Dummy 5	0.087	0.005	0.084	0.075
	(0.025)***	(0.021)	(0.044)*	(0.046)

Married Dummy	0.121	0.090	0.174	0.152
	(0.017)***	(0.015)***	(0.041)***	(0.040)***
Intercept	0.151	0.317	0.696	1.505
	(0.051)***	(0.049)***	(0.423)*	(0.260)***
R^2	0.57	0.48	0.27	0.34
N	21,173	25,350	4,566	4,892

* p<0.1; ** p<0.05; *** p<0.01

Table A2

	Black women	Black men	White women	White men
Tenure	0.069	0.065	0.030	0.034
	(0.003)***	(0.002)***	(0.006)***	(0.005)***
Tenure Squared	-0.002	-0.001	-0.001	-0.001
	(0.0001)***	(0.0001)***	(0.0002)**	(0.0002)***
Predicted Experience	0.062	0.063	0.052	0.041
	(0.004)***	(0.004)***	(0.007)***	(0.006)***
Predicted Experience Squared	-0.002	-0.002	-0.002	-0.001
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***
Education spline				
Primary	0.031	0.044	0.085	-0.032
	(0.004)***	(0.004)***	(0.056)	(0.034)
Secondary	0.145	0.118	0.182	0.183
	(0.007)***	(0.006)***	(0.035)***	(0.029)***
Matric	0.303	0.216	0.073	0.088
	(0.028)***	(0.020)***	(0.047)	(0.041)**
Tertiary	0.336	0.337	0.142	0.177
	(0.012)***	(0.010)***	(0.015)***	(0.013)***
Diploma/Certificate	0.486	0.334	0.130	0.193
	(0.025)***	(0.025)***	(0.033)***	(0.039)***
Rural Dummy	-0.236	-0.321	-0.177	-0.211
	(0.016)***	(0.015)***	(0.069)**	(0.048)***
Province Dummy 1	-0.360	-0.237	-0.073	-0.221
	(0.033)***	(0.036)***	(0.054)	(0.049)***
Province Dummy 2	-0.281	-0.120	-0.306	-0.222
	(0.046)***	(0.045)***	(0.074)***	(0.058)***
Province Dummy 3	-0.491	-0.286	-0.279	-0.219
	(0.033)***	(0.033)***	(0.054)***	(0.050)***
Province Dummy 4	-0.268	-0.034	0.018	-0.094
	(0.031)***	(0.032)	(0.056)	(0.055)*
Province Dummy 5	-0.187	0.027	-0.271	-0.127
	(0.033)***	(0.033)	(0.062)***	(0.051)**
Province Dummy 6	0.026	0.064	0.182	0.043
	(0.032)	(0.032)**	(0.051)***	(0.045)
Province Dummy 7	-0.219	-0.017	-0.219	-0.132
	(0.033)***	(0.034)	(0.056)***	(0.052)**
Province Dummy 8	-0.375	-0.226	-0.302	-0.139
	(0.034)***	(0.036)***	(0.085)***	(0.073)*
Household Head Dummy	-0.003	0.089	0.242	0.307
	(0.016)	(0.017)***	(0.041)***	(0.047)***
Wave Dummy 1	0.011	-0.026	-0.007	0.049
	(0.021)	(0.019)	(0.058)	(0.044)
Wave Dummy 2	-0.001	-0.066	0.023	-0.023
	(0.022)	(0.020)***	(0.044)	(0.052)
Wave Dummy 3	0.015	-0.053	-0.009	0.007
	(0.023)	(0.020)***	(0.048)	(0.045)
Wave Dummy 4	0.063	0.019	0.086	0.126
	(0.022)***	(0.019)	(0.042)**	(0.052)**
Wave Dummy 5	0.090	0.008	0.084	0.076
	(0.025)***	(0.021)	(0.044)*	(0.046)*
Married Dummy	0.128	0.088	0.175	0.161

	(0.017)***	(0.015)***	(0.041)***	(0.039)***
Intercept	0.467	0.611	0.919	1.813
	(0.040)***	(0.043)***	(0.356)***	(0.192)***
R^2	0.57	0.48	0.27	0.34
N	21,173	25,350	4,566	4,892

Table A3

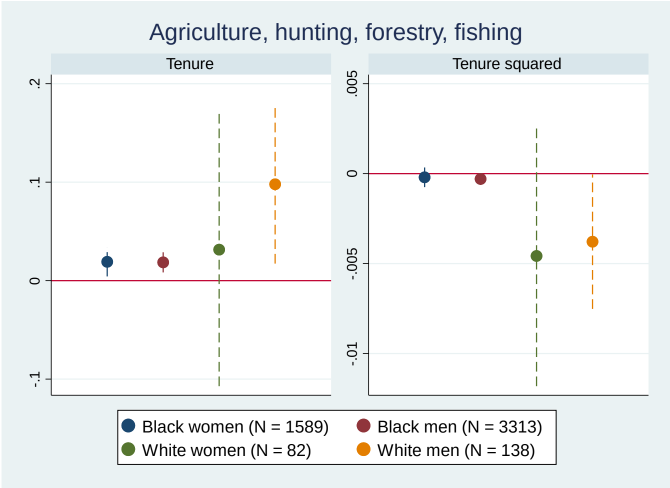
	Black women	Black men	White women	White men
Tenure	0.047	0.047	0.026	0.034
	(0.003)***	(0.002)***	(0.005)***	(0.005)***
Tenure Squared	-0.001	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)**	(0.000)***
Occupation Dummy 1	-0.359	-0.260	-0.062	-0.180
	(0.091)***	(0.065)***	(0.082)	(0.064)***
Occupation Dummy 2	-0.423	-0.313	-0.236	-0.191
	(0.081)***	(0.046)***	(0.052)***	(0.047)***
Occupation Dummy 3	-0.697	-0.543	-0.432	-0.472
	(0.081)***	(0.046)***	(0.056)***	(0.056)***
Occupation Dummy 4	-1.006	-0.813	-0.640	-0.579
	(0.084)***	(0.045)***	(0.065)***	(0.057)***
Occupation Dummy 5	-1.004	-0.806	-0.817	-0.428
	(0.113)***	(0.067)***	(0.100)***	(0.145)***
Occupation Dummy 6	-1.032	-0.688	-0.535	-0.439
	(0.085)***	(0.045)***	(0.113)***	(0.045)***
Occupation Dummy 7	-0.958	-0.719	-0.641	-0.565
	(0.087)***	(0.045)***	(0.110)***	(0.067)***
Occupation Dummy 8	-1.055	-0.845	-0.702	-0.621
	(0.081)***	(0.045)***	(0.118)***	(0.080)***
Occupation Dummy 9	-1.055	-0.782	-0.689	-0.866
	(0.121)***	(0.081)***	(0.459)	(0.103)***
Industry Dummy 1	0.858	0.952	0.445	0.514
	(0.086)***	(0.024)***	(0.141)***	(0.093)***
Industry Dummy 2	0.400	0.741	0.313	0.378
	(0.035)***	(0.025)***	(0.134)**	(0.088)***
Industry Dummy 3	0.820	0.859	0.259	0.480
	(0.118)***	(0.052)***	(0.162)	(0.113)***
Industry Dummy 4	0.496	0.532	0.332	0.171
	(0.063)***	(0.028)***	(0.159)**	(0.110)
Industry Dummy 5	0.211	0.416	0.155	0.219
	(0.032)***	(0.026)***	(0.134)	(0.091)**
Industry Dummy 6	0.682	0.514	0.276	0.210
	(0.067)***	(0.034)***	(0.134)**	(0.102)**
Industry Dummy 7	0.620	0.606	0.318	0.370
	(0.036)***	(0.031)***	(0.136)**	(0.092)***
Industry Dummy 8	0.706	0.918	0.197	0.257
	(0.033)***	(0.027)***	(0.133)	(0.091)***
Industry Dummy 9	-0.017	0.096	-0.368	
	(0.090)	(0.045)**	(0.394)	
Industry Dummy 10	0.547	0.944	0.680	0.230
	(0.162)***	(0.138)***	(0.217)***	(0.229)
Predicted Experience	0.042	0.041	0.043	0.034
	(0.004)***	(0.003)***	(0.007)***	(0.006)***
Predicted Experience Squared	-0.002	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Education spline				
Primary	0.022	0.020	0.041	-0.025

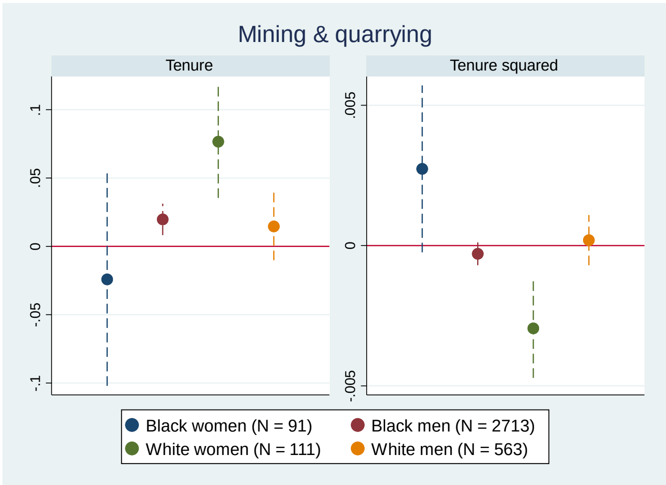
	(0.004)***	(0.004)***	(0.044)	(0.030)
Secondary	0.057	0.075	0.115	0.134
	(0.006)***	(0.005)***	(0.033)***	(0.028)***
Matric	0.129	0.152	0.064	0.055
	(0.025)***	(0.018)***	(0.045)	(0.039)
Tertiary	0.167	0.201	0.070	0.129
	(0.020)***	(0.014)***	(0.025)***	(0.016)***
Diploma/Certificate	0.228	0.136	0.114	0.127
	(0.029)***	(0.028)***	(0.033)***	(0.038)***
Rural Dummy	-0.209	-0.181	-0.147	-0.148
	(0.015)***	(0.015)***	(0.068)**	(0.050)***
Province Dummy 1	-0.523	-0.309	-0.108	-0.205
	(0.035)***	(0.033)***	(0.051)**	(0.048)***
Province Dummy 2	-0.432	-0.180	-0.331	-0.225
	(0.047)***	(0.039)***	(0.073)***	(0.055)***
Province Dummy 3	-0.645	-0.359	-0.276	-0.227
	(0.035)***	(0.031)***	(0.052)***	(0.049)***
Province Dummy 4	-0.414	-0.113	-0.038	-0.100
	(0.033)***	(0.029)***	(0.052)	(0.053)*
Province Dummy 5	-0.350	-0.180	-0.280	-0.186
	(0.035)***	(0.029)***	(0.061)***	(0.053)***
Province Dummy 6	-0.134	-0.026	0.123	0.015
	(0.034)***	(0.029)	(0.049)**	(0.044)
Province Dummy 7	-0.367	-0.152	-0.229	-0.163
	(0.035)***	(0.030)***	(0.055)***	(0.052)***
Province Dummy 8	-0.538	-0.365	-0.304	-0.190
	(0.036)***	(0.032)***	(0.083)***	(0.071)***
Household Head Dummy	0.036	0.096	0.220	0.263
	(0.015)**	(0.016)***	(0.039)***	(0.045)***
Wave Dummy 1	-0.010	-0.030	-0.010	0.027
	(0.019)	(0.017)*	(0.055)	(0.042)
Wave Dummy 2	-0.020	-0.047	0.008	-0.050
	(0.020)	(0.018)***	(0.041)	(0.052)
Wave Dummy 3	0.008	-0.040	-0.033	-0.029
	(0.021)	(0.018)**	(0.045)	(0.043)
Wave Dummy 4	0.063	0.036	0.067	0.101
	(0.019)***	(0.018)**	(0.039)*	(0.050)**
Wave Dummy 5	0.084	0.026	0.071	0.069
	(0.022)***	(0.019)	(0.041)*	(0.043)
Married Dummy	0.098	0.058	0.141	0.135
	(0.015)***	(0.014)***	(0.037)***	(0.037)***
Intercept	1.734	1.259	1.769	2.153
	(0.087)***	(0.062)***	(0.321)***	(0.188)***
R^2	0.65	0.58	0.34	0.40
N	21,160	25,314	4,561	4,884

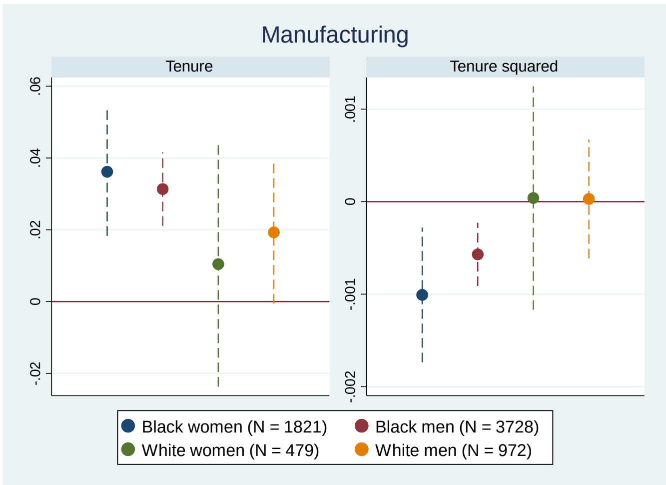
Table A4

	Black women	Black men	White women	White men
Tenure wage effect – *linear*:				
Unskilled (*base*)	0.060	0.054	-0.015	0.026
	(0.005)***	(0.004)***	(0.062)	(0.019)
Domestic worker	-0.019			
	(0.007)***			
Semi-skilled	0.003	-0.002	0.056	0.018
	(0.007)	(0.004)	(0.062)	(0.020)
Skilled	-0.038	-0.044	0.032	-0.001
	(0.008)***	(0.007)***	(0.062)	(0.020)
Tenure wage effect – *quadratic*:				
Unskilled (*base*)	-0.001	-0.001	0.001	-0.0003
	(0.0002)***	(0.0001)***	(0.003)	(0.001)
Domestic worker	0.0002			
	(0.0003)			
Semi-skilled	-0.0001	0.0001	-0.002	-0.001
	(0.0003)	(0.0002)	(0.003)	(0.001)
Skilled	0.001	0.001	-0.002	0
	(0.0003)***	(0.0003)***	(0.003)	(0.001)
Semi-skilled occupation	0.141	0.115	0.071	0.059
	(0.035)***	(0.022)***	(0.165)	(0.118)
Skilled occupation	0.784	0.841	0.483	0.538
	(0.051)***	(0.043)***	(0.167)***	(0.121)***
Domestic worker	0.122			
	(0.088)			
Industry Dummy 1	0.823	0.954	0.474	0.493
	(0.084)***	(0.025)***	(0.135)***	(0.086)***
Industry Dummy 2	0.339	0.751	0.316	0.357
	(0.031)***	(0.027)***	(0.129)**	(0.081)***
Industry Dummy 3	0.872	0.856	0.270	0.446
	(0.118)***	(0.053)***	(0.159)*	(0.109)***
Industry Dummy 4	0.471	0.566	0.369	0.172
	(0.062)***	(0.029)***	(0.152)**	(0.104)*
Industry Dummy 5	0.194	0.415	0.146	0.201
	(0.031)***	(0.028)***	(0.126)	(0.085)**
Industry Dummy 6	0.748	0.529	0.276	0.173
	(0.071)***	(0.036)***	(0.130)**	(0.095)*
Industry Dummy 7	0.634	0.555	0.325	0.316
	(0.036)***	(0.031)***	(0.131)**	(0.086)***
Industry Dummy 8	0.686	0.898	0.163	0.175
	(0.033)***	(0.027)***	(0.125)	(0.083)**
Industry Dummy 9	-0.059	0.080	-0.404	-0.312
	(0.087)	(0.032)**	(0.259)	(0.122)**
Industry Dummy 10	0.595	0.960	0.716	0.268
	(0.164)***	(0.141)***	(0.222)***	(0.232)
Predicted Experience	0.043	0.037	0.044	0.035
	(0.004)***	(0.004)***	(0.007)***	(0.006)***
Predicted Experience Squared	-0.002	-0.001	-0.001	-0.001
	(0.0002)***	(0.0001)***	(0.0002)***	(0.0002)***
Education spline				
Primary	0.021	0.021	0.028	-0.016

	(0.004)***	(0.004)***	(0.045)	(0.028)
Secondary	0.063	0.079	0.116	0.140
	(0.006)***	(0.005)***	(0.034)***	(0.028)***
Matric	0.160	0.154	0.075	0.053
	(0.025)***	(0.018)***	(0.046)	(0.039)
Tertiary	0.189	0.206	0.092	0.126
	(0.012)***	(0.011)***	(0.018)***	(0.014)***
Diploma/Certificate	0.232	0.130	0.082	0.128
	(0.024)***	(0.024)***	(0.031)***	(0.038)***
Rural Dummy	-0.213	-0.186	-0.136	-0.126
	(0.015)***	(0.015)***	(0.072)*	(0.049)**
Province Dummy 1	-0.519	-0.306	-0.097	-0.202
	(0.034)***	(0.033)***	(0.051)*	(0.048)***
Province Dummy 2	-0.420	-0.171	-0.331	-0.220
	(0.047)***	(0.041)***	(0.072)***	(0.055)***
Province Dummy 3	-0.635	-0.350	-0.261	-0.221
	(0.034)***	(0.032)***	(0.053)***	(0.049)***
Province Dummy 4	-0.408	-0.106	-0.035	-0.096
	(0.032)***	(0.030)***	(0.052)	(0.054)*
Province Dummy 5	-0.342	-0.166	-0.268	-0.181
	(0.034)***	(0.030)***	(0.061)***	(0.053)***
Province Dummy 6	-0.118	-0.017	0.135	0.029
	(0.033)***	(0.030)	(0.049)***	(0.045)
Province Dummy 7	-0.358	-0.143	-0.220	-0.157
	(0.034)***	(0.031)***	(0.056)***	(0.053)***
Province Dummy 8	-0.529	-0.350	-0.298	-0.174
	(0.035)***	(0.032)***	(0.084)***	(0.072)**
Household Head Dummy	0.025	0.095	0.212	0.259
	(0.015)*	(0.016)***	(0.040)***	(0.046)***
Wave Dummy 1	-0.003	-0.024	-0.013	0.022
	(0.019)	(0.017)	(0.055)	(0.042)
Wave Dummy 2	-0.017	-0.040	0.013	-0.049
	(0.020)	(0.018)**	(0.041)	(0.053)
Wave Dummy 3	0.010	-0.031	-0.031	-0.020
	(0.021)	(0.018)*	(0.046)	(0.043)
Wave Dummy 4	0.068	0.046	0.074	0.098
	(0.019)***	(0.018)***	(0.040)*	(0.050)*
Wave Dummy 5	0.087	0.031	0.077	0.069
	(0.022)***	(0.019)	(0.043)*	(0.043)
Married Dummy	0.097	0.060	0.140	0.140
	(0.015)***	(0.014)***	(0.039)***	(0.038)***
Intercept	0.627	0.380	1.224	1.487
	(0.044)***	(0.045)***	(0.294)***	(0.191)***
R^2	0.65	0.58	0.33	0.40
N	21,160	25,314	4,561	4,884





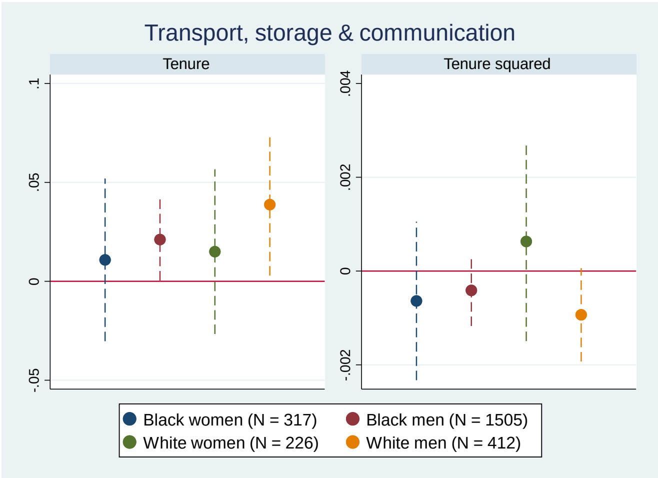


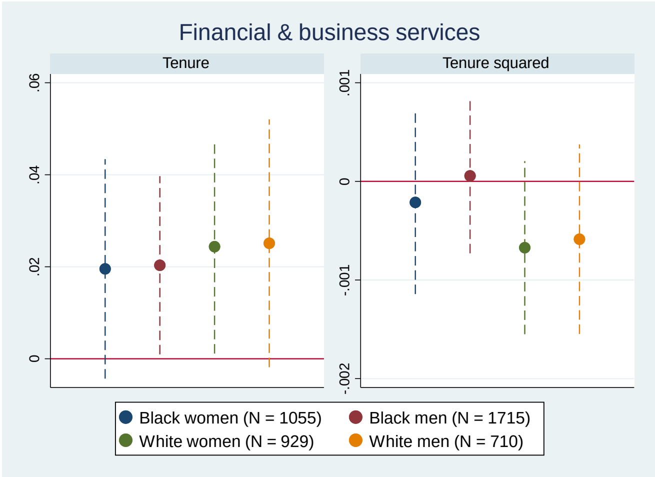
Electricity, gas & water supply

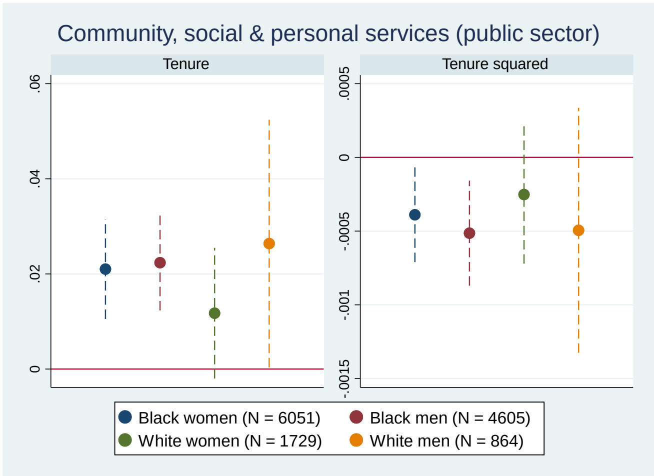
Too few observations: (black women – 100) (black men – 347) (white women – 24) (white men – 103)


Construction
Tenure
Tenure squared
.4
.2
0
-.2
-.4
.005
0
-.005
-.01
Black women (N = 226)
Black men (N = 1995)
White women (N = 41)
White men (N = 155)


Wholesale & retail
tenure
tenure2
.06
.04
.02
0
.001
0
-.001
-.002
Black women (N = 2844)
Black men (N = 3185)
White women (N = 789)
White men (N = 791)


Transport, storage & communication
Tenure
Tenure squared
.1
.05
0
-.05
.004
.002
0
-.002
Black women (N = 317)
Black men (N = 1505)
White women (N = 226)
White men (N = 412)


Financial & business services
Tenure
Tenure squared
.06
.04
.02
0
.001
0
-.001
-.002
Black women (N = 1055)
Black men (N = 1715)
White women (N = 929)
White men (N = 710)


Community, social & personal services (public sector)
Tenure
Tenure squared
.06
.04
.02
0
.0005
0
-.0005
-.001
-.0015
Black women (N = 6051)
Black men (N = 4605)
White women (N = 1729)
White men (N = 864)

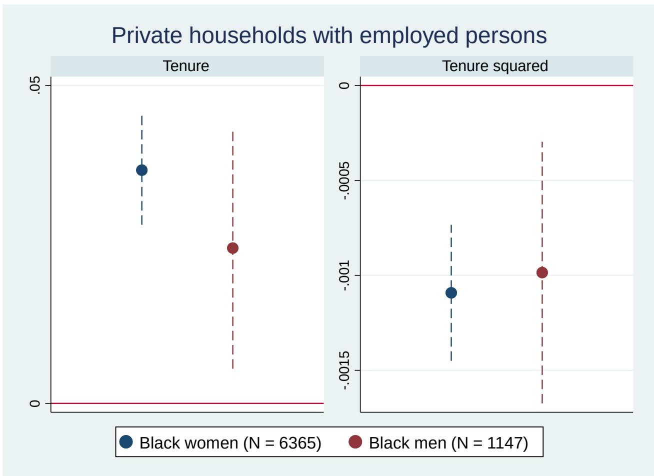

Private households with employed persons
Tenure
Tenure squared
.05
0
0
-.0005
-.001
-.0015
Black women (N = 6365)
Black men (N = 1147)

Table A5

	Black women	Black men	White women	White men
Tenure wage effect – *linear*:				
Private – formal sector (*base*)	0.041 (0.003)***	0.042 (0.002)***	0.029 (0.007)***	0.036 (0.006)***
Informal sector	0.036 (0.014)***	-0.023 (0.009)***	0.023 (0.035)	-0.055 (0.054)
Public sector	-0.001 (0.006)	0.007 (0.005)	-0.022 (0.010)**	-0.021 (0.014)
Tenure wage effect – *quadratic*:				
Private – formal sector (*base*)	-0.001 (0.0001)***	-0.001 (0.0001)***	-0.001 (0.0003)***	-0.001 (0.0002)***
Informal sector	-0.001 (0.001)*	0.001 (0.0003)*	-0.001 (0.001)	0.003 (0.002)
Public sector	0.0002 (0.0002)	-0.0002 (0.0002)	0.001 (0.0004)**	0.001 (0.0004)*
Informal sector	-0.586 (0.047)***	-0.388 (0.034)***	-0.300 (0.160)*	-0.129 (0.144)
Public sector	0.421 (0.046)***	0.284 (0.041)***	0.228 (0.063)***	0.140 (0.094)
Occupation Dummy 1	-0.388 (0.095)***	-0.240 (0.064)***	-0.077 (0.083)	-0.184 (0.064)***
Occupation Dummy 2	-0.455 (0.083)***	-0.329 (0.046)***	-0.241 (0.052)***	-0.192 (0.047)***
Occupation Dummy 3	-0.699 (0.083)***	-0.551 (0.045)***	-0.433 (0.056)***	-0.476 (0.056)***
Occupation Dummy 4	-0.953 (0.086)***	-0.819 (0.044)***	-0.626 (0.064)***	-0.570 (0.058)***
Occupation Dummy 5	-1.010 (0.114)***	-0.791 (0.066)***	-1.028 (0.114)***	-0.396 (0.138)***
Occupation Dummy 6	-0.984 (0.087)***	-0.650 (0.044)***	-0.544 (0.114)***	-0.440 (0.045)***
Occupation Dummy 7	-0.937 (0.088)***	-0.697 (0.044)***	-0.641 (0.110)***	-0.568 (0.067)***
Occupation Dummy 8	-1.047 (0.084)***	-0.835 (0.044)***	-0.705 (0.116)***	-0.609 (0.081)***
Occupation Dummy 9	-1.486 (0.128)***	-1.196 (0.085)***	-0.957 (0.477)**	-0.858 (0.103)***
Industry Dummy 1	0.897 (0.084)***	0.975 (0.024)***	0.438 (0.139)***	0.518 (0.093)***
Industry Dummy 2	0.438 (0.034)***	0.777 (0.025)***	0.309 (0.132)**	0.382 (0.088)***
Industry Dummy 3	0.781 (0.118)***	0.824 (0.053)***	0.252 (0.158)	0.478 (0.112)***
Industry Dummy 4	0.531 (0.058)***	0.629 (0.029)***	0.323 (0.158)**	0.185 (0.110)*
Industry Dummy 5	0.270 (0.032)***	0.475 (0.026)***	0.144 (0.132)	0.223 (0.091)**
Industry Dummy 6	0.744 (0.065)***	0.640 (0.033)***	0.258 (0.132)*	0.220 (0.102)**
Industry Dummy 7	0.668 (0.035)***	0.648 (0.030)***	0.313 (0.135)**	0.375 (0.092)***

Industry Dummy 8	0.485 (0.037)***	0.740 (0.033)***	0.130 (0.132)	0.237 (0.097)**
Industry Dummy 9	0.435 (0.097)***	0.525 (0.052)***	-0.111 (0.414)	
Industry Dummy 10	0.518 (0.160)***	0.947 (0.124)***	0.658 (0.220)***	0.230 (0.229)
Predicted Experience	0.040 (0.004)***	0.038 (0.003)***	0.043 (0.007)***	0.034 (0.006)***
Predicted Experience Squared	-0.002 (0.0002)***	-0.001 (0.0001)***	-0.001 (0.0002)***	-0.001 (0.0002)***
Education spline				
Primary	0.020 (0.004)***	0.020 (0.004)***	0.043 (0.044)	-0.023 (0.030)
Secondary	0.054 (0.006)***	0.070 (0.005)***	0.112 (0.033)***	0.134 (0.028)***
Matric	0.112 (0.024)***	0.138 (0.018)***	0.065 (0.044)	0.056 (0.039)
Tertiary	0.155 (0.020)***	0.187 (0.015)***	0.069 (0.025)***	0.128 (0.016)***
Diploma/Certificate	0.191 (0.029)***	0.132 (0.028)***	0.110 (0.033)***	0.126 (0.037)***
Rural Dummy	-0.200 (0.014)***	-0.168 (0.014)***	-0.167 (0.064)***	-0.152 (0.050)***
Province Dummy 1	-0.528 (0.034)***	-0.282 (0.032)***	-0.115 (0.051)**	-0.204 (0.048)***
Province Dummy 2	-0.428 (0.045)***	-0.182 (0.039)***	-0.322 (0.073)***	-0.223 (0.055)***
Province Dummy 3	-0.651 (0.034)***	-0.357 (0.030)***	-0.284 (0.052)***	-0.224 (0.048)***
Province Dummy 4	-0.414 (0.032)***	-0.112 (0.029)***	-0.045 (0.052)	-0.102 (0.053)*
Province Dummy 5	-0.353 (0.034)***	-0.175 (0.029)***	-0.272 (0.060)***	-0.185 (0.053)***
Province Dummy 6	-0.123 (0.033)***	-0.009 (0.028)	0.124 (0.049)**	0.018 (0.044)
Province Dummy 7	-0.371 (0.034)***	-0.144 (0.030)***	-0.230 (0.055)***	-0.153 (0.053)***
Province Dummy 8	-0.552 (0.035)***	-0.356 (0.031)***	-0.303 (0.083)***	-0.187 (0.071)***
Household Head Dummy	0.036 (0.015)**	0.089 (0.015)***	0.218 (0.039)***	0.268 (0.045)***
Wave Dummy 1	-0.016 (0.019)	-0.033 (0.017)**	-0.015 (0.055)	0.022 (0.042)
Wave Dummy 2	-0.016 (0.020)	-0.051 (0.017)***	0.008 (0.041)	-0.053 (0.052)
Wave Dummy 3	0.011 (0.020)	-0.047 (0.018)***	-0.040 (0.045)	-0.035 (0.042)
Wave Dummy 4	0.076 (0.019)***	0.046 (0.017)***	0.061 (0.039)	0.095 (0.050)*
Wave Dummy 5	0.084 (0.021)***	0.031 (0.019)*	0.067 (0.041)*	0.063 (0.043)
Married Dummy	0.095 (0.015)***	0.047 (0.014)***	0.139 (0.037)***	0.132 (0.038)***

Intercept	1.768 (0.089)***	1.273 (0.062)***	1.776 (0.324)***	2.132 (0.187)***
R^2	0.67	0.60	0.34	0.41
N	21,160	25,314	4,561	4,884

Table A6

	Black women	Black men	White women	White men
Tenure wage effect – *linear*:				
Non-permanent/No contract (*base*)	0.036	0.027	0.005	0.040
	(0.005)***	(0.006)***	(0.026)	(0.028)
Permanent	0.006	0.011	0.019	0.024
	(0.006)	(0.006)*	(0.025)	(0.025)
Contract	-0.016	-0.011	-0.003	-0.040
	(0.005)***	(0.004)**	(0.014)	(0.014)***
Tenure wage effect – *quadratic*:				
Non-permanent/No contract (*base*)	-0.001	-0.001	-0.0005	-0.0004
	(0.0002)***	(0.0002)***	(0.001)	(0.001)
Permanent	0.00002	-0.00003	0.00005	-0.001
	(0.0003)	(0.0003)	(0.001)	(0.001)
Contract	0.0003	0.0003	0.00001	0.001
	(0.0002)*	(0.0002)*	(0.001)	(0.0005)**
Permanent	0.062	0.151	0.069	0.092
	(0.023)***	(0.020)***	(0.069)	(0.078)
Contract	0.260	0.268	0.075	0.388
	(0.025)***	(0.021)***	(0.060)	(0.072)***
Informal sector	-0.413	-0.328	-0.234	-0.104
	(0.038)***	(0.027)***	(0.098)**	(0.103)
Public sector	0.431	0.295	0.129	0.057
	(0.030)***	(0.027)***	(0.037)***	(0.054)
Occupation Dummy 1	-0.357	-0.235	-0.071	-0.178
	(0.095)***	(0.063)***	(0.084)	(0.064)***
Occupation Dummy 2	-0.414	-0.322	-0.230	-0.183
	(0.083)***	(0.045)***	(0.052)***	(0.046)***
Occupation Dummy 3	-0.672	-0.565	-0.432	-0.463
	(0.083)***	(0.044)***	(0.056)***	(0.056)***
Occupation Dummy 4	-0.907	-0.812	-0.622	-0.551
	(0.086)***	(0.043)***	(0.065)***	(0.056)***
Occupation Dummy 5	-0.973	-0.759		-0.326
	(0.112)***	(0.064)***		(0.145)**
Occupation Dummy 6	-0.940	-0.628	-0.535	-0.416
	(0.087)***	(0.044)***	(0.113)***	(0.045)***
Occupation Dummy 7	-0.896	-0.697	-0.625	-0.528
	(0.089)***	(0.043)***	(0.113)***	(0.066)***
Occupation Dummy 8	-1.003	-0.807	-0.663	-0.576
	(0.084)***	(0.043)***	(0.113)***	(0.080)***
Occupation Dummy 9	-1.379	-1.110	-0.879	-0.984
	(0.128)***	(0.084)***	(0.461)*	(0.105)***
Industry Dummy 1	0.835	0.893	0.403	0.440
	(0.083)***	(0.024)***	(0.142)***	(0.095)***
Industry Dummy 2	0.373	0.734	0.292	0.325
	(0.034)***	(0.024)***	(0.135)**	(0.089)***
Industry Dummy 3	0.726	0.772	0.245	0.420
	(0.113)***	(0.053)***	(0.161)	(0.112)***
Industry Dummy 4	0.498	0.646	0.324	0.120
	(0.059)***	(0.029)***	(0.160)**	(0.112)
Industry Dummy 5	0.233	0.450	0.143	0.192
	(0.032)***	(0.025)***	(0.136)	(0.092)**

Industry Dummy 6	0.689 (0.063)***	0.633 (0.032)***	0.245 (0.136)*	0.158 (0.103)
Industry Dummy 7	0.586 (0.036)***	0.584 (0.030)***	0.297 (0.138)**	0.318 (0.093)***
Industry Dummy 8	0.430 (0.037)***	0.716 (0.032)***	0.124 (0.136)	0.172 (0.099)*
Industry Dummy 9	0.418 (0.097)***	0.530 (0.050)***	-0.114 (0.402)	
Industry Dummy 10	0.446 (0.169)***	0.920 (0.129)***	0.659 (0.226)***	0.209 (0.214)
Predicted Experience	0.037 (0.003)***	0.035 (0.003)***	0.042 (0.007)***	0.031 (0.006)***
Predicted Experience Squared	-0.001 (0.0001)***	-0.001 (0.0001)***	-0.001 (0.0002)***	-0.001 (0.0002)***
Education spline				
Primary	0.019 (0.004)***	0.019 (0.004)***	0.051 (0.043)	-0.043 (0.029)
Secondary	0.054 (0.006)***	0.066 (0.005)***	0.117 (0.033)***	0.133 (0.029)***
Matric	0.101 (0.024)***	0.125 (0.017)***	0.046 (0.044)	0.042 (0.039)
Tertiary	0.148 (0.020)***	0.181 (0.014)***	0.068 (0.025)***	0.125 (0.016)***
Diploma/Certificate	0.172 (0.029)***	0.115 (0.027)***	0.103 (0.033)***	0.121 (0.037)***
Rural Dummy	-0.185 (0.014)***	-0.159 (0.014)***	-0.159 (0.064)**	-0.141 (0.046)***
Province Dummy 1	-0.471 (0.034)***	-0.223 (0.031)***	-0.109 (0.052)**	-0.213 (0.048)***
Province Dummy 2	-0.444 (0.044)***	-0.189 (0.038)***	-0.321 (0.073)***	-0.236 (0.054)***
Province Dummy 3	-0.635 (0.033)***	-0.352 (0.029)***	-0.286 (0.053)***	-0.245 (0.048)***
Province Dummy 4	-0.387 (0.031)***	-0.086 (0.028)***	-0.040 (0.053)	-0.107 (0.053)**
Province Dummy 5	-0.340 (0.034)***	-0.165 (0.028)***	-0.259 (0.059)***	-0.188 (0.053)***
Province Dummy 6	-0.109 (0.033)***	-0.006 (0.027)	0.122 (0.050)**	0.011 (0.043)
Province Dummy 7	-0.358 (0.034)***	-0.147 (0.029)***	-0.235 (0.056)***	-0.196 (0.052)***
Province Dummy 8	-0.524 (0.034)***	-0.321 (0.030)***	-0.319 (0.083)***	-0.208 (0.073)***
Household Head Dummy	0.035 (0.015)**	0.084 (0.015)***	0.213 (0.039)***	0.263 (0.045)***
Wave Dummy 1	-0.022 (0.019)	-0.048 (0.017)***	-0.030 (0.055)	0.006 (0.041)
Wave Dummy 2	-0.031 (0.020)	-0.072 (0.017)***	-0.006 (0.041)	-0.073 (0.051)
Wave Dummy 3	-0.002 (0.021)	-0.078 (0.018)***	-0.053 (0.046)	-0.057 (0.041)
Wave Dummy 4	0.050 (0.019)***	0.009 (0.017)	0.046 (0.040)	0.057 (0.049)

Wave Dummy 5	0.046	-0.014	0.050	0.018
	(0.021)**	(0.018)	(0.042)	(0.042)
Married Dummy	0.092	0.038	0.137	0.123
	(0.015)***	(0.013)***	(0.038)***	(0.037)***
Intercept	1.618	1.115	1.637	1.996
	(0.089)***	(0.063)***	(0.327)***	(0.191)***
R^2	0.68	0.61	0.34	0.42
N	20,731	24,777	4,524	4,833

Table A7

	Black women	Black men	White women	White men
Tenure wage effect – *linear*:				
Small firm (*base*)	0.035 (0.003)***	0.026 (0.003)***	0.020 (0.007)***	0.033 (0.007)***
Large firm	-0.015 (0.005)***	-0.000 (0.004)	-0.008 (0.011)	-0.012 (0.009)
Tenure wage effect – *quadratic*:				
Small firm (*base*)	-0.001 (0.0001)***	-0.001 (0.0001)***	-0.0004 (0.0004)	-0.001 (0.0002)***
Large firm	0.0004 (0.0002)**	0.0001 (0.0001)	0.0001 (0.0004)	0.0005 (0.0003)
Large firm	0.168 (0.028)***	0.170 (0.019)***	0.237 (0.055)***	0.201 (0.053)***
Permanent	0.092 (0.016)***	0.188 (0.015)***	0.120 (0.051)**	0.162 (0.060)***
Contract	0.177 (0.015)***	0.200 (0.013)***	0.036 (0.034)	0.208 (0.039)***
Informal sector	-0.399 (0.038)***	-0.304 (0.027)***	-0.221 (0.097)**	-0.104 (0.108)
Public sector	0.421 (0.030)***	0.280 (0.027)***	0.112 (0.037)***	0.034 (0.052)
Occupation Dummy 1	-0.325 (0.093)***	-0.202 (0.064)***	-0.066 (0.082)	-0.167 (0.063)***
Occupation Dummy 2	-0.385 (0.082)***	-0.296 (0.045)***	-0.216 (0.051)***	-0.169 (0.046)***
Occupation Dummy 3	-0.652 (0.082)***	-0.565 (0.045)***	-0.424 (0.054)***	-0.473 (0.056)***
Occupation Dummy 4	-0.880 (0.085)***	-0.814 (0.044)***	-0.593 (0.063)***	-0.539 (0.057)***
Occupation Dummy 5	-0.956 (0.111)***	-0.759 (0.064)***		-0.319 (0.146)**
Occupation Dummy 6	-0.912 (0.086)***	-0.620 (0.044)***	-0.504 (0.111)***	-0.411 (0.044)***
Occupation Dummy 7	-0.893 (0.088)***	-0.692 (0.043)***	-0.637 (0.111)***	-0.527 (0.066)***
Occupation Dummy 8	-0.986 (0.083)***	-0.809 (0.043)***	-0.686 (0.108)***	-0.578 (0.081)***
Occupation Dummy 9	-1.343 (0.127)***	-1.086 (0.084)***	-0.888 (0.464)*	-0.918 (0.104)***
Industry Dummy 1	0.818 (0.081)***	0.803 (0.025)***	0.308 (0.144)**	0.390 (0.094)***
Industry Dummy 2	0.371 (0.034)***	0.700 (0.024)***	0.259 (0.137)*	0.326 (0.087)***
Industry Dummy 3	0.733 (0.117)***	0.753 (0.052)***	0.195 (0.158)	0.388 (0.111)***
Industry Dummy 4	0.517 (0.058)***	0.640 (0.029)***	0.320 (0.156)**	0.155 (0.113)
Industry Dummy 5	0.264 (0.032)***	0.470 (0.025)***	0.146 (0.138)	0.228 (0.091)**
Industry Dummy 6	0.694 (0.062)***	0.615 (0.031)***	0.239 (0.138)*	0.157 (0.103)

Industry Dummy 7	0.610 (0.036)***	0.576 (0.030)***	0.295 (0.139)**	0.343 (0.091)***
Industry Dummy 8	0.456 (0.037)***	0.717 (0.032)***	0.125 (0.137)	0.204 (0.097)**
Industry Dummy 9	0.446 (0.097)***	0.535 (0.050)***	-0.067 (0.401)	
Industry Dummy 10	0.478 (0.172)***	0.930 (0.127)***	0.638 (0.201)***	0.225 (0.223)
Predicted Experience	0.037 (0.003)***	0.034 (0.003)***	0.042 (0.007)***	0.030 (0.006)***
Predicted Experience Squared	-0.001 (0.0001)***	-0.001 (0.0001)***	-0.001 (0.0002)***	-0.001 (0.0002)***
Education spline				
Primary	0.019 (0.004)***	0.018 (0.004)***	0.053 (0.042)	-0.039 (0.027)
Secondary	0.054 (0.006)***	0.065 (0.005)***	0.110 (0.033)***	0.129 (0.029)***
Matric	0.095 (0.024)***	0.118 (0.017)***	0.056 (0.044)	0.046 (0.039)
Tertiary	0.148 (0.020)***	0.178 (0.014)***	0.066 (0.025)***	0.122 (0.015)***
Diploma/Certificate	0.180 (0.029)***	0.132 (0.028)***	0.098 (0.032)***	0.117 (0.036)***
Rural Dummy	-0.181 (0.014)***	-0.153 (0.014)***	-0.134 (0.066)**	-0.116 (0.047)**
Province Dummy 1	-0.476 (0.034)***	-0.226 (0.031)***	-0.092 (0.050)*	-0.219 (0.047)***
Province Dummy 2	-0.443 (0.044)***	-0.167 (0.038)***	-0.290 (0.073)***	-0.221 (0.054)***
Province Dummy 3	-0.647 (0.033)***	-0.353 (0.029)***	-0.269 (0.052)***	-0.246 (0.047)***
Province Dummy 4	-0.399 (0.032)***	-0.099 (0.028)***	-0.029 (0.052)	-0.102 (0.053)*
Province Dummy 5	-0.349 (0.034)***	-0.167 (0.028)***	-0.237 (0.059)***	-0.194 (0.052)***
Province Dummy 6	-0.122 (0.033)***	-0.016 (0.027)	0.110 (0.048)**	-0.002 (0.042)
Province Dummy 7	-0.365 (0.034)***	-0.148 (0.029)***	-0.217 (0.056)***	-0.201 (0.051)***
Province Dummy 8	-0.535 (0.034)***	-0.321 (0.030)***	-0.285 (0.084)***	-0.202 (0.072)***
Household Head Dummy	0.035 (0.015)**	0.083 (0.015)***	0.209 (0.039)***	0.257 (0.044)***
Wave Dummy 1	-0.020 (0.019)	-0.044 (0.017)***	-0.005 (0.053)	0.012 (0.041)
Wave Dummy 2	-0.035 (0.020)*	-0.074 (0.017)***	0.015 (0.040)	-0.069 (0.050)
Wave Dummy 3	-0.003 (0.021)	-0.079 (0.018)***	-0.028 (0.045)	-0.055 (0.041)
Wave Dummy 4	0.052 (0.019)***	0.011 (0.017)	0.073 (0.039)*	0.054 (0.049)
Wave Dummy 5	0.046 (0.021)**	-0.016 (0.018)	0.070 (0.041)*	0.024 (0.042)

Married Dummy	0.094	0.041	0.141	0.125
	(0.015)***	(0.013)***	(0.037)***	(0.037)***
Intercept	1.564	1.100	1.531	1.985
	(0.087)***	(0.062)***	(0.322)***	(0.159)***
R^2	0.68	0.62	0.35	0.42
N	20,731	24,777	4,524	4,833

Table A8

	Black women	Black men	White women	White men
Tenure	0.032 (0.003)***	0.026 (0.002)***	0.017 (0.005)***	0.025 (0.005)***
Tenure squared	-0.001 (0.000)***	-0.000 (0.000)***	-0.000 (0.000)	-0.000 (0.000)**
Firm size dummy 1	-0.087 (0.026)***	0.133 (0.035)***	-0.134 (0.110)	-0.258 (0.167)
Firm size dummy 2	0.024 (0.034)	0.222 (0.036)***	-0.009 (0.107)	-0.192 (0.161)
Firm size dummy 3	0.111 (0.034)***	0.258 (0.036)***	-0.049 (0.108)	-0.175 (0.162)
Firm size dummy 4	0.125 (0.033)***	0.325 (0.035)***	0.033 (0.103)	-0.074 (0.160)
Firm size dummy 5	0.181 (0.032)***	0.432 (0.034)***	0.183 (0.103)*	0.021 (0.158)
Permanent	0.095 (0.015)***	0.187 (0.015)***	0.117 (0.052)**	0.153 (0.062)**
Contract	0.163 (0.015)***	0.179 (0.013)***	0.026 (0.034)	0.203 (0.039)***
Informal sector	-0.351 (0.037)***	-0.228 (0.026)***	-0.208 (0.100)**	-0.113 (0.114)
Public sector	0.387 (0.030)***	0.266 (0.027)***	0.091 (0.038)**	0.026 (0.053)
Occupation Dummy 1	-0.342 (0.095)***	-0.193 (0.065)***	-0.069 (0.084)	-0.173 (0.063)***
Occupation Dummy 2	-0.399 (0.084)***	-0.301 (0.045)***	-0.220 (0.051)***	-0.174 (0.047)***
Occupation Dummy 3	-0.653 (0.083)***	-0.566 (0.045)***	-0.420 (0.055)***	-0.483 (0.057)***
Occupation Dummy 4	-0.886 (0.086)***	-0.811 (0.044)***	-0.586 (0.064)***	-0.536 (0.058)***
Occupation Dummy 5	-0.966 (0.112)***	-0.752 (0.064)***		-0.309 (0.151)**
Occupation Dummy 6	-0.928 (0.088)***	-0.618 (0.045)***	-0.487 (0.112)***	-0.409 (0.045)***
Occupation Dummy 7	-0.914 (0.090)***	-0.691 (0.044)***	-0.645 (0.120)***	-0.538 (0.067)***
Occupation Dummy 8	-1.003 (0.084)***	-0.806 (0.044)***	-0.687 (0.108)***	-0.574 (0.083)***
Occupation Dummy 9	-1.318 (0.128)***	-1.007 (0.082)***	-0.862 (0.474)*	-1.078 (0.179)***
Industry Dummy 1	0.835 (0.082)***	0.793 (0.025)***	0.306 (0.148)**	0.383 (0.095)***
Industry Dummy 2	0.379 (0.035)***	0.678 (0.024)***	0.256 (0.142)*	0.325 (0.088)***
Industry Dummy 3	0.787 (0.112)***	0.743 (0.054)***	0.199 (0.166)	0.391 (0.111)***
Industry Dummy 4	0.527 (0.059)***	0.613 (0.029)***	0.288 (0.158)*	0.146 (0.113)
Industry Dummy 5	0.292	0.459	0.157	0.236

	(0.032)***	(0.025)***	(0.144)	(0.092)**
Industry Dummy 6	0.712	0.641	0.236	0.158
	(0.063)***	(0.030)***	(0.143)	(0.103)
Industry Dummy 7	0.631	0.563	0.307	0.360
	(0.036)***	(0.030)***	(0.144)**	(0.091)***
Industry Dummy 8	0.493	0.715	0.145	0.212
	(0.038)***	(0.032)***	(0.144)	(0.098)**
Industry Dummy 9	0.490	0.629	-0.094	
	(0.098)***	(0.052)***	(0.422)	
Industry Dummy 10	0.549	0.969	0.626	0.209
	(0.178)***	(0.134)***	(0.208)***	(0.242)
Predicted Experience	0.038	0.035	0.044	0.029
	(0.003)***	(0.003)***	(0.007)***	(0.006)***
Predicted Experience Squared	-0.001	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Education spline	0.019	0.018	0.043	-0.032
Primary	(0.004)***	(0.004)***	(0.042)	(0.028)
	0.052	0.064	0.109	0.124
Secondary	(0.006)***	(0.005)***	(0.034)***	(0.028)***
	0.091	0.114	0.050	0.032
Matric	(0.024)***	(0.017)***	(0.045)	(0.039)
	0.147	0.173	0.066	0.124
Tertiary	(0.020)***	(0.014)***	(0.025)***	(0.016)***
	0.179	0.126	0.102	0.118
Diploma/Certificate	(0.029)***	(0.028)***	(0.033)***	(0.036)***
	-0.174	-0.154	-0.132	-0.114
Rural Dummy	(0.014)***	(0.014)***	(0.067)*	(0.049)**
	-0.470	-0.196	-0.093	-0.231
Province Dummy 1	(0.034)***	(0.031)***	(0.050)*	(0.047)***
	-0.442	-0.143	-0.275	-0.214
Province Dummy 2	(0.044)***	(0.039)***	(0.074)***	(0.055)***
	-0.639	-0.340	-0.273	-0.245
Province Dummy 3	(0.033)***	(0.029)***	(0.052)***	(0.048)***
	-0.403	-0.095	-0.033	-0.104
Province Dummy 4	(0.032)***	(0.028)***	(0.054)	(0.053)*
	-0.348	-0.154	-0.236	-0.185
Province Dummy 5	(0.034)***	(0.028)***	(0.059)***	(0.052)***
	-0.126	-0.013	0.096	-0.005
Province Dummy 6	(0.033)***	(0.027)	(0.049)*	(0.043)
	-0.363	-0.139	-0.216	-0.196
Province Dummy 7	(0.034)***	(0.029)***	(0.056)***	(0.051)***
	-0.541	-0.309	-0.290	-0.203
Province Dummy 8	(0.034)***	(0.031)***	(0.084)***	(0.072)***
	0.033	0.095	0.204	0.265
Household Head Dummy	(0.014)**	(0.015)***	(0.038)***	(0.045)***
	-0.020	-0.038	-0.004	0.003
Wave Dummy 1	(0.018)	(0.016)**	(0.054)	(0.042)
	-0.032	-0.074	0.024	-0.075
Wave Dummy 2	(0.020)	(0.018)***	(0.041)	(0.050)
	-0.003	-0.080	-0.029	-0.058
Wave Dummy 3	(0.021)	(0.018)***	(0.046)	(0.041)

Wave Dummy 4	0.055 (0.019)***	0.013 (0.017)	0.074 (0.039)*	0.046 (0.049)
Wave Dummy 5	0.046 (0.021)**	-0.017 (0.018)	0.067 (0.041)	0.008 (0.042)
Married Dummy	0.087 (0.015)***	0.031 (0.013)**	0.133 (0.036)***	0.126 (0.037)***
Intercept	1.517 (0.093)***	0.857 (0.068)***	1.648 (0.345)***	2.155 (0.226)***
R^2	0.68	0.63	0.35	0.42
N	20,485	24,289	4,451	4,719

Table A9: Tenure regression – 1st stage IV

	Black women	Black men	White women	White men
Tenure instrument	0.9894	0.8276	0.9164	1.0166
	(0.0817)***	(0.0872)***	(0.1547)***	(0.1754)***
Tenure squared instrument	-0.0005	0.0068	0.0053	-0.0025
	(0.0052)	(0.0055)	(0.0088)	(0.0102)
Firm size dummy 1	1.2098	0.3920	-2.0074	-0.8508
	(0.2011)***	(0.1993)**	(0.6388)***	(1.0158)
Firm size dummy 2	1.7703	0.7020	-1.2483	-0.5819
	(0.2326)***	(0.2106)***	(0.6542)*	(1.0115)
Firm size dummy 3	1.9187	0.6733	-1.3322	-0.1423
	(0.2277)***	(0.2091)***	(0.6399)**	(0.9965)
Firm size dummy 4	1.9599	0.8317	-0.6346	0.0813
	(0.2313)***	(0.2081)***	(0.6321)	(0.9847)
Firm size dummy 5	2.5908	1.5641	-0.2103	1.8112
	(0.2306)***	(0.2030)***	(0.6144)	(0.9718)*
Permanent	2.7910	3.4468	3.4981	3.8602
	(0.0932)***	(0.1000)***	(0.4279)***	(0.3276)***
Contract	0.4511	0.3518	-0.0235	1.0728
	(0.1054)***	(0.1026)***	(0.2869)	(0.3089)***
Informal sector	-0.0789	0.0470	-1.6092	-0.9004
	(0.2139)	(0.1663)	(0.9336)*	(0.6456)
Public sector	1.8984	2.3313	3.5711	2.8531
	(0.1820)***	(0.2222)***	(0.3408)***	(0.4551)***
Occupation Dummy 1	0.9429	0.7969	-1.4623	-0.4846
	(0.5970)	(0.3993)**	(0.4760)***	(0.5093)
Occupation Dummy 2	1.3754	0.2350	-1.5878	-0.6412
	(0.5575)**	(0.3421)	(0.4007)***	(0.3933)
Occupation Dummy 3	0.5849	-0.1048	-1.5776	0.1050
	(0.5480)	(0.3517)	(0.3860)***	(0.5274)
Occupation Dummy 4	-0.1477	-0.5724	-1.8282	-0.1733
	(0.5560)	(0.3341)*	(0.4489)***	(0.4057)
Occupation Dummy 5	-1.5205	-1.3850		1.2801
	(0.7710)**	(0.4035)***		(1.4691)
Occupation Dummy 6	0.0113	-1.0025	-1.2474	-0.8434
	(0.5948)	(0.3442)***	(0.8472)	(0.3721)**
Occupation Dummy 7	0.1598	-1.2259	-3.7228	-0.7005
	(0.6102)	(0.3434)***	(1.1944)***	(0.6020)
Occupation Dummy 8	-0.3986	-1.2832	-3.8597	-0.6568
	(0.5575)	(0.3407)***	(0.9224)***	(0.6445)
Occupation Dummy 9	0.0237	-0.5943	-2.0575	-5.4993
	(0.9895)	(0.6105)	(2.3636)	(1.2095)***
Industry Dummy 1	-0.4717	1.5823	0.0637	1.4583
	(0.8022)	(0.2287)***	(1.0780)	(0.8500)*
Industry Dummy 2	-0.2155	-0.4839	1.3950	0.9327
	(0.2439)	(0.1851)***	(1.0617)	(0.7699)
Industry Dummy 3	-1.0374	0.6832	6.0159	1.8187
	(0.5507)*	(0.3581)*	(2.4099)**	(1.0240)*
Industry Dummy 4	-1.8622	-1.3532	2.1032	0.0898
	(0.3185)***	(0.2228)***	(1.5282)	(0.8485)
Industry Dummy 5	0.0922	-1.0501	0.4921	-0.0157

	(0.2182)	(0.1813)***	(1.0182)	(0.7774)
Industry Dummy 6	-0.4404	-0.4643	1.3173	3.4351
	(0.3378)	(0.2340)**	(1.0750)	(0.9011)***
Industry Dummy 7	-0.9632	-2.3856	0.8740	0.1392
	(0.2419)***	(0.2127)***	(1.0200)	(0.8064)
Industry Dummy 8	-0.0192	-0.5615	1.1038	1.0069
	(0.2486)	(0.2423)**	(1.0349)	(0.8528)
Industry Dummy 9	0.5893	-0.6839	2.5307	
	(0.8213)	(0.3069)**	(2.0895)	
Industry Dummy 10	-0.4825	-1.6273	-1.2206	-1.3621
	(1.0453)	(0.9121)*	(1.3202)	(1.4412)
Predicted Experience	0.6769	0.3899	0.4453	0.3480
	(0.0280)***	(0.0253)***	(0.0544)***	(0.0523)***
Predicted Experience Squared	0.0030	0.0074	-0.0006	0.0015
	(0.0015)*	(0.0013)***	(0.0021)	(0.0016)
Education spline				
Primary	-0.1386	-0.0949	0.4383	-0.2216
	(0.0296)***	(0.0329)***	(0.4285)	(0.3423)
Secondary	0.0517	-0.0390	-0.6550	-0.8672
	(0.0417)	(0.0391)	(0.3657)*	(0.2873)***
Matric	-1.1604	-0.8242	-1.1096	-0.0592
	(0.1271)***	(0.1178)***	(0.4597)**	(0.3762)
Tertiary	-1.4987	-1.4371	-0.8055	-0.7438
	(0.1076)***	(0.0871)***	(0.1017)***	(0.1270)***
Diploma/Certificate	-1.8481	-0.7142	-0.3032	-0.4331
	(0.1685)***	(0.1736)***	(0.2710)	(0.3122)
Rural Dummy	0.1839	-0.0095	-0.2955	-1.4188
	(0.1005)*	(0.1005)	(0.4634)	(0.4756)***
Province Dummy 1	0.0652	0.4509	0.0330	0.3167
	(0.2113)	(0.2081)**	(0.3277)	(0.4181)
Province Dummy 2	-0.4322	0.1588	0.3668	-0.1505
	(0.2807)	(0.3719)	(0.4883)	(0.4660)
Province Dummy 3	0.3611	0.4785	-0.3866	-0.0224
	(0.2224)	(0.1978)**	(0.3084)	(0.4230)
Province Dummy 4	0.4805	1.2009	-0.4401	-1.1026
	(0.2032)**	(0.1858)***	(0.4186)	(0.4766)**
Province Dummy 5	0.1239	0.5357	-0.3566	-0.3686
	(0.2149)	(0.1979)***	(0.4300)	(0.5038)
Province Dummy 6	-0.0548	0.5393	-0.3495	-1.2189
	(0.2016)	(0.1849)***	(0.2634)	(0.3300)***
Province Dummy 7	0.0446	0.9188	0.4284	-0.3040
	(0.2170)	(0.1981)***	(0.3622)	(0.4509)
Province Dummy 8	0.2373	0.9993	-1.2330	-2.7036
	(0.2233)	(0.2195)***	(0.5212)**	(0.5364)***
Household Head Dummy	0.2396	0.3912	-0.1674	0.6511
	(0.0907)***	(0.0909)***	(0.2962)	(0.2981)**
Wave Dummy 1	-0.3766	-0.2035	-0.3670	-0.3946
	(0.1376)***	(0.1386)	(0.2950)	(0.3573)
Wave Dummy 2	-0.5382	-0.3910	-0.0457	0.0328
	(0.1344)***	(0.1396)***	(0.3796)	(0.4037)
Wave Dummy 3	-0.5604	-0.7324	-0.5071	-0.2379
	(0.1382)***	(0.1425)***	(0.3412)	(0.3958)

Wave Dummy 4	-0.6866 (0.1438)***	-0.6349 (0.1405)***	-0.8091 (0.3002)***	-0.5883 (0.3806)
Wave Dummy 5	-0.8502 (0.1439)***	-0.6943 (0.1383)***	-0.7404 (0.3334)**	-0.8191 (0.3675)**
Married Dummy	0.1477 (0.0896)*	0.8729 (0.0942)***	0.6555 (0.2338)***	0.0841 (0.2750)
Intercept	-0.5821 (0.6617)	0.4905 (0.4807)	0.0450 (3.1512)	2.1490 (2.3618)
R^2	0.48	0.47	0.41	0.42
N	20,485	24,289	4,451	4,719

Table A10: Log hourly wage – Control function

	Black women	Black men	White women	White men
Tenure	0.0171	0.0167	-0.0026	0.009
	(0.0062)***	(0.0051)***	(0.0110)	(0.011)
Tenure squared	-0.0008	-0.0005	-0.0008	-0.000
	(0.0002)***	(0.0002)***	(0.0005)	(0.000)
1st stage residuals	0.0214	0.0112	0.0310	0.019
	(0.0059)***	(0.0047)**	(0.0095)***	(0.011)*
Tenure*residuals	-0.0009	-0.0001	-0.0004	-0.001
	(0.0004)**	(0.0004)	(0.0009)	(0.001)
Tenure squared*residuals	0.0000	0.0000	0.0000	0.000
	(0.0000)**	(0.0000)	(0.0000)	(0.000)
Firm size dummy 1	-0.0682	0.1364	-0.1906	-0.267
	(0.0264)***	(0.0350)***	(0.1115)*	(0.166)
Firm size dummy 2	0.0548	0.2283	-0.0386	-0.197
	(0.0354)	(0.0358)***	(0.1070)	(0.161)
Firm size dummy 3	0.1413	0.2644	-0.0844	-0.176
	(0.0353)***	(0.0362)***	(0.1083)	(0.162)
Firm size dummy 4	0.1570	0.3328	0.0170	-0.071
	(0.0347)***	(0.0354)***	(0.1027)	(0.159)
Firm size dummy 5	0.2239	0.4477	0.1781	0.045
	(0.0343)***	(0.0346)***	(0.1026)*	(0.159)
Permanent	0.1429	0.2221	0.2160	0.209
	(0.0215)***	(0.0204)***	(0.0591)***	(0.072)***
Contract	0.1696	0.1825	0.0232	0.219
	(0.0152)***	(0.0131)***	(0.0335)	(0.041)***
Informal sector	-0.3508	-0.2275	-0.2369	-0.131
	(0.0370)***	(0.0258)***	(0.0954)**	(0.114)
Public sector	0.4177	0.2893	0.1989	0.059
	(0.0318)***	(0.0282)***	(0.0438)***	(0.061)
Occupation Dummy 1	-0.3301	-0.1843	-0.1045	-0.180
	(0.0959)***	(0.0651)***	(0.0835)	(0.063)***
Occupation Dummy 2	-0.3803	-0.2994	-0.2634	-0.181
	(0.0845)***	(0.0454)***	(0.0522)***	(0.047)***
Occupation Dummy 3	-0.6465	-0.5673	-0.4625	-0.485
	(0.0840)***	(0.0455)***	(0.0557)***	(0.057)***
Occupation Dummy 4	-0.8920	-0.8177	-0.6361	-0.538
	(0.0863)***	(0.0443)***	(0.0652)***	(0.057)***
Occupation Dummy 5	-0.9968	-0.7660		-0.297
	(0.1122)***	(0.0643)***		(0.148)**
Occupation Dummy 6	-0.9304	-0.6289	-0.5157	-0.418
	(0.0884)***	(0.0449)***	(0.1140)***	(0.045)***
Occupation Dummy 7	-0.9138	-0.7053	-0.7432	-0.546
	(0.0902)***	(0.0444)***	(0.1233)***	(0.067)***
Occupation Dummy 8	-1.0124	-0.8199	-0.7935	-0.583
	(0.0846)***	(0.0443)***	(0.1109)***	(0.083)***
Occupation Dummy 9	-1.3222	-1.0133	-0.9056	-1.171
	(0.1281)***	(0.0823)***	(0.4704)*	(0.185)***
Industry Dummy 1	0.8272	0.8101	0.3032	0.399
	(0.0822)***	(0.0255)***	(0.1489)**	(0.094)***
Industry Dummy 2	0.3742	0.6738	0.2892	0.335
	(0.0346)***	(0.0246)***	(0.1436)**	(0.088)***

Industry Dummy 3	0.7689	0.7503	0.3606	0.410
	(0.1114)***	(0.0543)***	(0.1707)**	(0.111)***
Industry Dummy 4	0.4955	0.5994	0.3439	0.143
	(0.0601)***	(0.0294)***	(0.1616)**	(0.113)
Industry Dummy 5	0.2917	0.4490	0.1672	0.231
	(0.0323)***	(0.0256)***	(0.1447)	(0.092)**
Industry Dummy 6	0.7016	0.6366	0.2714	0.200
	(0.0633)***	(0.0302)***	(0.1449)*	(0.103)*
Industry Dummy 7	0.6130	0.5392	0.3316	0.361
	(0.0367)***	(0.0323)***	(0.1449)**	(0.091)***
Industry Dummy 8	0.4909	0.7101	0.1703	0.222
	(0.0377)***	(0.0322)***	(0.1448)	(0.098)**
Industry Dummy 9	0.5008	0.6211	-0.0351	
	(0.0981)***	(0.0528)***	(0.4177)	
Industry Dummy 10	0.5400	0.9549	0.5893	0.188
	(0.1776)***	(0.1345)***	(0.2053)***	(0.244)
Predicted Experience	0.0495	0.0390	0.0554	0.036
	(0.0049)***	(0.0040)***	(0.0077)***	(0.007)***
Predicted Experience Squared	-0.0013	-0.0010	-0.0012	-0.001
	(0.0002)***	(0.0002)***	(0.0002)***	(0.000)***
Education spline	0.0163	0.0175	0.0577	-0.036
Primary	(0.0038)***	(0.0035)***	(0.0408)	(0.028)
	0.0529	0.0639	0.0954	0.113
Secondary	(0.0060)***	(0.0049)***	(0.0338)***	(0.030)***
	0.0712	0.1054	0.0101	0.032
Matric	(0.0246)***	(0.0173)***	(0.0453)	(0.039)
	0.1221	0.1583	0.0430	0.114
Tertiary	(0.0212)***	(0.0154)***	(0.0257)*	(0.017)***
	0.1469	0.1189	0.0918	0.110
Diploma/Certificate	(0.0305)***	(0.0278)***	(0.0333)***	(0.037)***
	-0.1707	-0.1535	-0.1440	-0.130
Rural Dummy	(0.0144)***	(0.0140)***	(0.0676)**	(0.051)**
	-0.4685	-0.1912	-0.0959	-0.227
Province Dummy 1	(0.0340)***	(0.0314)***	(0.0498)*	(0.048)***
	-0.4493	-0.1409	-0.2639	-0.214
Province Dummy 2	(0.0444)***	(0.0388)***	(0.0736)***	(0.055)***
	-0.6323	-0.3351	-0.2874	-0.243
Province Dummy 3	(0.0334)***	(0.0291)***	(0.0512)***	(0.048)***
	-0.3946	-0.0831	-0.0452	-0.116
Province Dummy 4	(0.0315)***	(0.0282)***	(0.0532)	(0.054)**
	-0.3450	-0.1478	-0.2497	-0.189
Province Dummy 5	(0.0337)***	(0.0282)***	(0.0577)***	(0.052)***
	-0.1271	-0.0077	0.0830	-0.019
Province Dummy 6	(0.0330)***	(0.0274)	(0.0483)*	(0.045)
	-0.3630	-0.1305	-0.2066	-0.197
Province Dummy 7	(0.0337)***	(0.0291)***	(0.0554)***	(0.052)***
	-0.5363	-0.2984	-0.3275	-0.236
Province Dummy 8	(0.0339)***	(0.0308)***	(0.0821)***	(0.077)***
	0.0362	0.0979	0.1975	0.273
Household Head Dummy	(0.0145)**	(0.0146)***	(0.0382)***	(0.045)***
	-0.0258	-0.0406	-0.0163	-0.002
Wave Dummy 1	(0.0184)	(0.0165)**	(0.0533)	(0.042)
	-0.0403	-0.0783	0.0228	-0.075

Wave Dummy 2	(0.0203)**	(0.0176)***	(0.0400)	(0.050)
	-0.0101	-0.0868	-0.0432	-0.061
Wave Dummy 3	(0.0207)	(0.0180)***	(0.0455)	(0.041)
	0.0463	0.0074	0.0513	0.038
Wave Dummy 4	(0.0196)**	(0.0175)	(0.0395)	(0.050)
	0.0337	-0.0227	0.0488	-0.002
Wave Dummy 5	(0.0207)	(0.0182)	(0.0412)	(0.042)
	0.0882	0.0401	0.1475	0.130
Married Dummy	(0.0147)***	(0.0135)***	(0.0366)***	(0.037)***
	1.5106	0.8609	1.6087	2.182
Intercept	(0.0936)***	(0.0686)***	(0.3378)***	(0.226)***
R^2	0.68	0.63	0.36	0.42
N	20,485	24,289	4,451	4,719

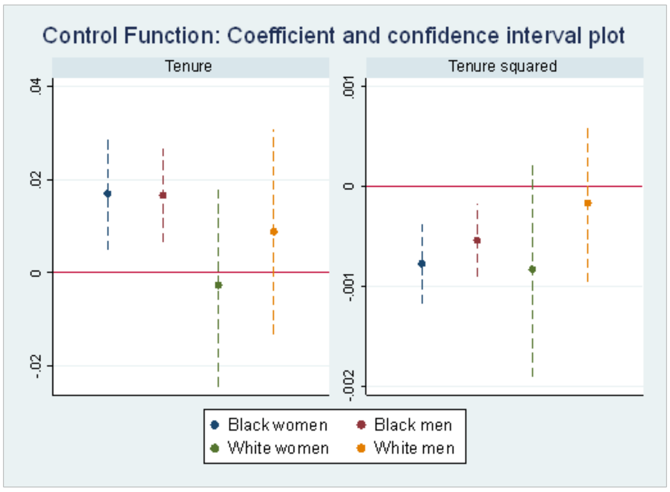


Figure A1

CHAPTER 4

AN EMPLOYER LEARNING MODEL OF THE SOUTH AFRICAN RACIAL WAGE GAP

ABSTRACT

The job-seeker-vacancy matching relationship is characterised by imperfect information and uncertainty. Employers are imperfectly informed about the productivity of job applicants, who in turn face imperfect information about the availability and nature of job vacancies. The resulting uncertainty leads to inefficiencies in job search and matching which may contribute to unemployment. When faced with asymmetric information about job-applicants, employers may resort to statistical discrimination and base hiring and promotion decisions partly on readily observable characteristics. This would disadvantage high productivity workers who are unable to send credible signals to employers. There were indications that this information asymmetry was particularly acute in the South African labour market (Levinsohn, 2007; and Abel, Burger & Piraino, 2017). This may be one of the reasons for very high unemployment and persistent wage inequality by race and educational attainment.

This paper investigates the impact of this kind of statistical discrimination as a determinant of wage gaps between races, age groups and education levels. 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 predictions of this model are tested by estimating reduced-form and structural models on South African labour market data.

Both the reduced-form and structural estimates provide evidence in support of the hypothesis that South African employers engage in statistical discrimination based on race, age and educational attainment when making employment and wage decisions. Black youth and men with the completed secondary school were found to have greater *ex-ante* uncertainty around their expected productivity. Thus, they faced a more significant disadvantage at the hiring stage while benefitting more from employer learning. The greater uncertainty is arguably driven partly by the 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. It is argued that this uncertainty is likely to be particularly pronounced for young black job-seekers

1. INTRODUCTION

Two decades have passed since South Africa's political transition in 1994, yet large racial differences in earnings persist. Earnings differences are the single most significant contributors to the high-income inequality that has become synonymous with South Africa. The inequality of labour market earnings is deeply rooted in apartheid-era policies that generated persistent differences in human capital. Underlying the differences in human capital is low quantity and quality of schooling received by blacks together with low labour market returns compared to whites (Burger & Jafta, 2006; Burger & van der Berg, 2011; Branson & Leibbrandt, 2013; and Branson, Garlick, Lam and Leibbrandt, 2012). Labour market discrimination has also played a role in the earnings inequality between blacks and whites (Allanson, Atkins and Hinks, 2002).

This paper aims to extend the literature on earning differences by investigating an often cited but scarcely researched feature of the South African labour market. Employers face a great deal of uncertainty when predicting and assessing the expected productivity of job applicants. There were indications that this information asymmetry was particularly acute in the South African labour market (Duff & Fryer, 2005; Levinsohn, 2007, Schoer & Rankin, 2011; Schoer, Rankin & Roberts, 2014; and Abel et al., 2017). Furthermore, this may be one of the reasons for the country's very high unemployment rate. The researcher argued and provided empirical evidence that uncertainty in worker productivity systematically differed by race, age and level of school attainment. Additionally, the study shows that systematic differences in worker uncertainty have an impact on initial wages and subsequent wage growth and the nature of employment contracts.

When faced with asymmetric information about job applicants, employers may resort to statistical discrimination by making hiring, wage offers and promotion based partly on readily observable characteristics. The researcher investigated the impact of this kind of labour market discrimination as a determinant of wage inequality. This allows the study to take the literature on labour market discrimination a step further than existing studies that only indirectly measure labour market discrimination as a residual component of an earnings regression. Addressing differences in human capital is an essential long-term policy objective, however, in the short-term, there may be measurable success achieved if the policy was targeted at other causes of earnings differences. The findings of this paper provide the necessary empirical evidence to guide such short-term policymaking. The short-term policies could, *inter alia*, include general skills assessment and certification by the Department of Labour's labour centres.

In this paper, the researcher constructed a theoretical model of worker uncertainty that allowed the uncertainty to be resolved over the employment spell with the current employer. The model combined insights from traditional models of statistical discrimination (e.g. Aigner & Cain, 1977) and employer learning to produce testable predictions regarding the impact of information asymmetry on earnings differences. The model relied on differences in the variance of productivity to generate labour market discrimination by allowing the variance of productivity to be a function of observable characteristics. This represented a departure from traditional models of statistical discrimination that relied on differences in the accuracy of the signal of productivity to generate labour market discrimination. Differences in the variance of productivity were motivated by the large variation in learner performance and school quality that were well documented in the South African schooling literature (van der Berg, 2007; van der Berg, 2008; and Branson & Leibbrandt, 2013).

The study performed reduced form and structural estimation by using South African labour market data to test the model's predictions. Both the reduced form and structural estimates provided evidence in support of the hypothesis that South African employers engaged in statistical discrimination based on race, age and schooling attainment when making employment and wage decisions. Black youth and men with completed secondary schooling were found to have greater *ex-ante* uncertainty around their expected productivity, thus benefitting more from employer learning. The study further showed that this uncertainty was driven by variation in worker productivity that was in turn driven by the low and variable quality of pre-tertiary schooling received by many South Africans.

2. BACKGROUND AND CONTEXT: SOUTH AFRICAN LITERATURE

Earnings differences between black and white men in South Africa follows a racial hierarchy that is evident in other labour market outcomes. The literature pointed to two main explanations for the persistence of high earnings inequality in favour of white men. Firstly, there is a large and persistent human capital differential between the two groups that favours white men. Under the apartheid government, the schooling system was divided along racial lines with unequal educational funding, support and management (Branson & Leibbrandt, 2013:7). As a result, blacks acquired fewer years of educational attainment compared to whites. The quality of the education received by blacks was also inferior (Moll, 1998; Lam, Ardington & Leibbrandt, 2011; van der Berg, 2007; Burger & van der Burg, 2011; and Branson & Leibbrandt, 2013). Access to schooling for blacks, however, began to increase in the last years of the apartheid regime and a period of convergence in educational attainment emerged between the two groups. The quality of schooling in black schools remained low and possibly deteriorated further as the expansion in access to schooling gained momentum after the political transition (Moll, 1998; van der Berg, 2007; and Branson & Leibbrandt, 2013).

The second primary explanation advanced in the literature for the persistence of earnings differences between the two racial groups relates to the evidence of labour market discrimination suffered by suffered by black workers. This evidence is based on decomposition techniques that decompose the earnings difference between black and white men into a component reflecting differences in human capital and a residual component. The residual component is then used as a measure of the extent of labour market discrimination. Allanson, Atkins and Hinks (2000) found that differences in the human capital accounted for approximately two-thirds of the difference in earnings between black and white men. The remaining one-third was accounted for by labour market discrimination suffered by black men. The labour market discrimination component was found to be persistent even after the implementation of affirmative action policies (Burger & Jafta, 2006).

The above literature on earnings differences has several significant shortcomings. The bulk of this literature has been focused on improving the understanding of human capital differentials and how these differentials can be overcoming with the use of government policy. The critical policy recommendation has been improving the education system. Fixing the education system is an important policy objective. However, a policy objective that can only be significantly realised in the long-term. In the short-term, the study may have to look at other policies that perhaps target other causes of earnings differences. This paper aims to provide the necessary empirical evidence to guide such short-term policymaking.

The labour market discrimination literature offers no concrete policy recommendations. Burger and Jafta (2006) provided evidence which indicated that affirmative action policies were largely ineffective in combating labour market discrimination. Part of the problem is that this literature almost exclusively only deals with measuring the potential magnitude of the effect of labour market discrimination on earnings differences. No attempts are made investigate the nature, cause and transmission mechanism of discrimination in the labour market on the one hand and labour market outcomes on the hand. Furthermore, this literature only measures labour market discrimination indirectly as the residual of an earnings regression after controlling for human capital differences. This paper aims to take the literature a step further than existing studies by modelling labour market discrimination as a process driven by information asymmetries deeply rooted in the South African schooling system.

There were indications that information asymmetry was particularly acute in the South African labour market (Levinsohn, 2007, Schoer et al., 2014; Schoer & Rankin, 2011; Duff & Fryer, 2005; and Abel et al. 2017). Uncertainty on the employers' side plagues the assessment of the potential productivity of job-seekers. There is a large body of evidence which indicates that employers' ability to accurately assess the potential productivity of job-seekers may systematically differ by race, age and level of educational attainment. The large variation in both learner performance and school quality between and within population groups can be plausibly linked to the uncertainty faced by employers when assessing the productivity of job-seekers. There is a research gap in the literature regarding the impact of this uncertainty on labour market outcomes.

The literature on the economics of education in South Africa points to two channels through which uncertainty regarding the potential productivity of job-seekers may operate. Firstly, the evidence points to a lack of credible signals of worker productivity for job-seekers who never completed secondary schooling. Also, there was a weakening of the secondary school certificate as a signal of a job seeker's potential productivity for those who did not obtain a tertiary school qualification (Duff & Fryer, 2005; Schoer & Rankin, 2011; Schoer et al., 2014; and Levinsohn, 2007). The low quality of schooling received by the majority of learners, coupled with the massive increase in the supply of job-seekers with a secondary school certificate, are the main culprits for the problems associated with the signals of worker productivity.

Variation in the accuracy of the signals of worker productivity is an incredibly valuable source of uncertainty for employers when they evaluate the suitability of job-seekers for employment and the wage level to set. Variation in the accuracy of the signals of worker productivity is the principal motivation for many models of statistical discrimination. The study focussed on another equally important source of uncertainty in the assessment of worker productivity that is neglected in the international literature. This is of immense importance for the South African case. The evidence on the South African education system points to more significant variation in schooling outcomes for blacks compared to whites. The more significant variation in schooling outcomes for blacks feeds into greater variation in labour market productivity. Greater variation in productivity, in turn, leads to greater uncertainty on the part of the employer.

In addition to lower learner performance, black schools have higher variation in learner performance (van der Berg, 2002, 2007 & 2008). Within the black population, inequality regarding educational attainment and the quality of education was growing. This inequality appeared to strongly correlate with socio-economic status (van der Berg, 2002 & 2008; and Branson & Leibbrandt, 2013). Those with lower socioeconomic statuses and residing in rural areas tend to have lower schooling outcomes. The effect of the low and variable quality of black schools meant that black learners acquired fewer numerical and comprehension skills (Moll, 1998).

Chamberlain and van der Berg (2002); Burger and van der Berg (2011); Branson, Ardington, Lam and Leibbrandt (2013); and Lam et al. (2011) have expressed concerns regarding the effective level of learning and cognitive gains achieved. This was attributed to the high variation in learner performance and the low and variable quality of schooling received by mainly black learners. The performance of black learners was weak and highly variable, even when compared to other African and developing countries that dedicated fewer resources to education (van der Berg, 2007). Furthermore, black learners also had higher grade repetition rates compared to their white counterparts (Lam, Leibbrandt and Mlatsheni, 2007). This further undermines educational attainment for black learners and further widen the variation in productivity.

Consequently, the study's task in this paper is to construct a theoretical model that models uncertainty regarding worker productivity as being driven by variation in worker productivity across groups. The study reviews the theoretical and empirical literature on statistical discrimination before stipulating the details of the theoretical model in the next section.

3. STATISTICAL DISCRIMINATION: THEORY AND EMPIRICAL EVIDENCE

Information asymmetry and its impact on the assessment of worker productivity is a subject of many theoretical models in the labour economics literature. Examples of these include the job-matching model of Jovanovic (1979), implicit contract model of Harris and Holstrom (1982) and adverse selection model of Salop and Salop (1976). This paper, however, finds its theoretical roots in the statistical discrimination models first pioneered by Phelps (1972) and Arrow (1973), and further developed by Aigner and Cain (1977) and Lundberg and Startz (1983). When employers were faced with information asymmetry (regarding the skills set and expected productivity of job-seekers), they had an incentive to use easily observable characteristics to distinguish among workers, provided that these characteristics were correlated to productivity. This method was according to the statistical discrimination model. This led to an outcome where the average wage of a group was not proportional to its average productivity. Subsequently, this constituted economic discrimination (Aigner and Cain, 1977:178).

Early models of statistical discrimination like Phelps (1972) were premised on employers' perceived differences in average productivity between black and white workers. The modern models, on the other hand, rely on differences in employers' ability to assess the productivity of job-seekers from different racial or gender groups. The key features of these models were set out in Aigner and Cain's (1977) influential paper. Black and white workers were assumed to have the same average productivity. The employer, however, was not able to observe a worker's actual productivity. The employer must rely on a noisy signal of productivity when assessing a worker's suitability for employment. The signal of productivity can range from information contained in a resume and job application forms to a test score from a placement evaluation. The fundamental assumption for this model and many subsequent models of statistical discrimination was that the signal of productivity was less informative for black workers. Lang (1986) motivates this assumption with research originating from sociolinguistics and sociology that highlights cultural and communication (verbal and non-verbal) differences between blacks and whites. Lang argued that these differences made it difficult for managers and supervisors to assess workers belonging to groups other their own.

Aigner and Cain (1977) showed that a model with only the above features failed to generate an equilibrium outcome that constituted economic discrimination. To demonstrate labour market discrimination, the authors made one further crucial assumption. They assumed that employers were risk averse. With this additional assumption, the employer's employment decision and wage offer was also a function of the conditional variance of productivity. Subsequently, the model showed that blacks received lower wages on average, even though their average productivity was similar to that of whites. This constituted labour market discrimination since the average wages of blacks were not proportional to their average productivity (Aigner and Cain, 1977).

Lundberg and Startz (1983) extended the statistical discrimination model to incorporate a human capital investment option. This represented an improvement on the Aigner and Cain (1977) model that took pre-labour market human capital investment as given. The human capital investment is assumed to be costly, unobservable and undertaken before entering the labour market. The assumption that blacks have a less informative productivity signal is maintained. With black workers' productivity measured with greater error and human capital investments unobservable, black workers, receive lower returns to their human capital. As a result, blacks have a lower incentive to invest in human capital. The lower investment on human capital leads to lower average wages even though blacks start with average productivity that is equal to that of whites.

The models by Aigner and Cain (1977) and Lundberg and Startz (1983) have been influential but have also attracted some criticism. Assuming that employers are risk averse is hugely unpopular (Lang, 1986). In the next section, the researcher provides possible justification for this assumption and motivate why it is a reasonable assumption for the South African labour market. Additionally, a simple test is conducted that lends credence for the assumption of employer risk aversion. Lundberg and Startz's (1983) assumption of unobservable human capital investment was at odds with available US empirical evidence. The assumption was that blacks acquired less human capital than equally comparable whites (Lang, 1986; and Oettinger, 1996).

The statistical discrimination literature has traditionally been theoretical with very few empirical contributions. The earlier models offered very few predictions that could be tested empirically. The recent models, in contrast, have a dynamic structure and incorporate the employer learning hypothesis. These extensions have made the recent models of statistical discrimination more amenable to empirical testing.

Oettinger (1996) extended the statistical discrimination 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. One of the key predictions from the model relies on racial differences in the estimated returns to tenure, labour market experience and job mobility between black and white men. The model showed that 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) provide evidence consistent with this prediction.

Altonji and Pierret (2001) devised an alternative empirical test for statistical discrimination that relies on employers' ability to learn about the actual productivity of their workers by observing their output. As employers learn about the actual 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 by education. Interestingly, the authors find no evidence of statistical discrimination by 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.

4. THEORETICAL MODEL

In this section, the researcher develops a statistical discrimination model that incorporates learning by employers for the South African labour market. The model developed here is in the spirit of and follows the formulation of Aigner and Cain (1977). The model, however, defers from Aigner and Cain's (1977) model as it relies on differences in the variance of productivity, as opposed to differences in the accuracy of the signal of productivity, to generate labour market discrimination. The researcher allows the variance of productivity to be a function of observable characteristics. Group variation in productivity is motivated by low and variable learner performance and school quality within the black population and between the two population groups.

4.1 Model Setup

Suppose individual worker productivity, y, is determined as:

$$y = \alpha + \boldsymbol{\theta s} + u\sigma_u \tag{1}$$

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, $\hat{y}_t$:

$$\hat{y}_t = y + e_t\sigma_e \tag{2}$$

e_t captures the noise or error in employers' assessment of worker productivity and is assumed to be normally distributed with zero mean and a standard deviation of one. Employers can observe $\boldsymbol{s}$, which includes all individual attributes that can be obtained from résumés and job application forms, but not u. At period t, the firm can observe all the previous signals $(\hat{y}_0, \dots, \hat{y}_t)$, which can be used to form an expectation of the worker's productivity: $E(y|\boldsymbol{s}, \hat{y}_0, \dots, \hat{y}_t)$. The researcher further assume that firms are risk-averse as they may dislike the uncertainty that results from variation in worker productivity. To incorporate risk-aversion by employers, the study follow Aigner and Cain (1977) by allowing the firm's hiring decision and wage setting to be a function of not only the worker's conditional expected productivity but also the conditional variance y, written as $Var(y|\boldsymbol{s}, \hat{y}_0, \dots, \hat{y}_t)$.

Allowing firms to be risk-averse and to want to minimise uncertainty resulting from variation in worker productivity is a reasonable characterisation of the South African labour market. Evidence from the behavioural and experimental economics literature, using laboratory games, has shown a systematic pattern of distrust and bias against black participants by white participants (Burns, 2006; and van der Merwe & Burns, 2008). A willingness by white participants to enter into strategic interactions with black participants in these games is impeded by the distrust and bias that appears to be motivated by racial stereotypes (Burns, 2006; and van der Merwe & Burns, 2008). Consequently, strategic interactions between black and white men in the labour market, like engaging in an employment relationship, may be subject to the same systematic pattern of distrust and bias. There is also a growing perception by firms that once entered into; employment contracts are costly and burdensome to terminate in South Africa (Levinsohn, 2007, and Schoer & Rankin, 2011). This further heightens the level of risk since the majority of South African job-seekers receive the low and variable quality of schooling. Other labour market rigidities like adherence to minimum wages, affirmative action legislation, and bargaining council agreements that are in operation in the South African labour market further compound the risk factor involved in the employment process. The empirical analysis provides an explicit test for the assumption of risk aversion by employers.

The firm's wage offers 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 depend positively on expected worker productivity and negatively on its conditional variance. Thus, high variance workers incur a wage penalty and the importance of that penalty depends on δ. Risk neutral hiring decisions is a special case of equation (3) in which $\delta = 0$.

It follows from equation (3) that in period 0 the worker will earn

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

Solving for the conditional expectation and variance of productivity yields the following expression

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

More generally, equation (5) is expressed as follows for the period t wage[20]

[20] The reader is referred to the appendix for the derivation of equations (5) and (6)

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

Wages are therefore a function of the observable determinants of productivity, $\boldsymbol{\theta s}$, and the final two terms on the right-hand side of equation (6) represent the conditional expectation of productivity and the (negative) conditional variance of productivity. Expected productivity is updated based the on difference between productivity signals that employers receive via interviews and evaluations of the worker's productivity and the unconditional expected productivity: $\left(\frac{1}{t+1}\right)(\hat{y}_0 + \cdots + \hat{y}_t) - \alpha - \boldsymbol{\theta s}$, This difference is weighted by the variances of worker productivity, σ_u^2, and noise in employers assessment of worker productivity, σ_e^2. The additional information gleaned from such signals becomes less important as the worker's tenure increases, which is consistent with Lange's (2007) prediction that employer learning about worker productivity is front-loaded and revealed early in an employment spell.

The conditional variance of productivity term in equation (6) tends to zero since each successive period of employment provides more information and resolves uncertainty about the productivity of the employee. Equation (6), therefore, locates the sources of individual wage growth in two places. Firstly, wages may grow as the firm acquires positive new information about individual productivity relative to the group average,$(\hat{y}_0 + \cdots + \hat{y}_t) - \alpha - \boldsymbol{\theta s}$. Secondly, the additional information removes the uncertainty regarding the worker's productivity and thus the penalty attached to such uncertainty diminishes and allows the wage to converge on the worker's expected productivity.

4.2 Model Predictions

The study follows Aigner and Cain (1977) who define discrimination as differences in earnings across groups that is are 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 $E(y_1) = E(y_2) = \mu$. Suppose that the former has a larger conditional variance of productivity, $\sigma_{u1}^2 > \sigma_{u2}^2$, given the signal of productivity, $\hat{y}_t$. The researcher denote group 1 as the disadvantaged group, the group that suffers labour market discrimination in the form of statistical discrimination.

Assuming that group 1 workers have a larger conditional variance of productivity implies that employers face greater uncertainty in predicting the expected productivity of workers from this group. Risk-averse employers will attach a more substantial penalty against group 1 workers because of the greater dispersion around their productivity. Given that the two groups were assumed to have equal average productivity, equation (5) 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.

As the employer views the worker's output on the job, the employer will acquire new information about individual worker productivity relative to the group average. The arrival of new information will help resolve the *ex-ante* uncertainty and allow the employer to update his initial assessment of the worker's productivity. As the uncertainty gets resolved, the wage penalty associated with the uncertainty falls. The model, therefore, predicts greater subsequent relative wage growth for group 1 workers. This is a standard result of the employer learning hypothesis and suggests that changes in wages resulting from the arrival of new (positive) information regarding worker productivity (Kahn and Lange, 2014, and Sicilian, 1995). Assuming greater dispersion in productivity, $\sigma_{u1}^2 > \sigma_{u2}^2$, for group 1 workers, allows the employer to bridge the informational gap in expected productivity for the individual worker relative to the group average. This information gap is smaller for group 2 workers because this group is more homogenous and thus the arrival of information for the individual does not constitute new information.

Employer learning will lead to greater subsequent wage growth if the arrival of new information permits definite updating of the employer's initial assessment of worker productivity. Not all group 1 workers will turn out to be good workers and earn a subsequent positive assessment of their productivity. This is implied by the more significant variation in productivity for this group. Consequently, if employers continue to set wages equal to the uncertainty adjusted expected productivity in each period, the model predicts that the variance of wages will increase more rapidly over the employment spell for group 1 workers compared to the group 2 workers.

In section two, the study reviewed a large body evidence, which indicated that there is more variation in labour market productivity for black men driven by the following factors: (i) greater variation in educational attainment, (ii) low and variable learner performance, and (iii) low and variable quality of pre-tertiary schooling received by this group. In light of the preceding discussion, black men are considered to be group 1 (disadvantaged group) and white men to be group 2. Accordingly, the theory model makes the following predictions:

a) Black men will have lower initial wages, conditional on expected productivity;
b) Black men should experience greater within-firm wage growth; and

c) The conditional variance of wages for black men should be larger than white men, and the gap in the gap in the variance between the two groups should increase with tenure.

In other words, black men are the group that suffers statistical discrimination. However, this study will also investigate statistical discrimination based on age and level of educational attainment. The next section discusses the data used for the empirical analysis and descriptive analysis.

5. DATA AND DESCRIPTIVE ANALYSIS

The empirical analysis in the next section makes use of the individual cross-sectional waves of the Labour Force Surveys (LFS) together with the panel version – Labour Force Survey Panel (LFSP) collected by Statistics South Africa (Stats SA). The LFSs 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 the Quarterly Labour Force Surveys replaced them. The LFS was 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 approximately 30 000 households was maintained in each wave.

Stats SA's LFSP is the first nationally representative panel dataset of the South African labour market. It was constructed from the LFS cross-sectional surveys running from September 2001 to March 2004 (Stats SA, 2006). Individuals were only linked after the collection and release of the surveys since the surveys were designed as a rotating panel of dwelling units rather than individuals (Stats SA, 2006).

The estimation sample is restricted to black and white men between the ages of 18 to 60 working in formal, private sector firms. Workers in subsistence agriculture and those reporting to be self-employed were also excluded from the analysis. Workers with a reported tenure value that is above 20 years are also dropped from the analysis.

In the previous section, the theoretical model predicted (prediction C) that the variance of wages for black men should increase with tenure at a more rapid pace compared to their white counterparts. Figure 4.1 below, plots the (unconditional) standard deviation of the log of hourly wage against tenure. The blue profile for black men lies above the red profile for white men. Furthermore, the gap between the profiles increases with tenure.

For both groups, the study conducted statistical hypothesis testing of the equality of the variances at one year and ten years of tenure. For both groups we conducted robust statistical hypothesis tests[21] (Levene, 1960) of the equality of the variances at one and ten years of tenure. This hypothesis is rejected at the 99% level of significance for both groups. In other words, the positive relationship in the blue curve and negative relationship in the red curve between the variance of wages and tenure are statistically significant.

The way the prediction of the model has been tested here is very crude. However, the evidence provided is encouraging but not fully convincing. The model is not able to account for or to provide an interpretation for the falling variance of wages over tenure for white men. I have not been able to come up with a plausible interpretation of why the profile is decreasing for white men. In the next section, the study conducts formal testing of the model's other predictions.

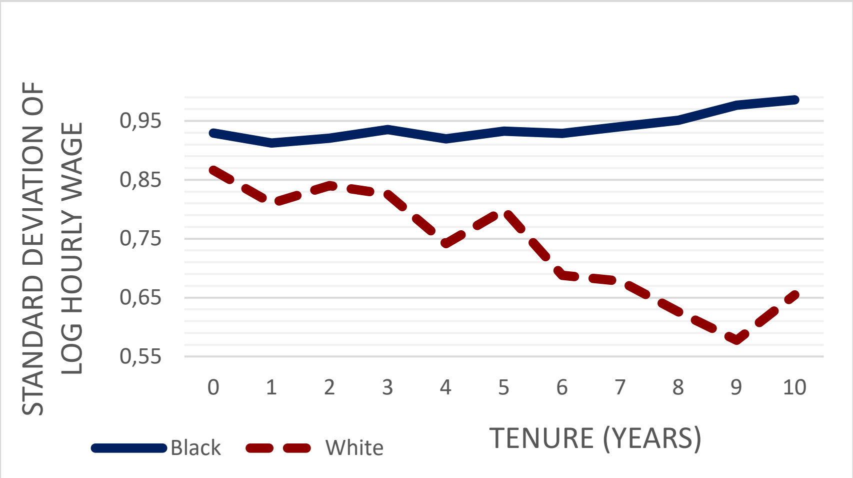


Figure 4.1: Tenure-wage (standard deviations) profiles by race

6. EMPIRICAL ANALYSIS

In this section, the study reports and discuss the results from the reduced form and structural estimation of the theoretical model.

6.1 Reduced-form estimates

The reduced form estimation is based on ordinary least squares (OLS) and exploits group-specific variation in the average wage gain due to having accumulated at least one year of tenure as an indication of employer learning. The estimated employer learning is then used to draw inferences about uncertainty regarding worker productivity for groups defined by race, age and educational attainment. Assuming that employers set wages equal to the uncertainty-adjusted expected productivity, conditional on a worker's productivity signal, initial average wages for disadvantaged workers (black, young and men with low levels of educational attainment) will

[21] The hypothesis testing was implemented with Stata's "robvar" command.

be lower relative to their 'true' productivity. This is due to the greater difficulty of predicting these workers expected productivity. The lower initial wage relative to 'true' productivity represents the penalty that a risk-averse employer will attach to the wages of workers whose productivity is more uncertain.

If employers continue to equate wages to the uncertainty-adjusted expected productivity in each period, then as the uncertainty around the worker's productivity is resolved, actual wages should converge to actual productivity. Therefore, there should be more rapid wage growth for disadvantaged workers since employers were more uncertain about their productivity. Since employer learning occurs early in an employment spell (Lange, 2007), the researcher should observe a steeper wage-tenure profile for these workers. 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. labour market.

The study proceeds to estimate a pooled OLS wage (hourly wages in logs) regression controlling for human capital, demographic and job characteristics. The researcher then adds a dummy variable equal to one if tenure is larger or equal to one, and zero otherwise. Adding this dummy variable in the 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). This tenure dummy variable then interacts with race, age (dummies), and education to allow for heterogeneous short-term returns across groups that potentially differ in productivity variance.

Table 4.1 presents the results for the pooled OLS wage regressions, but only coefficients for the key variables of interest are reported[22]. Other variables that are controlled for but not shown in Table 4.1 include province, firm size, wave fixed effects, household head status, and geographical classification of residence (i.e. rural vs urban), occupation and industry dummies.

In Table 4.1, the study 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*). The study specifies a separate dummy variable for individuals with 12 years of schooling plus diploma or certificate not obtained from a university (*diploma + certificate*).

[22] The reader is referred to the appendix section for the full list of coefficients – Table A1.

Table 4.1: Log hourly wage regression, pooled OLS

Variables	Model 1a	Model 1b	Model 1c	Model 1d
Primary	0.026 (0.003)***	0.026 (0.003)***	0.026 (0.004)***	0.026 (0.003)***
Secondary	0.075 (0.005)***	0.076 (0.005)***	0.077 (0.005)***	0.075 (0.005)***
Matric	0.151 (0.016)***	0.152 (0.016)***	0.153 (0.016)***	0.107 (0.028)***
Diploma&Certificate	0.231 (0.029)***	0.232 (0.029)***	0.231 (0.029)***	0.284 (0.044)***
Tertiary	0.146 (0.016)***	0.146 (0.016)***	0.148 (0.017)***	0.174 (0.024)***
Black	-0.749 (0.018)***	-0.816 (0.039)***	-0.749 (0.018)***	-0.749 (0.018)***
Tenure	0.036 (0.004)***	0.036 (0.004)***	0.037 (0.004)***	0.036 (0.004)***
Tenure^2	-0.001 (0.0002)***	-0.001 (0.0002)***	-0.001 (0.0002)***	-0.001 (0.0002)***
Potential Experience	0.023 (0.002)***	0.024 (0.002)***	0.026 (0.002)***	0.023 (0.002)***
Potential Experience^2	-0.0003 (0.00004)***	-0.0003 (0.00004)***	-0.0003 (0.00004)***	-0.0003 (0.00004)***
Tenure dummy (one year)	0.025 (0.018)	-0.046 (0.041)	-0.005 (0.024)	-0.032 (0.056)
Black*Tenure dummy		0.085 (0.040)**		
Age (18-24)*Tenure dummy			0.045 (0.031)	
Age (25-30)*Tenure dummy			0.050 (0.021)**	
Age (31-35)*Tenure dummy			0.011 (0.017)	
No Matric*Tenure dummy				0.044 (0.057)
Matric*Tenure dummy				0.100 (0.060)*
Intercept	1.435 (0.057)***	1.488 (0.065)***	1.392 (0.062)***	1.446 (0.057)***
R^2	0.64	0.64	0.64	0.64
N	27,118	27,118	27,118	27,118

Notes: These regressions control for 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*

The study observes from model 1a that the wage returns to incomplete secondary schooling (7.7%) are more than double that of primary schooling (2.6%). Completing secondary schooling (matric) brings about a further doubling of the wage returns to schooling (16.3%). A year of tertiary schooling increases the wage returns by a further 15.7%. While a post-secondary diploma or certificate increases wages 26% regardless of how long an individual took to complete it.

Holding the level of schooling and other variables controlled for in the wage regression constant, black men earn significantly lower wages compared to white men. This is captured by the negative and very large coefficient (-0.749) on the black dummy variable.

An additional year of tenure appears to be more valuable than an additional year of potential experience. In model 1b to model 1d, the researcher tries to determine whether the wage return due to the accumulation of the first year of tenure differs by race, age and level of schooling completed.

In model 1b, the coefficient on the tenure dummy variable interacted with black is large and statistically significant. There is an 8.9% additional wage return for black men that do not accrue to white men. 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.

The tenure dummy variable interacts with age dummies in model 1c. Men that are older than 35 years are the omitted category and form the comparison group for the age-tenure dummy interaction variables. The age-tenure dummy interaction is large and statistically significant only for men aged between 25 and 30. For these men, there is a 5% additional wage return that accrue to them in the first year of an employment spell.

In model 1d, the study specifies schooling dummy variables for incomplete secondary school and less, and for completed secondary schooling. These school dummy variables then interact with the tenure dummy variable. Men with more than 12 years of schooling are omitted category and serve as the comparison group for the school-tenure dummy interaction variables. The school-tenure dummy interaction is large and statistically significant only for men with 12 years of schooling. Relative to other men, these men enjoy an additional 10.5% wage return from accumulating the first year of an employment spell.

The results in Table 4.1 reveal that workers that are black, aged between 25 to 30, and have 12 years of school (completed secondary) enjoy greater wage growth in the first year of an employment spell, relative to their respective counterparts. The researcher interprets this as evidence consistent with the presence of greater *ex-ante* uncertainty about the productivity of these workers. The uncertainty is driven by greater variation in productivity for these workers and possibly by these workers having less informative productivity signals. Consequently, they benefit the most from 'employer learning' and uncertainty being resolved.

In Table 4.1, the researcher implicitly assumed that employer learning and the resolving of worker uncertainty takes place within the first year of an employment spell. To test the robustness of the results, were-ran all the regressions[23] in Table 4.1 but instead focused on the wage gain due to the accumulation of the first two years and first six months of an employment spell. These alternative specifications did not alter the pattern of the results presented in Table 4.1.

A further robustness check performed is correcting for sample selection bias that usually arises in wage regressions based on South African labour data. With high unemployment and the likelihood of obtaining employment varying by race, level of schooling and age, wage earners are very unlikely to be a random sample of the working-age population. The researcher address[24] this issue by running a Heckman sample selection model[25]. This too did not alter the pattern of the results presented in Table 4.1.

In Table 4.2 and 4.3 below, the study explores alternative channels through which employer learning and the resolving of worker uncertainty can operate. Faced with uncertainty about the potential productivity of a worker, a firm may choose to hire that worked on a contractor a non-permanent basis. If the worker proves to be a good hire with the arrival of positive new information regarding his productivity, the firm could then award that worker with a written contract or permanent employment and this could include or not include a rise in the worker's wage.

In Table 4.2, the study estimate the same regression as in Table 4.1 but with contract (takes on a value of one if a worker has written a contract of employment, zero otherwise) as the dependent variable. In Table 4.3, the dependent variable is permanent (takes on a value of one if employment is on a permanent basis, zero if it is casual, fixed-term, or seasonal). The results reported in these tables are consistent with and provide credence to the evidence reported in Table 4.1. Black men, those aged 25 to 35, and those with 12 or fewer years of schooling (i.e. incomplete and complete secondary schooling) are more likely to be offered a written contract and to transition into permanent employment in the first year of an employment spell relative to their respective counterparts. This is conditional on being employed without a written

[23] These results are contained in Table A2 (two years) and Table A3 (six months) in the appendix.
[24] The results are contained in Table A4 in the appendix.
[25] We specified three exclusion restrictions – presence of a social grant recipient in the household, number of elderly people in the household, and number of children in the household.

contract or on a non-permanent basis in the previous period. It is, however, worth pointing out that men with incomplete secondary schooling have a stronger likelihood of obtaining a written contract and to transition into permanent employment compared to men with complete secondary schooling. A possible explanation for this could be that a lack of credible signals of productivity might be a more significant concern for employers than the variation in the productivity for men with incomplete secondary schooling. This would then lead to a stronger preference by employers for utilising non-wage mechanisms (i.e. hiring on a non-employment basis or without a written contract) to insulate them against the uncertainty regarding worker productivity for workers with incomplete secondary schooling.

Table 4.2: Written contract of employment regression, pooled OLS

Contract (yes=1; no=0)	Model 2a	Model 2b	Model 2c	Model 2d
Tenure dummy (one year)	0.064 (0.012)***	-0.016 (0.023)	0.054 (0.015)***	-0.017 (0.028)
Black*Tenure dummy		0.096 (0.023)***		
Age (18-24)*Tenure dummy			0.004 (0.023)	
Age (25-30)*Tenure dummy			0.016 (0.014)	
Age (31-35)*Tenure dummy			0.022 (0.011)**	
No Matric*Tenure dummy				0.104 (0.029)***
Matric*Tenure dummy				0.055 (0.032)*
R^2	0.19	0.19	0.19	0.19
N	26,716	26,716	26,716	26,716
Other Controls	✓	✓	✓	✓

Notes: The regressions control for 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*

Table 4.3: Permanent employment regression, pooled OLS

Permanent (yes=1; other=0)	Model 3a	Model 3b	Model 3c	Model 3d
Tenure dummy (one year)	0.136 (0.012)***	-0.042 (0.020)**	0.119 (0.015)***	-0.010 (0.027)
Black*Tenure dummy		0.213 (0.021)***		
Age (18-24)*Tenure dummy			0.008 (0.020)	
Age (25-30)*Tenure dummy			0.027 (0.013)**	
Age (31-35)*Tenure dummy			0.030 (0.010)***	
No Matric*Tenure dummy				0.185 (0.028)***
Matric*Tenure dummy				0.104 (0.031)***
R^2	0.23	0.24	0.23	0.23
N	27,020	27,020	27,020	27,020
Other control	✓	✓	✓	✓

Notes: The regressions control for 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*

The empirical evidence provided thus far reveal that workers from disadvantaged groups earned lower wages and employed on non-permanent contracts. However, these workers experience more rapid subsequent wage growth and a greater likelihood of transitioning to permanent employment contracts during the first year of employment. The researcher interprets this evidence as being consistent with the hypothesis and thus supportive of the model's predictions. The remainder of this section will report and discuss results from the structural estimation of the theoretical model.

6.2 Structural Estimation Results

Up to this point, the researcher has provided empirical evidence based on reduced form estimation of the theory model's predictions. These results provided empirical evidence in favour of greater *ex-ante* uncertainty regarding the productivity of black men, men that are between the ages of 25 and 35, and men that have 12 years and less of completed schooling. The uncertainty regarding these disadvantaged groups could be driven by a lack of credible signals of productivity, by greater variation in productivity, or by both. To the extent that uncertainty in worker productivity affects earnings differences, it is thus vital for policy-making that the researcher establishes which of these factors is the key driver. The reduced form estimation could not distinguish between a lack of credible signals of productivity or greater variation in worker productivity. With the structural estimation of the theory model, the researcher can distinguish between these sources of uncertainty. In the structural estimation, the researcher holds constant the variation in the noise or error in employers' assessment of worker productivity and allow the variation in worker productivity to varying with the worker's observable characteristics. This allows us to offer precise and well-targeted policy recommendations.

The structural parameters of the theoretical model are estimated using maximum likelihood estimation. From equation (6) above, the researcher takes the expectation conditional on $\boldsymbol{s}$ and t. This gives us the expected log hourly wage function to be estimated:

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

The observable determinants of worker productivity ($\boldsymbol{s}$) are assumed to be schooling, potential experience, race and tenure. The researcher then allow the variance of worker productivity to be determined by this function $\sigma_u^2 = \exp(\rho + \boldsymbol{\lambda}\tilde{\boldsymbol{s}})$, where $\tilde{\boldsymbol{s}}$ is a vector of the workers' observable characteristics that the researcher allow to determine the variance of worker productivity. Included in $\tilde{\boldsymbol{s}}$ is school dummies (specified in the same manner as in the OLS regressions reported in Table 1 above), age dummies (specified in the same manner as in the OLS regressions reported in Table 1 above), and a race dummy for black men.

The likelihood function is given by equation (8) below:

$$L = log\left\{\emptyset\left[\frac{w_t - E(w_t|\boldsymbol{s},t)}{\sigma_u^2/sqrt\{\sigma_u^2+\left(\frac{1}{t+1}\right)\sigma_e^2\}}\right]\right\} - log\left(\frac{\sigma_u^2}{sqrt\{\sigma_u^2+\left(\frac{1}{t+1}\right)\sigma_e^2\}}\right) \quad (8)$$

$\emptyset \rightarrow$ normal density operator.

A combination of the Newton-Raphson, Davidson-Fletcher-Powell, and Broyden-Fletcher-Goldfarb-Shanno methods were used for finding the numerical solution to the maximisation problem.

To distinguish between the two sources – variation in the signal of productivity and variation in productivity – of uncertainty regarding worker productivity, the researcher normalise σ_e^2 to take on a value of one. For robustness, the researcher experimented with different normalization values (0.5 and 2) and this did not alter the pattern of the results for the structural estimates[26].

In Table 4.4 below, the present researcher results for the restricted and unrestricted versions of the model. The restricted model is essentially a Mincerian-like wage regression and represents

[26] The results for the different normalization values of σ_e^2 are reported in Table A7 of the appendix.

the risk-neutral special case of the model with the following restriction: $\delta = 0$, in equation (7). The unrestricted model is defined by equation (7) and estimates the expected log hourly wages and the variance of worker productivity simultaneously.

The top panel of Table 4.4 shows that the common parameters have very similar estimated coefficients 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 less concave. This suggests that the tenure-wage effect in the restricted model includes the effects of employer learning as uncertainty is resolved. Explicitly accounting for the variation in worker productivity as the researcher does in the unrestricted model, makes the tenure-wage profile flatter and less concave as depicted by Figure 4.2 below. In the context of the theoretical model, the non-linearity in the tenure-wage profile appears to be primarily a product of the non-linearity in the rate of employer learning.

Because the restricted model is nested within the unrestricted model, this allows us to perform a likelihood ratio test of the two models. This primarily provides a test for the employer risk averse assumption that is instrumental to the model and many other models of statistical discrimination that follow Aigner and Cain's (1977) formulation. The likelihood ratio test static is 3009 and leads us to firmly reject the null hypothesis and thus to prefer the unrestricted model. This is a significant result because Aigner and Cain's model has attracted sharp criticism for the employer risk averse assumption. The researcher has demonstrated that this assumption is empirically supported by the data, at least by the South African data.

Table 4.4: Structural estimation of the theoretical model, maximum likelihood estimation

	Unrestricted	Restricted
Log hourly wage		
Primary	0.071	0.072
	(0.003)***	(0.003)**
Secondary	0.153	0.156
	(0.004)***	(0.005)**
Matric	0.274	0.279
	(0.013)***	(0.017)**
Diploma&Certificate	0.307	0.306
	(0.017)***	(0.022)**
Tertiary	0.307	0.304
	(0.008)***	(0.010)**
Potential Experience	0.048	0.048
	(0.002)***	(0.002)**
Potential Experience^2	-0.001	-0.001
	(0.00003)***	(0.00004)**
Black	-0.877	-0.859
	(0.013)***	(0.017)**
Tenure	0.039	0.066
	(0.006)***	(0.003)**
Tenure^2	-0.0005	-0.0015
	(0.0003)*	(0.0002)**
Intercept	0.980	0.748
	(0.048)***	(0.035)**
Productivity variance		
No Matric dummy	0.028	
	(0.010)**	
Matric dummy	0.022	
	(0.011)**	
Black	0.070	
	(0.009)***	
Age dummy (18-24)	0.082	
	(0.010)***	
Age dummy (25-30)	0.046	
	(0.008)***	
Age dummy (31-35)	-0.018	
	(0.008)**	
Intercept	-0.179	
	(0.011)***	
Delta	0.459	
	(0.094)***	
LR Chi^2(8)	3009.74	
N	38,493	38,493

* p<0.1; ** p<0.05; *** p<0.01

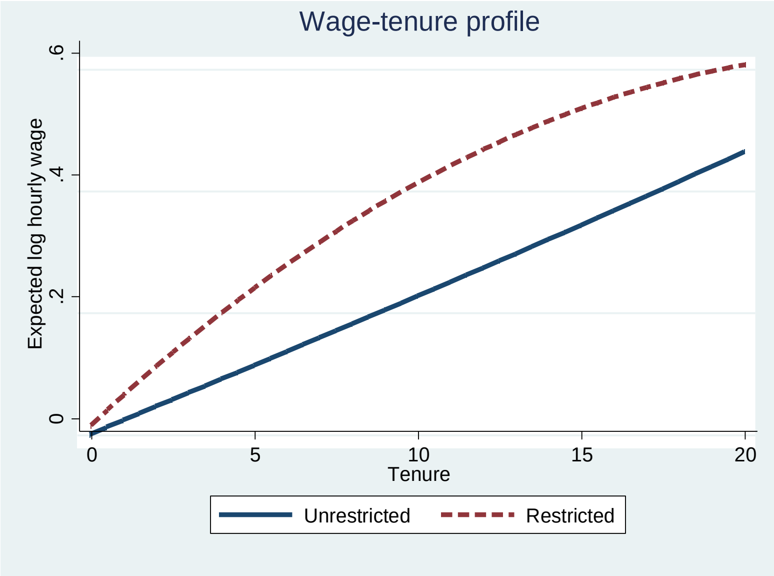


Figure 4.2: Wage-tenure profiles by race

The bottom panel of Table 4.4 reports the results for the parameter estimation of the variance of worker productivity from the unrestricted model. The results suggest that, relative to men with tertiary schooling, there is greater variation in productivity amongst the men with 12 or fewer years of schooling. The parameter estimates for the age dummy variables suggests a negative relationship between the extent of variation in productivity and age. Men that are 24 and younger have greater variation around their productivity. This variation is almost halved for men in the 25 to 30 age category. The positive and statistically significant coefficient on black (0.07) indicates that there is greater variation in productivity amongst black men relative to their white counterparts.

The theoretical model obtains these results and echo the literature discussed in section two that suggests greater variation worker productivity for disadvantaged groups. By holding the variation in the signal in productivity constant, the researcher has demonstrated that the variation in worker productivity plays a vital role in the uncertainty faced by employers when they have to assess the expected productivity of job applicants. In the model, the importance of this uncertainty is determined by delta (δ). This parameter is estimated as 0.459 and indicates the importance of the penalty incurred by workers with greater uncertainty around their expected productivity.

In Table 4.4, the researcher looked at the individual effects of race, age and schooling on the variation in worker productivity. For many workers though, some of these attributes are not mutually exclusive. With this in mind, in Table 4.5[27] the researcher interacts the attributes of

[27] Table 5 only reports the parameter estimates for the worker productivity variance. The full set of results are to be found in Table A8 of the appendix.

interest to investigate which of these c attributes reinforce or cancel each other concerning their impact on the variation of worker productivity. This would be important for policymakers tasked with drafting policies to address the uncertainty of job applicants' expected productivity.

Table 4.5: Structural estimation of the theoretical model, maximum likelihood estimation

	Model 5a	Model 5b	Model 5c	Model 5d
Productivity variance				
No Matric dummy	0.028 (0.010)***	0.030 (0.010)***	0.036 (0.011)***	0.028 (0.010)***
Matric dummy	0.022 (0.011)**	0.023 (0.011)**	-0.013 (0.017)	-0.010 (0.014)
Black	0.070 (0.009)***	0.040 (0.013)***	0.046 (0.013)***	0.066 (0.009)***
Age dummy (18-24)	0.082 (0.010)***	0.032 (0.024)	0.082 (0.010)***	0.059 (0.012)***
Age dummy (25-30)	0.046 (0.008)***	-0.008 (0.022)	0.045 (0.008)***	0.035 (0.009)***
Age dummy (31-35)	-0.018 (0.008)**	-0.069 (0.022)***	-0.018 (0.008)**	-0.023 (0.009)***
Black*Age (18-24)		0.059 (0.026)**		
Black*Age (25-30)		0.061 (0.024)***		
Black*Age (31-35)		0.058 (0.023)**		
Black*Matric			0.050 (0.019)***	
Matric*Age (18-24)				0.085 (0.022)***
Matric*Age (25-30)				0.049 (0.017)***
Matric*Age (31-35)				0.031 (0.018)*
Intercept	-0.179 (0.011)***	-0.154 (0.014)***	-0.163 (0.013)***	-0.170 (0.012)***
Delta	0.459 (0.094)***	0.496 (0.095)***	0.481 (0.095)***	0.452 (0.094)***
N	38,493	38,493	38,493	38,493

* p<0.1; ** p<0.05; *** p<0.01

In model 4b, the researcher interacts race with age. The parameter estimate on the black variable remains positive and statistically significant but is smaller in magnitude. The coefficients on the age dummies for ages 18 to 30 are now smaller and statistically insignificant. This suggests that black men drive the larger variation in worker productivity found in Table 4.4 for these young workers. In model 4c, the researcher interacts race with the completed secondary schooling (i.e. matric) dummy. This too reveals that black men drive the variation in productivity for men with completed secondary schooling. Model 4d interacts the completed secondary schooling dummy with the age dummies. This reveals that the greater variation in productivity for men with completed secondary schooling is confined to younger men. These results point to young black men graduating from secondary schooling more recently as the most disadvantaged. This is consistent with this group receiving lower and more variable quality of schooling. Consequently, there is greater uncertainty about these workers and this could explain why unemployment is largely concentrated amongst this group.

7. CONCLUSION

This paper provides a theoretical and empirical investigation of the impact of information asymmetries between employer and job-seekers on the average wages of black and white South African men. The theoretical contribution of the paper illustrated the importance of the variation worker productivity as a source of uncertainty. The current literature on statistical discrimination almost exclusively focuses on the variation in the signal of worker productivity. Variation in the signal of productivity is important, but in the context of South Africa, variation in worker productivity is arguably a more significant concern. This is due to the immense variation learner performance and school quality that makes the task of predicting the potential productivity of job applicants insurmountable for many employers.

The theoretical model was tested with South African labour market data using reduced form and structural estimation techniques. The reduced form estimates revealed that black men, men in their youth, and men with only completed secondary schooling have more rapid within-firm wage growth in the first year of an employment spell. This was interpreted as evidence of the greater *ex-ante* uncertainty regarding the expected productivity of these workers being resolved as employers view their performance on the job.

With the structural estimation, the researcher was able to provide empirical support for the employer risk- aversion assumption. This is a key assumption for many statistical discrimination models, and the results suggest that the data do not support the sharp criticism levelled against this assumption. The parameter estimation revealed greater variation in productivity for black, young, and men with 12 and fewer years of schooling. This variation in productivity was, however, largely driven by young black men who have recently graduated from secondary schooling. By holding the variation in the signal in productivity constant, the researcher was able to demonstrate that the variation in worker productivity plays an important role in the uncertainty faced by employers when they have to assess the expected productivity of job applicants.

The South African literature and policy debate on earnings differences between black and white men have largely centred on addressing human capital differences. The researcher argues that this is only achievable in the very long-term. In the short-term, addressing other causes of earnings differences like uncertainty in worker productivity may be more fruitful. The findings of this paper provide the necessary empirical evidence to guide such short-term policymaking. The short-term policies could, *among other things*, include general skills assessment and certification by the Department of Labour's labour centres.

There are, however, some critical shortcomings of the theoretical model. The model is silent on unemployment. The researcher mostly assumes a two-state environment where unemployment as a separate state is not modelled. Unemployment is extremely high in South Africa with a distribution that is skewed. The researcher speculates that the model provides an additional reason for why the researcher observes such high unemployment amongst young black men. The model is also silent on the impact of other labour market rigidities like minimum wages and centralised wage bargaining. These shortcomings will serve as useful avenues for future work.

8. APPENDIX

This section provides three sets of information that relate to the main body of this research paper. Firstly, the researcher provides detailed mode steps for the derivation of equation (5) and (6). Secondly, the researcher provides tables that report the coefficient estimates of all variables included in the regressions the researcher estimate in the empirical analysis section. Lastly, the researcher provides tables that report the results of the exercises the researcher conduct for robustness check. These results were discussed in the main text.

8.1 Derivation of equation (5) and (6) of the theoretical model

Equation (4) above gives the period 0 wage that a worker will earn:

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

Solving first for the first term of equation (4), the researcher has:

$$E(y|\boldsymbol{s}, \hat{y}_0) = \alpha + \boldsymbol{\theta s} + \sigma_u E(u|\boldsymbol{s}, \hat{y}_0)$$

$$= \hat{y}_0 - \sigma_e E(e_0|\boldsymbol{s}, \hat{y}_0)$$

Since employers know $\boldsymbol{s}$ and $\widehat{y_0}$ then:

$$E(e_0|\boldsymbol{s}, \hat{y}_0) = E(e_0|\hat{y}_0 - \alpha - \boldsymbol{\theta s}) = E(e_0|u\sigma_u + e_0\sigma_e)$$

In working out $E(e_0|u\sigma_u + e_0\sigma_e)$ it is useful to remember that it attempts to answer the question: suppose you observe $u\sigma_u + e_0\sigma_e$, what is your expected value of e_0. The answer needs to be expressed in terms of $u\sigma_u + e_0\sigma_e$, since this is what you observe. A good starting point is to assume that the answer is a linear function of $u\sigma_u + e_0\sigma_e$:

$$E(e_0|u\sigma_u + e_0\sigma_e) = a + b(u\sigma_u + e_0\sigma_e)$$

Where a and b are unknowns. $a = 0$, since the researcher have assumed that u and e_0 are normally distributed with means of zero – i.e. they are centred at zero.

$$b = \frac{Cov(u\sigma_u + e_0\sigma_e, e_0)}{Var(u\sigma_u + e_0\sigma_e)}$$

$$b = \frac{\sigma_e}{\sigma_u^2 + \sigma_e^2}$$

Substituting back into $E(y|\boldsymbol{s}, \hat{y}_0) = \alpha + \boldsymbol{\theta s} + \sigma_u E(u|\boldsymbol{s}, \hat{y}_0)$, the researcher get:

$$E(y|\boldsymbol{s}, \hat{y}_0) = \hat{y}_0 - \sigma_e \left(\frac{\sigma_e}{\sigma_u^2 + \sigma_e^2}\right)(u\sigma_u + e_0\sigma_e)$$

This simplifies to the following expression:

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

The last term of equation (4) is calculated as follows:

$$Var(y|\boldsymbol{s}, \hat{y}_0) = E[y - E(y|\boldsymbol{s}, \hat{y}_0)]^2$$

$$Var(y|\boldsymbol{s}, \hat{y}_0) = E\left[\alpha + \boldsymbol{\theta s} + u\sigma_u - \alpha - \boldsymbol{\theta s} - \left(\frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}\right)(\hat{y}_0 - \alpha - \boldsymbol{\theta s})\right]^2$$

$$Var(y|\boldsymbol{s}, \hat{y}_0) = \left(\frac{\sigma_e^2}{\sigma_u^2 + \sigma_e^2}\right)^2 \sigma_u^2 + \left(\frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}\right)^2 \sigma_e^2$$

Putting the simplified terms back together in equation (4) gives us equation (5):

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

Equation (6) is derived in the same manner as equation (5).

8.2 Full results tables and robustness check results

Table A1: Log hourly wage regression, pooled OLS

Variables	Model 1a	Model 1b	Model 1c	Model 1d
Primary	0.026 (0.003)***	0.026 (0.003)***	0.026 (0.004)***	0.026 (0.003)***
Secondary	0.075 (0.005)***	0.076 (0.005)***	0.077 (0.005)***	0.075 (0.005)***
Matric	0.151 (0.016)***	0.152 (0.016)***	0.153 (0.016)***	0.107 (0.028)***
Diploma&Certificate	0.231 (0.029)***	0.232 (0.029)***	0.231 (0.029)***	0.284 (0.044)***
Tertiary	0.146 (0.016)***	0.146 (0.016)***	0.148 (0.017)***	0.174 (0.024)***
Black	-0.749 (0.018)***	-0.816 (0.039)***	-0.749 (0.018)***	-0.749 (0.018)***
Tenure	0.036 (0.004)***	0.036 (0.004)***	0.037 (0.004)***	0.036 (0.004)***
Tenure^2	-0.001 (0.0002)***	-0.001 (0.0002)***	-0.001 (0.0002)***	-0.001 (0.0002)***
Potential Experience	0.023 (0.002)***	0.024 (0.002)***	0.026 (0.002)***	0.023 (0.002)***
Potential Experience^2	-0.0003 (0.00004)***	-0.0003 (0.00004)***	-0.0003 (0.00004)***	-0.0003 (0.00004)***
Tenure dummy (one year)	0.025 (0.018)	-0.046 (0.041)	-0.005 (0.024)	-0.032 (0.056)
Black*Tenure dummy		0.085 (0.040)**		
Age (18-24)*Tenure dummy			0.045 (0.031)	
Age (25-30)*Tenure dummy			0.050 (0.021)**	
Age (31-35)*Tenure dummy			0.011 (0.017)	
No Matric*Tenure dummy				0.044 (0.057)
Matric*Tenure dummy				0.100 (0.060)*
Occupation dummy 1	-0.005 (0.058)	-0.005 (0.058)	-0.006 (0.058)	-0.005 (0.058)
Occupation dummy 2	-0.187 (0.036)***	-0.189 (0.036)***	-0.188 (0.036)***	-0.187 (0.036)***
Occupation dummy 3	-0.456 (0.037)***	-0.460 (0.037)***	-0.456 (0.037)***	-0.456 (0.037)***
Occupation dummy 4	-0.772 (0.036)***	-0.774 (0.036)***	-0.772 (0.036)***	-0.770 (0.036)***
Occupation dummy 5	-0.513 (0.089)***	-0.513 (0.089)***	-0.513 (0.089)***	-0.513 (0.089)***
Occupation dummy 6	-0.521 (0.033)***	-0.523 (0.033)***	-0.521 (0.033)***	-0.521 (0.033)***
Occupation dummy 7	-0.592 (0.034)***	-0.595 (0.034)***	-0.591 (0.034)***	-0.591 (0.034)***

Occupation dummy 8	-0.748 (0.035)***	-0.749 (0.034)***	-0.748 (0.035)***	-0.747 (0.035)***
Industry dummy 1	0.834 (0.020)***	0.833 (0.020)***	0.837 (0.020)***	0.835 (0.020)***
Industry dummy 2	0.664 (0.021)***	0.664 (0.021)***	0.665 (0.021)***	0.664 (0.021)***
Industry dummy 3	0.841 (0.053)***	0.841 (0.053)***	0.840 (0.053)***	0.839 (0.053)***
Industry dummy 4	0.509 (0.024)***	0.510 (0.024)***	0.509 (0.024)***	0.509 (0.024)***
Industry dummy 5	0.512 (0.021)***	0.512 (0.021)***	0.514 (0.021)***	0.513 (0.021)***
Industry dummy 6	0.624 (0.029)***	0.625 (0.029)***	0.626 (0.028)***	0.624 (0.029)***
Industry dummy 7	0.579 (0.026)***	0.578 (0.026)***	0.580 (0.026)***	0.579 (0.026)***
Industry dummy 8	0.631 (0.032)***	0.631 (0.032)***	0.632 (0.032)***	0.633 (0.032)***
Industry dummy 9	-0.180 (0.085)**	-0.183 (0.085)**	-0.179 (0.085)**	-0.177 (0.085)**
Industry dummy 10	0.991 (0.202)***	0.994 (0.203)***	0.988 (0.201)***	0.991 (0.201)***
Rural dummy	-0.132 (0.014)***	-0.133 (0.014)***	-0.132 (0.014)***	-0.132 (0.014)***
Province 1	-0.234 (0.029)***	-0.231 (0.028)***	-0.235 (0.028)***	-0.234 (0.028)***
Province 2	-0.137 (0.033)***	-0.136 (0.033)***	-0.138 (0.033)***	-0.137 (0.033)***
Province 3	-0.355 (0.026)***	-0.353 (0.026)***	-0.355 (0.026)***	-0.355 (0.026)***
Province 4	-0.125 (0.025)***	-0.123 (0.025)***	-0.126 (0.025)***	-0.125 (0.025)***
Province 5	-0.152 (0.026)***	-0.150 (0.026)***	-0.153 (0.026)***	-0.152 (0.026)***
Province 6	-0.025 (0.024)	-0.023 (0.024)	-0.025 (0.024)	-0.025 (0.024)
Province 7	-0.146 (0.026)***	-0.145 (0.026)***	-0.148 (0.026)***	-0.147 (0.026)***
Province 8	-0.375 (0.030)***	-0.373 (0.030)***	-0.376 (0.030)***	-0.375 (0.030)***
Household Head	0.127 (0.014)***	0.127 (0.014)***	0.127 (0.014)***	0.127 (0.014)***
Firm size	0.076 (0.004)***	0.076 (0.004)***	0.076 (0.004)***	0.076 (0.004)***
Wave dummy 1	-0.012 (0.016)	-0.011 (0.016)	-0.011 (0.016)	-0.012 (0.016)
Wave dummy 2	-0.062 (0.017)***	-0.062 (0.017)***	-0.062 (0.017)***	-0.062 (0.017)***
Wave dummy 3	-0.051 (0.017)***	-0.051 (0.017)***	-0.051 (0.017)***	-0.051 (0.017)***
Wave dummy 4	0.027 (0.018)	0.027 (0.018)	0.027 (0.018)	0.027 (0.018)
Wave dummy 5	0.027	0.027	0.027	0.027

	(0.017)	(0.018)	(0.017)	(0.017)
Intercept	1.435	1.488	1.392	1.446
	(0.057)***	(0.065)***	(0.062)***	(0.057)***
R^2	0.64	0.64	0.64	0.64
N	27,118	27,118	27,118	27,118

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A2: Robustness check – 2-year tenure dummy

Variables	Model 2a	Model 2b	Model 2c	Model 2d
Primary	0.026 (0.003)***	0.026 (0.003)***	0.026 (0.004)***	0.026 (0.003)***
Secondary	0.075 (0.005)***	0.076 (0.005)***	0.076 (0.005)***	0.075 (0.005)***
Matric	0.151 (0.016)***	0.152 (0.016)***	0.152 (0.016)***	0.120 (0.022)***
Diploma&Certificate	0.231 (0.029)***	0.233 (0.029)***	0.231 (0.029)***	0.263 (0.036)***
Tertiary	0.146 (0.016)***	0.146 (0.016)***	0.147 (0.016)***	0.163 (0.020)***
Black	-0.748 (0.018)***	-0.801 (0.029)***	-0.749 (0.018)***	-0.748 (0.018)***
Tenure	0.036 (0.005)***	0.036 (0.005)***	0.037 (0.005)***	0.036 (0.005)***
Tenure^2	-0.001 (0.0002)***	-0.001 (0.0002)***	-0.001 (0.0002)***	-0.001 (0.0002)***
Potential Experience	0.023 (0.002)***	0.024 (0.002)***	0.025 (0.002)***	0.023 (0.002)***
Potential Experience^2	-0.0003 (0.00004)***	-0.0003 (0.00004)***	-0.0003 (0.00004)***	-0.0003 (0.00004)***
Tenure dummy (2 years)	0.019 (0.020)	-0.047 (0.035)	-0.003 (0.024)	-0.018 (0.047)
Black*Tenure dummy		0.078 (0.032)**		
Age (18-24)* Tenure dummy			0.010 (0.033)	
Age (25-30)* Tenure dummy			0.044 (0.021)**	
Age (31-35)* Tenure dummy			0.002 (0.017)	
No Matric* Tenure dummy				0.023 (0.046)
Matric*Tenure dummy				0.072 (0.048)
Intercept	1.443 (0.057)***	1.483 (0.060)***	1.420 (0.059)***	1.453 (0.057)***
R^2	0.64	0.64	0.64	0.64
N	27,118	27,118	27,118	27,118

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*

Table A3: Robustness check – 6-month tenure dummy

	Model 3a	Model 3b	Model 3c	Model 3d
Primary	0.026	0.026	0.026	0.026
	(0.003)***	(0.003)***	(0.004)***	(0.003)***
Secondary	0.075	0.076	0.076	0.075
	(0.005)***	(0.005)***	(0.005)***	(0.005)***
Matric	0.152	0.151	0.152	0.140
	(0.016)***	(0.016)***	(0.016)***	(0.037)***
Diploma&Certificate	0.231	0.231	0.231	0.295
	(0.029)***	(0.029)***	(0.029)***	(0.054)***
Tertiary	0.146	0.146	0.147	0.178
	(0.017)***	(0.017)***	(0.017)***	(0.029)***
Black	-0.749	-0.846	-0.750	-0.749
	(0.018)***	(0.047)***	(0.018)***	(0.018)***
Tenure	0.038	0.038	0.038	0.038
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Tenure^^{2}	-0.001	-0.001	-0.001	-0.001
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0002)***
Potential Experience	0.023	0.024	0.025	0.023
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Potential Experience^^{2}	-0.0003	-0.0003	-0.0003	-0.0003
	(0.00004)***	(0.00004)***	(0.00004)***	(0.00004)***
Tenure dummy (6 months)	0.023	-0.068	0.008	-0.067
	(0.019)	(0.047)	(0.025)	(0.071)
Black*Tenure dummy		0.109		
		(0.049)**		
Age (18-24)*Tenure dummy			0.015	
			(0.031)	
Age (25-30)*Tenure dummy			0.030	
			(0.021)	
Age (31-35)*Tenure dummy			0.006	
			(0.017)	
No Matric* Tenure dummy				0.093
				(0.073)
Matric* Tenure dummy				0.106
				(0.077)
Intercept	1.429	1.508	1.405	1.425
	(0.058)***	(0.068)***	(0.064)***	(0.059)***
R^2	0.64	0.64	0.64	0.64
N	27,118	27,118	27,118	27,118

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*

Table A4: Log hourly wage regression, Heckman Sample Selection Model

	Model 4a	Model 4b	Model 4c	Model 4d
Primary	0.063 (0.003)***	0.063 (0.003)***	0.064 (0.003)***	0.064 (0.003)***
Secondary	0.120 (0.005)***	0.120 (0.005)***	0.120 (0.005)***	0.120 (0.005)***
Matric	0.187 (0.019)***	0.189 (0.019)***	0.187 (0.019)***	0.097 (0.033)***
Diploma&Certificate	0.332 (0.023)***	0.332 (0.023)***	0.332 (0.023)***	0.420 (0.039)***
Tertiary	0.270 (0.011)***	0.270 (0.011)***	0.271 (0.011)***	0.314 (0.019)***
Black	-0.712 (0.018)***	-0.819 (0.040)***	-0.711 (0.018)***	-0.711 (0.018)***
Tenure	0.049 (0.002)***	0.049 (0.002)***	0.049 (0.002)***	0.050 (0.002)***
Tenure^^{2}	-0.001 (0.0001)***	-0.001 (0.0001)***	-0.001 (0.0001)***	-0.001 (0.0001)***
Potential Experience	0.024 (0.004)***	0.025 (0.004)***	0.024 (0.004)***	0.024 (0.004)***
Potential Experience^^{2}	-0.0002 (0.0001)***	-0.0002 (0.0001)***	-0.0002 (0.0001)***	-0.0002 (0.0001)***
Tenure dummy (one year)	0.025 (0.017)	-0.087 (0.041)**	0.014 (0.022)	-0.043 (0.048)
Black*Tenure dummy		0.125 (0.042)***		
Age (18-24)*Tenure dummy			0.040 (0.033)	
Age (25-30)*Tenure dummy			-0.006 (0.022)	
Age (31-35)*Tenure dummy			0.031 (0.018)*	
No Matric*Tenure dummy				0.046 (0.050)
Matric*Tenure dummy				0.155 (0.054)***
Intercept	0.802 (0.092)***	0.882 (0.096)***	0.795 (0.095)***	0.821 (0.093)***
Mills (lambda)	-0.176 (0.050)***	-0.168 (0.050)***	-0.180 (0.050)***	-0.175 (0.050)***
N	49,581	49,581	49,581	49,581

* p<0.1; ** p<0.05; *** p<0.01

Table A5: Written contract of employment regression, pooled OLS

	Model 5a	Model 5b	Model 5c	Model 5d
Primary	0.009 (0.003)***	0.009 (0.003)***	0.010 (0.003)***	0.009 (0.003)***
Secondary	0.014 (0.004)***	0.014 (0.004)***	0.014 (0.004)***	0.014 (0.004)***
Matric	0.036 (0.011)***	0.036 (0.011)***	0.036 (0.011)***	0.074 (0.020)***
Diploma&Certificate	0.042 (0.014)***	0.043 (0.014)***	0.042 (0.014)***	0.072 (0.024)***
Tertiary	0.009 (0.008)	0.009 (0.008)	0.009 (0.008)	0.024 (0.012)**
Black	-0.051 (0.011)***	-0.128 (0.022)***	-0.051 (0.011)***	-0.051 (0.011)***
Tenure	0.017 (0.003)***	0.017 (0.003)***	0.017 (0.003)***	0.017 (0.003)***
Tenure^^{2}	-0.001 (0.0001)***	-0.001 (0.0001)***	-0.001 (0.0001)***	-0.001 (0.0001)***
Potential Experience	0.005 (0.001)***	0.006 (0.001)***	0.006 (0.002)***	0.006 (0.001)***
Potential Experience^^{2}	-0.0001 (0.00003)***	-0.0001 (0.00003)***	-0.0001 (0.00003)***	-0.0001 (0.00003)***
Tenure dummy (one year)	0.064 (0.012)***	-0.016 (0.023)	0.054 (0.015)***	-0.017 (0.028)
Black*Tenure dummy		0.096 (0.023)***		
Age (18-24)*Tenure dummy			0.004 (0.023)	
Age (25-30)*Tenure dummy			0.016 (0.014)	
Age (31-35)*Tenure dummy			0.022 (0.011)**	
No Matric*Tenure dummy				0.104 (0.029)***
Matric*Tenure dummy				0.055 (0.032)*
Occupation dummy 1	0.022 (0.027)	0.022 (0.027)	0.021 (0.027)	0.022 (0.027)
Occupation dummy 2	0.009 (0.018)	0.007 (0.018)	0.009 (0.018)	0.007 (0.018)
Occupation dummy 3	0.004 (0.021)	-0.000 (0.020)	0.003 (0.020)	0.002 (0.020)
Occupation dummy 4	-0.012 (0.019)	-0.014 (0.019)	-0.013 (0.019)	-0.015 (0.019)
Occupation dummy 5	-0.056 (0.046)	-0.057 (0.046)	-0.057 (0.046)	-0.058 (0.046)
Occupation dummy 6	-0.038 (0.018)**	-0.040 (0.018)**	-0.039 (0.018)**	-0.040 (0.018)**
Occupation dummy 7	-0.033 (0.018)*	-0.037 (0.018)**	-0.034 (0.018)*	-0.037 (0.018)**
Occupation dummy 8	-0.082 (0.019)***	-0.083 (0.019)***	-0.082 (0.019)***	-0.084 (0.019)***

Industry dummy 1	0.249 (0.014)***	0.249 (0.014)***	0.250 (0.014)***	0.248 (0.014)***
Industry dummy 2	0.139 (0.015)***	0.139 (0.015)***	0.139 (0.015)***	0.139 (0.015)***
Industry dummy 3	0.185 (0.026)***	0.186 (0.026)***	0.185 (0.026)***	0.185 (0.026)***
Industry dummy 4	0.023 (0.019)	0.024 (0.019)	0.023 (0.019)	0.024 (0.019)
Industry dummy 5	0.096 (0.015)***	0.095 (0.015)***	0.096 (0.015)***	0.095 (0.015)***
Industry dummy 6	0.054 (0.019)***	0.054 (0.019)***	0.053 (0.019)***	0.054 (0.019)***
Industry dummy 7	0.191 (0.017)***	0.189 (0.017)***	0.190 (0.017)***	0.189 (0.017)***
Industry dummy 8	0.119 (0.022)***	0.118 (0.022)***	0.119 (0.022)***	0.118 (0.022)***
Industry dummy 9	0.490 (0.045)***	0.486 (0.045)***	0.491 (0.045)***	0.488 (0.045)***
Industry dummy 10	0.082 (0.079)	0.085 (0.079)	0.083 (0.078)	0.082 (0.079)
Rural dummy	-0.022 (0.009)**	-0.022 (0.009)**	-0.022 (0.009)**	-0.022 (0.009)**
Province 1	-0.146 (0.020)***	-0.143 (0.020)***	-0.147 (0.020)***	-0.145 (0.019)***
Province 2	0.081 (0.021)***	0.082 (0.021)***	0.081 (0.021)***	0.082 (0.021)***
Province 3	0.063 (0.017)***	0.065 (0.017)***	0.063 (0.017)***	0.064 (0.017)***
Province 4	-0.037 (0.017)**	-0.035 (0.017)**	-0.037 (0.017)**	-0.036 (0.017)**
Province 5	0.001 (0.017)	0.003 (0.017)	0.001 (0.017)	0.002 (0.017)
Province 6	-0.000 (0.016)	0.002 (0.016)	-0.000 (0.016)	0.001 (0.016)
Province 7	0.072 (0.017)***	0.074 (0.017)***	0.071 (0.017)***	0.073 (0.017)***
Province 8	-0.055 (0.020)***	-0.052 (0.020)***	-0.055 (0.020)***	-0.053 (0.020)***
Household Head	0.024 (0.009)***	0.024 (0.009)***	0.022 (0.009)**	0.024 (0.009)***
Wave dummy 1	0.099 (0.011)***	0.099 (0.012)***	0.098 (0.011)***	0.099 (0.012)***
Wave dummy 2	0.095 (0.012)***	0.096 (0.012)***	0.095 (0.012)***	0.096 (0.012)***
Wave dummy 3	0.130 (0.012)***	0.130 (0.012)***	0.129 (0.012)***	0.130 (0.012)***
Wave dummy 4	0.150 (0.012)***	0.150 (0.012)***	0.149 (0.012)***	0.150 (0.012)***
Wave dummy 5	0.194 (0.012)***	0.194 (0.012)***	0.194 (0.012)***	0.194 (0.012)***
Firm size dummy 1	0.035 (0.027)	0.034 (0.027)	0.035 (0.027)	0.035 (0.027)
Firm size dummy 2	0.121	0.120	0.120	0.121

	(0.027)***	(0.027)***	(0.027)***	(0.027)***
Firm size dummy 3	0.194	0.194	0.194	0.194
	(0.026)***	(0.026)***	(0.026)***	(0.026)***
Firm size dummy 4	0.226	0.227	0.226	0.227
	(0.026)***	(0.026)***	(0.026)***	(0.026)***
Firm size dummy 5	0.273	0.273	0.273	0.274
	(0.025)***	(0.025)***	(0.025)***	(0.025)***
Intercept	0.049	0.110	0.042	0.028
	(0.041)	(0.044)**	(0.044)	(0.042)
R^2	0.19	0.19	0.19	0.19
N	26,716	26,716	26,716	26,716

* p<0.1; ** p<0.05; *** p<0.01

Table A6: Permanent employment regression, pooled OLS

	Model 6a	Model 6b	Model 6c	Model 6d
Primary	0.003	0.003	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Secondary	0.006	0.006	0.006	0.006
	(0.003)*	(0.003)*	(0.003)*	(0.003)*
Matric	0.061	0.061	0.061	0.124
	(0.010)***	(0.010)***	(0.010)***	(0.020)***
Diploma&Certificate	0.028	0.029	0.027	0.083
	(0.011)**	(0.011)***	(0.011)**	(0.021)***
Tertiary	0.002	0.002	0.002	0.031
	(0.005)	(0.005)	(0.005)	(0.011)***
Black	-0.091	-0.261	-0.092	-0.091
	(0.009)***	(0.021)***	(0.009)***	(0.009)***
Tenure	0.044	0.044	0.043	0.043
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Tenure^^{2}	-0.002	-0.002	-0.002	-0.002
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***
Potential Experience	0.003	0.004	0.004	0.004
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Potential Experience^^{2}	-0.00004	-0.0001	-0.00004	-0.0001
	(0.00002)*	(0.00002)**	(0.00003)	(0.00002)**
Tenure dummy (one year)	0.136	-0.042	0.119	-0.010
	(0.012)***	(0.020)**	(0.015)***	(0.027)
Black*Tenure dummy		0.213		
		(0.021)***		
Age (18-24)*Tenure dummy			0.008	
			(0.020)	
Age (25-30)*Tenure dummy			0.027	
			(0.013)**	
Age (31-35)*Tenure dummy			0.030	
			(0.010)***	
No Matric*Tenure dummy				0.185
				(0.028)***
Matric*Tenure dummy				0.104
				(0.031)***
Occupation dummy 1	-0.037	-0.037	-0.038	-0.037
	(0.019)**	(0.018)**	(0.019)**	(0.018)**
Occupation dummy 2	-0.033	-0.037	-0.033	-0.036
	(0.013)***	(0.012)***	(0.013)***	(0.012)***
Occupation dummy 3	-0.023	-0.032	-0.024	-0.028
	(0.014)*	(0.013)**	(0.014)*	(0.013)**
Occupation dummy 4	-0.043	-0.048	-0.044	-0.047
	(0.013)***	(0.013)***	(0.013)***	(0.013)***
Occupation dummy 5	-0.142	-0.143	-0.143	-0.145
	(0.040)***	(0.040)***	(0.040)***	(0.040)***
Occupation dummy 6	-0.062	-0.067	-0.063	-0.066
	(0.012)***	(0.012)***	(0.012)***	(0.012)***
Occupation dummy 7	-0.040	-0.048	-0.041	-0.047
	(0.012)***	(0.012)***	(0.012)***	(0.012)***
Occupation dummy 8	-0.109	-0.112	-0.110	-0.112
	(0.013)***	(0.013)***	(0.013)***	(0.013)***

Industry dummy 1	0.015	0.014	0.017	0.014
	(0.013)	(0.012)	(0.013)	(0.012)
Industry dummy 2	-0.051	-0.049	-0.050	-0.050
	(0.013)***	(0.013)***	(0.013)***	(0.013)***
Industry dummy 3	-0.050	-0.048	-0.049	-0.049
	(0.025)*	(0.025)*	(0.025)*	(0.025)**
Industry dummy 4	-0.223	-0.220	-0.223	-0.221
	(0.017)***	(0.017)***	(0.017)***	(0.017)***
Industry dummy 5	-0.047	-0.049	-0.047	-0.048
	(0.014)***	(0.013)***	(0.014)***	(0.013)***
Industry dummy 6	-0.080	-0.078	-0.080	-0.079
	(0.016)***	(0.016)***	(0.016)***	(0.016)***
Industry dummy 7	0.000	-0.002	-0.000	-0.002
	(0.015)	(0.015)	(0.015)	(0.015)
Industry dummy 8	-0.049	-0.050	-0.049	-0.049
	(0.018)***	(0.018)***	(0.018)***	(0.018)***
Industry dummy 9	0.175	0.166	0.176	0.170
	(0.040)***	(0.041)***	(0.040)***	(0.041)***
Industry dummy 10	-0.057	-0.051	-0.056	-0.057
	(0.055)	(0.057)	(0.055)	(0.056)
Rural dummy	0.008	0.007	0.008	0.008
	(0.009)	(0.009)	(0.009)	(0.009)
Province 1	-0.022	-0.014	-0.022	-0.019
	(0.017)	(0.017)	(0.017)	(0.017)
Province 2	0.000	0.002	-0.001	0.001
	(0.019)	(0.019)	(0.019)	(0.019)
Province 3	0.002	0.007	0.002	0.004
	(0.015)	(0.015)	(0.015)	(0.015)
Province 4	-0.091	-0.086	-0.092	-0.089
	(0.015)***	(0.015)***	(0.015)***	(0.015)***
Province 5	0.015	0.020	0.015	0.017
	(0.016)	(0.016)	(0.016)	(0.016)
Province 6	-0.000	0.004	-0.001	0.001
	(0.014)	(0.014)	(0.014)	(0.014)
Province 7	-0.029	-0.024	-0.030	-0.025
	(0.016)*	(0.016)	(0.016)*	(0.016)
Province 8	-0.049	-0.042	-0.049	-0.045
	(0.018)***	(0.018)**	(0.018)***	(0.018)***
Household Head	0.041	0.041	0.039	0.041
	(0.008)***	(0.008)***	(0.008)***	(0.008)***
Wave dummy 1	0.023	0.024	0.023	0.024
	(0.010)**	(0.010)**	(0.010)**	(0.010)**
Wave dummy 2	0.012	0.012	0.011	0.012
	(0.010)	(0.010)	(0.010)	(0.010)
Wave dummy 3	0.012	0.013	0.011	0.012
	(0.011)	(0.010)	(0.010)	(0.010)
Wave dummy 4	0.033	0.032	0.032	0.033
	(0.010)***	(0.010)***	(0.010)***	(0.010)***
Wave dummy 5	0.022	0.023	0.022	0.023
	(0.010)**	(0.010)**	(0.010)**	(0.010)**
Firm size dummy 1	0.039	0.038	0.039	0.040
	(0.026)	(0.026)	(0.026)	(0.026)
Firm size dummy 2	0.072	0.071	0.072	0.072

	(0.025)***	(0.025)***	(0.025)***	(0.025)***
Firm size dummy 3	0.079	0.079	0.079	0.079
	(0.024)***	(0.024)***	(0.024)***	(0.024)***
Firm size dummy 4	0.094	0.094	0.094	0.095
	(0.024)***	(0.024)***	(0.024)***	(0.024)***
Firm size dummy 5	0.086	0.087	0.086	0.088
	(0.024)***	(0.024)***	(0.024)***	(0.024)***
Intercept	0.486	0.622	0.473	0.451
	(0.037)***	(0.040)***	(0.039)***	(0.037)***
R^2	0.23	0.24	0.23	0.23
N	27,020	27,020	27,020	27,020

* p<0.1; ** p<0.05; *** p<0.01

Table A7: Structural estimation of the theoretical model, maximum likelihood estimation

	Model 7a $\sigma_e^2 = 1$	Model 7b $\sigma_e^2 = 0.5$	Model 7c $\sigma_e^2 = 2$
Log hourly wage			
Primary	0.071 (0.003)***	0.071 (0.003)**	0.069 (0.003)**
Secondary	0.153 (0.004)***	0.156 (0.004)**	0.149 (0.004)**
Matric	0.274 (0.013)***	0.275 (0.013)**	0.266 (0.014)**
Diploma&Certificate	0.307 (0.017)***	0.306 (0.017)**	0.305 (0.018)**
Tertiary	0.307 (0.008)***	0.301 (0.008)**	0.313 (0.008)**
Potential Experience	0.048 (0.002)***	0.048 (0.001)**	0.044 (0.002)**
Potential Experience^2	-0.001 (0.00003)***	-0.001 (0.00003)**	-0.001 (0.00003)**
Black	-0.877 (0.013)***	-0.867 (0.012)**	-0.874 (0.014)**
Tenure	0.039 (0.006)***	0.051 (0.005)**	0.006 (0.008)
Tenure^2	-0.0005 (0.0003)*	-0.001 (0.0002)**	0.001 (0.0003)*
Intercept	0.980 (0.048)***	0.869 (0.038)**	1.377 (0.075)**
Productivity variance			
No Matric dummy	0.028 (0.010)***	0.025 (0.012)*	0.038 (0.009)**
Matric dummy	0.022 (0.011)**	0.024 (0.012)	0.028 (0.009)**
Black	0.070 (0.009)***	0.078 (0.011)**	0.067 (0.008)**
Age spline (18-24)	0.082 (0.010)***	0.043 (0.011)**	0.119 (0.008)**
Age spline (25-30)	0.046 (0.008)***	0.031 (0.009)**	0.062 (0.006)**
Age spline (31-35)	-0.018 (0.008)**	-0.031 (0.009)**	-0.004 (0.006)
Intercept	-0.179 (0.011)***	-0.297 (0.013)**	0.012 (0.010)
Delta	0.459 (0.094)***	0.660 (0.183)**	0.555 (0.069)**
N	38,493	38,493	38,493

* p<0.1; ** p<0.05; *** p<0.01

Table A8: Structural estimation of the theoretical model, maximum likelihood estimation

	Model 8a	Model 8b	Model 8c	Model 8d
Log hourly wage				
Primary	0.071	0.071	0.071	0.071
	(0.003)***	(0.003)***	(0.003)***	(0.003)***
Secondary	0.153	0.153	0.153	0.154
	(0.004)***	(0.004)***	(0.004)***	(0.004)***
Matric	0.274	0.273	0.277	0.276
	(0.013)***	(0.013)***	(0.014)***	(0.013)***
Diploma&Certificate	0.307	0.307	0.308	0.307
	(0.017)***	(0.017)***	(0.017)***	(0.017)***
Tertiary	0.307	0.308	0.310	0.308
	(0.008)***	(0.008)***	(0.008)***	(0.008)***
Potential Experience	0.048	0.048	0.048	0.048
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Potential Experience^^{2}	-0.001	-0.001	-0.001	-0.001
	(0.00003)***	(0.00003)***	(0.00003)***	(0.00003)***
Black	-0.877	-0.881	-0.876	-0.876
	(0.013)***	(0.013)***	(0.013)***	(0.013)***
Tenure	0.039	0.037	0.038	0.039
	(0.006)***	(0.006)***	(0.006)***	(0.006)***
Tenure^^{2}	-0.0005	-0.0004	-0.0004	-0.0005
	(0.0003)*	(0.0003)	(0.0003)	(0.0003)*
Intercept	0.980	1.000	0.989	0.974
	(0.048)***	(0.048)***	(0.048)***	(0.048)***
Productivity variance				
No Matric dummy	0.028	0.030	0.036	0.028
	(0.010)***	(0.010)***	(0.011)***	(0.010)***
Matric dummy	0.022	0.023	-0.013	-0.010
	(0.011)**	(0.011)**	(0.017)	(0.014)
Black	0.070	0.040	0.046	0.066
	(0.009)***	(0.013)***	(0.013)***	(0.009)***
Age dummy (18-24)	0.082	0.032	0.082	0.059
	(0.010)***	(0.024)	(0.010)***	(0.012)***
Age dummy (25-30)	0.046	-0.008	0.045	0.035
	(0.008)***	(0.022)	(0.008)***	(0.009)***
Age dummy (31-35)	-0.018	-0.069	-0.018	-0.023
	(0.008)**	(0.022)***	(0.008)**	(0.009)***
Black*Age (18-24)		0.059		0.085
		(0.026)**		
Black*Age (25-30)		0.061		
		(0.024)***		
Black*Age (31-35)		0.058		
		(0.023)**		
Black*Matric			0.050	
			(0.019)***	
Matric*Age (18-24)				(0.022)***
				0.049
Matric*Age (25-30)				(0.017)***
				0.031
Matric*Age (31-35)				(0.018)*
				(0.022)***

Intercept	-0.179 (0.011)***	-0.154 (0.014)***	-0.163 (0.013)***	-0.170 (0.012)***
Delta	0.459 (0.094)***	0.496 (0.095)***	0.481 (0.095)***	0.452 (0.094)***
N	38,493	38,493	38,493	38,493

* p<0.1; ** p<0.05; *** p<0.01

CHAPTER 5

CONCLUSION

1. SUMMARY OF THE DISSERTATION

Income inequality in South Africa is mainly driven by inequality in the labour market. The aim of this dissertation is to investigate the dynamic aspects of the link between income inequality and the labour market. More specifically, it focussed on understanding the roles of job tenure and labour market experience as drivers of income inequality.

In this regard, the dissertation attempted to answer several research questions including:

- how do workers accumulate on-the-job skills,
- to what extent are these skills transferrable from one firm to another when workers when workers change jobs,
- to what extent do these skills only improve the productivity of the worker in the current firm where the skills were acquired, and
- what impact do these skills have on the growth of wages and income inequality.

Answers to these questions were provided based on the analysis of wage returns to labour market experience and job tenure for South African worker. Several different theoretical explanations for the observed correlations were scrutinised, using a variety of econometric techniques, including panel data methods, instrumental variable analysis and structural econometric techniques. The empirical analysis was based on a nationally representative panel data set collected by Stats SA in the latter years of the first decade into democracy.

The data set used does not contain direct measures of labour marker experience. This is the norm for developing country data sets. Chapter two therefore identified conditions that lead to the failure and inappropriate use of Mincer's (1974) widely used proxy: potential experience. The chapter proceeded to demonstrate that use of this proxy lead to misleading conclusions regarding the experience-wage profiles of South African workers, particularly for groups that experience longer periods of non-employment. As an alternative to potential experience, the chapter proposes a method of adjusting potential experience by the expected fraction of the workers' working life spent in employment. This proposed measure is then compared to a related variable proposed by Elsby and Shapiro (2011), and Mincer's (1974) potential experience proxy. The analysis finds that the use of potential experience produces experience-wage profiles that are flatter for women and black men compared to experience-wage profiles that are based on more accurate measures of labour market experience. In addition, it is found that the inappropriate use of Mincer's (1974) potential experience proxy inflates the conditional racial and gender wage gaps: between-group differences in time spent in employment are incorrectly interpreted as wage effects. This measure also produces misleading estimates of the between-group differences in the wage returns to labour market experience.

Chapter three investigates another key component of the dynamic structure of wages: the wage returns to job tenure for South African workers. There are important theoretical and empirical debates regarding the wage effects of job tenure, and this chapter aims to contribute to this literature by proving evidence from a developing country. The empirical analysis demonstrated the importance of controlling for racial and gender differences in occupation and industry choice, type of sector, features of the employment contract, type of employment and firm size when estimating the wage returns to job tenure for South African workers.

The second part of this chapter addressed concerns regarding endogeneity bias in the estimated wage returns to job tenure. The source of the bias stems from unobserved heterogeneity in the quality of individual and worker-firm matches. A control function implementation of Altonji and Shakotko's (1987) IV estimator was used to correct the bias. This produced estimates of the wage returns to job tenure that are modest: black workers receive a 10% wage increase after 10 years of job and there is no effect for white workers. This result coincides with what other researchers have found for other countries.

Chapter four investigates whether information asymmetry regarding the productivity of job applicants contributes to the racial wage gap among South African men. The information asymmetry leads to *ex ante* uncertainty on the part of the employer at the hiring stage regarding the productivity of workers. This uncertainty leads to lower a likelihood of employment and lower starting wages for workers with greater uncertainty regarding their expected productivity. The uncertainty is resolved for hired workers through an employer learning process whereby the employer updates their beliefs of the worker's productivity as more information is received and the worker's output is observed.

A theoretical model of worker productivity uncertainty and employer learning is developed for the South African labour market. This model is then estimated using a reduced-form and structural estimation methods. The structural estimation is based on a non-linear systems maximum likelihood estimator, and the results show that there exists greater *ex ante* uncertainty regarding the productivity of black men relative to white men. Our interpretation is that this may be driven by low and variable quality of pre-tertiary education together with the lack of credible productivity signals. These results point to young black men graduating from secondary school more recently as facing the greatest disadvantaged in this regard. This is consistent with this group receiving lower and more variable quality of schooling. Consequently, there is greater uncertainty about these workers and this could be one reason why unemployment is largely concentrated amongst this group.

2. IMPLICATIONS FOR THE RESEARCH FINDINGS

What implications do these results have for labour market inequality and income inequality in South Africa? The results presented in this dissertation show that after an initial period of disadvantage, black workers benefit the most from an additional year spent with the same employer and in the labour market. This suggests that wage inequality between black and white workers should decrease over the life-cycle. This coincides with Leibbrandt et al. (2012) and van der Berg's (2014) finding that between group inequalities has been falling in the post-Apartheid era. The results provided in this study provide a possible answer of why this might be the case.

This evidence could also be interpreted as evidence of why income inequality has been increasing intra-racially. Access to tertiary education is expanding for black workers; those with tertiary qualifications are better able and placed to distinguish themselves from the group in terms of potential productivity. The availability of better labour market signals through tertiary qualifications translates to a greater likelihood of employment, and a lower wage penalty due to more precise assessments of potential productivity.

However, with the large fraction of the black population in unemployment, the results obtained in the dissertation suggest that the current trend of rising income inequality among the black population may continue. This is because the unemployed miss opportunities to increase their skills, earnings capacity and access to credible signals of expected productivity through previous work experience.

3. SUGGESTIONS FOR FUTURE RESEARCH

There are important research gaps left open by this dissertation that remain as topics for future research. Related to chapter two, it would be of interest to allow for unobservable heterogeneity in the likelihood of employment in the adjustment of potential experience by the employment profile. Related to chapter three, administrative data like the payroll data collected by the South African Revenue Service could be used to estimate wage returns to job tenure. The availability of matched worker-firm micro data could also open up interesting avenues for further research on this topic. One such avenue could be to estimate the net wage effects of workers moving from one employer to another. Wage returns to job mobility is the third component of the dynamic structure of wages. Lastly and related to chapter four, it would be of policy interest to investigate jointly the relative contributions of the variation in worker productivity and noisy or unreliable productivity signals towards the uncertainty faced by employers when dealing with young black males. Additionally, the theoretical model could be extended to include important features of the South African labour market like unemployment and collective bargaining.

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