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**Exploring Gender Wage “Discrimination in South Africa, 1995-
2004:
A Quantile Regression Approach**

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EXPLORING GENDER WAGE “DISCRIMINATION” IN SOUTH AFRICA, 1995-2004: A QUANTILE REGRESSION APPROACH

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Abstract: This paper uses quantile regression and counterfactual decomposition methods to investigate whether a ‘glass ceiling’ exists or if instead a ‘sticky floor’ is more prevalent among the African populace in the South African ‘formal’ labour market. Furthermore, it assesses whether the incidence of gender wage ‘discrimination’ has been widening or narrowing across the entire wage distribution from 1995-2004. Given that it is almost ten years after the abolition of legalised discrimination and the introduction of affirmative action legislation, one would have expected that the gaps between male and female wages in general and in particular, the component of these gaps attributable to different returns to characteristics ‘discrimination’ might have decreased. Surprisingly, the results of this study suggest that the gaps increased between 1995 and 2004. In addition, there is evidence of a sticky floor in the South African labour market.

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l) Introduction

For a long time, African women were subjected to both legalised and informal social discrimination which has hampered their full integration in the South African labour market. Hence the post-Apartheid regime has since 1994, implemented fundamental constitutional changes to ensure fair access and treatment of women in the labour market. For example, there is the Employment Equity Act (1998) which abolishes discrimination in the work place (Maziya, 2001). With these enabling policies one would expect to see a decline in labour market inequalities which is matched with progressive changes in the place of African women in the job market. Indeed, analyses of micro-data collected from the mid-1990s onwards attest to an improved assimilation of women in the labour market. However, this is associated with persistent inequity among the workforce. For instance, women still earn significantly less than men, see Figure 1.1. Despite the abolition of legalised discrimination and the introduction of Affirmative Action legislation, there is still wide acknowledgement that a significant portion of these wage differentials is due to **gender** discrimination. Quite worryingly, the latter has received less attention in the literature than it deserves as it has always stood on the shadow of institutionalised racism (Isemonger and Roberts, 1999).

To be explicit, the few studies which were devoted to gender “discrimination” and especially its wage aspect include Casale (1998), Isemonger and Roberts (1999), Winter (1999), Hinks (2002), Rospabe (2001a) and Gruen (2004) *inter alia*. These studies have exclusively investigated the gender pay gaps at the conditional mean of the wage distributions. As a result, they have neglected the distributional implications of standardising the size of the wage gaps across the entire wage distribution. This caveat creates a huge potential for studies which seek to understand the South African gender wage gap conundrum by carrying out distributional analyses.

Also, to this point, there is still a dearth of information on whether the incidence of gender wage “discrimination” increased or decreased over time. This is because existing works have utilised different analytical methods making comparative analyses of their results fraught with difficulties (although their scope spreads over the period from 1994 to 2004). Even so, most of these studies have suggested the presence of “discrimination” for a maximum period of one year. Hence, they have not provided us with any systematic analysis of whether “discrimination” is increasing or decreasing. Obviously, this limited focus fails to reveal long term trends of the gender wage gaps. Generally, such trends are important in assessing the effectiveness of counter legislation.

In light of the limitations in the existing works, this paper aims to contribute to the debate by applying quantile regression and counterfactual decomposition methods adjusted for the quantile regression framework to investigate whether a ‘glass ceiling²’ exists or if instead a “sticky floor”³ is more prevalent among the African populace in the South African “formal” labour market. In addition, we aim to assess whether the incidence of

² Glass ceiling is a situation where the gender gaps are typically wider at the top of the wage distribution.

³ A Sticky floor is a situation whereby the gender gaps are wider at the bottom of the wage distribution.

gender wage “discrimination”⁴ has been increasing or decreasing across the entire wage distribution from 1995-2004. By addressing these issues, this research helps in taking stock of the achievements made in gender mainstreaming after 10 years of South Africa’s democratic independence. In carrying out such an audit, it is critical that all decisions are underpinned by sound research that systematically explores the prevalence of labour market discrimination. This is critical because the existence of labour market discrimination inevitably negates any endeavours to close gender disparities regarding participation in economic activities.

Ten years after the abolition of legalised discrimination and the introduction of affirmative action legislation, one would have expected that the gaps between male and female wages might have decreased⁵. However, we will show that on the contrary, they seem to be rising from 1995-2004. It will also be revealed that the South African gender wage gap is wider at the bottom percentiles of the wage distribution “sticky floor” than at the top.

Turning to the organisation of this study, section two reviews some empirical literature which employed the quantile regression approach. Thereafter, section three poses the human capital earnings functions and the specification of the empirical wage model while section four expounds on the methodology and data analyses. Section five presents the results of the study while the conclusions and policy recommendations are dealt with in section six.

II) Quantile Regression and the Gender Wage Gap: A brief review

Generally, Buchinsky (1994, 1995 and 1998) instigated the application of quantile regression in the context of wage estimation and returns to education. Although, his focus was on wage disparities among women, his work has been influential to studies on gender wage disparities, especially the sample selection correction procedure⁶.

Following Buchinsky’s seminal work, a small but growing literature has adopted this methodology. For example, Albrecht *et al* (2004) used quantile regression decomposition methods based on Machado and Mata (2001 2005) (MM)⁷ to analyse the gender pay gap the Netherlands. The outcomes from the decompositions revealed that the majority of the gender wage gap was due to differences between returns to labour market attributes

⁴ Sex wage discrimination is defined as a situation whereby persons who are equally productive in a physical or material sense, receive different wages solely because of their gender. (Altonji and Blank, 1999:3168). Discrimination here is in quotes because it is difficult to get its exact measure due to difficulties faced in disentangling the effects of omitted variables like intrinsic characteristics from the unexplained component of the wage gap which is attributable to discrimination.

⁵ Following Oaxaca and Blinder (1973) economists decompose the gender pay gap into two components which include rewards to different levels of human capital endowments and the unexplained element which is usually described as discrimination.

⁶ The method entails estimating a labour force participation model and obtaining an index of labour force participation, which is transformed into several power series expansions. The power series expansions are then included in the wage equation as controls for selection bias. This formulation is adopted since the form of selection bias over the different percentiles of the wage distribution is unknown. However, there is currently little consensus regarding the most appropriate correction procedure for selectivity bias in quantile regression models.

⁷ MM’s bootstrap procedure entails constructing a counterfactual male distribution, namely what women would have been paid if they were paid like men given their characteristics. The generated wage distribution will be used together with the actual female wage distribution, to construct the counterfactual wage gap which yields part of the raw wage gap explained by different rewards.

rather than to disparities in characteristics. This result mainly occurred in the top half of the distribution (strong “glass ceiling” effect).

In contrast to the above study which pooled individuals with different levels of education, other studies stratified their samples by education groups. For example, de la Rica *et al* (2005) discovered that in Spain for the more educated there is a “glass ceiling” while for the less educated there is a “sticky floor”.

Besides, Kee (2005) conducted a sectoral analysis of the gender pay gap in both the public and private sectors of the Australian labour market. The study detected a strong glass ceiling effect in the private sector. Another conclusion was that the gender wage gap accelerated across the distribution even after extensive controls, suggesting that the observed pay gap was a result of differences in returns to gender.

As for the developing countries, most studies, which pursued the quantile regression approach, did not decompose the raw gender pay gap along the wage distribution. Instead, they estimated pooled quantile regressions and assessed the evolution of a gender dummy along the wage distribution. This approach may lead such studies to detect the gender wage premia but under identify its source. Typical studies include Hyder and Reilly (2005) and Ajward and Kurukulasuriya (2002) who investigated Pakistani and Sri Lankan cases respectively. Specifically, the latter investigated ethnic and gender wage disparities in Sri Lanka’s formal sector using the Sri Lanka Integrated Survey (1999-2000). They discovered that the premium paid to male workers in the labour force was more pronounced at the top of the wage distribution.

In a recent development, Gunawardena (2006) addressed the above limitation by applying quantile regression estimation and decomposition methods to explore gender wage gaps in Sri Lanka. More importantly, the study’s findings contradict those reported in Ajward and Kurukulasuriya (2002). In particular, a sticky floor was detected in both the public and private sectors. However, there were no controls for sectoral selection bias which limits this work.

In the African context, Nielsen and Rosholm (2001) used quantile regression to investigate sectoral wage gaps in Zambia. In so doing, the study scrutinised the raw gender pay gap and concluded that between 1991 and 1993 the gender pay gap in the private sector was lower at the bottom of the distribution, but in 1996 it was similar across all quantiles. As in the Sri Lankan (2002) and Pakistan cases, the Zambia study did not conduct a decomposition analysis of the wage gap. As a result, the factors that drive the gender pay gaps in the three studies remained unknown. All the same, none of the South African studies carried out on this topic has made recourse to quantile regression techniques (see e.g. Casale (1998), Isemonger and Roberts (1999), Winter (1999), Hinks (2002), Rospabe (2001) and Gruen (2004)). Overall, we conclude that the application of quantile regression in the context of gender wage gaps in developing countries is still in its infancy. Hence, by utilising these new approaches, this study will not only make a significant methodological contribution but will also help in the formulation of target oriented labour market policy and intervention mechanisms⁸. This latter is possible as the quantile regression decomposition methods provide different coefficients of gender wage “discrimination” for the distinct percentiles of the conditional wage distribution.

⁸ The latter occurs by providing different coefficients of gender wage “discrimination” for the distinct percentiles of the conditional wage distribution.

III) Earnings Functions

The earnings functions utilised in the study are an extension of the ‘standard’ Mincerian (1974) income function. A detailed derivation of the latter is given e.g. in Cahuc and Zylberberg (2004:69-87). Based on this derivation a wage model of the following form results:

$$\ln y_i = \rho_0 + \rho_1 s_i + \rho_2 x_i - \rho_3 x_i^2 + u_i \quad (i)$$

Equation (i) expresses an individual’s log hourly income ($\ln y_i$) as a function of his/her measured human capital stock which depends on years of education (s), years of experience (x) and its square (X^2). Notionally, earnings should increase with the accumulation of human capital as it enhances productivity, that is, ρ_1 and ρ_2 are > 0 . The square of the years of experience captures the non-linear effect of experience, as it often follows a parabolic shape which peaks somewhere in midlife, thus ρ_3 is < 0 . This study extends the Mincerian wage model to include other controls often included in analyses of gender pay gaps in South Africa. The variables are defined according to data availability and they can be categorised into controls for human capital (education, experience and hours worked), individual characteristics (marital status, having young children), geographical location (provinces) sector of employment, trade union membership, occupation, industry of employment and controls for sample selection bias⁹. Controlling for selection bias entails estimating employment models which are modelled as follows.

Modelling Employment

The process of selection into employment is often modelled as a binary choice model where individuals are confronted with the ‘choice’ of being employed or remaining unemployed. The assumption underlying such an approach is that all unemployment is voluntary (Bhorat and Leibbrandt, 2001b: 113; Chamberlain and van der Berg, 2002), which is clearly not the case in South Africa (Kingdon and Knight, 2000). As a result, it is not appropriate to model selection into employment in this manner (Bhorat and Leibbrandt, 2001b). Instead, an individual can choose to participate in the labour market but, the individual’s choice to participate does not guarantee employment. Thus, there is selection into employment. This means that controlling for sample selection bias involves estimating the earnings functions in three sequential phases; predicting participation, employment and eventual earnings separately by gender. Accordingly, we specify the log odds that an individual will participate in the labour market as a function of age, age-squared, education, presence of children aged below 15 years in the household, provinces, non-labour income, marital status and urban residence. In contrast to the labour force participation models, household formation variables, to be exact, household size and the proportion of working age females in the household are also included in the employment equations¹⁰.

⁹ While we are aware of the possible endogeneity of some of the covariates, data limitations limit us in controlling for the problems; hence the reader should be aware of this.

¹⁰ These models are estimated based on the broad definition of labour force participation.

IV) Methodology

This section presents the study's estimation framework which consists of two stages. The first stage involves estimating separate human capital earnings functions for men and women at different percentiles of the wage distributions using quantile regression, (accounting for female sample selection bias). The process of controlling for selection bias entails firstly, estimating probit models of women's labour force participation decision. This enables us to compute sample selection correction terms (λ s) which control for selection into employment. Secondly, we fit employment probits on the sample of female participants, controlling for selectivity. We also compute (λ s) from the employment process and these are eventually included in the wage models. The second stage involves using quantile regression decomposition methods to analyse the size and components of the gender wage gaps over the entire conditional wage distribution. The aforesaid estimation techniques are described below.

A. Quantile Regression (QR)

Following Koenker and Bassett (1978) and Buchinsky (1998), the model of QR in a (log) wage-equation setting can be described as follows. Let (w_i, x_i) be a random sample, where w_i denotes the (logged) monthly gross wage of an individual i and x_i is a vector $K \times 1$ of regressors, and let $Q_\theta(w_i | x_i)$ be θ^{th} -order quantile of the conditional distribution of w_i given x_i . Then, under the assumption of a linear specification, the model can be defined as

$$\ln w_i = x_i' \beta_\theta + u_{\theta i} \quad Q_\theta(w_i | x_i) = \ln x_i' \beta_\theta \quad (\text{ii})$$

where the distribution of the error term $u_{\theta i}$, $F_{u_\theta}(\cdot)$, is left unspecified, just assuming that $u_{\theta i}$ satisfies $Q_\theta(u_{\theta i} | x_i) = 0$. Unlike in least squares where the parameter estimates minimise the sum of squared errors, in quantile regression the estimation procedure is to minimise the absolute sum of the errors from a particular quantile of the log earnings across workers. Hence, the θ_{th} regression quantile parameter ($0 < \theta < 1$), is defined as the solution to the problem:

$$\min_{\beta \in R^k} \left\{ \sum_{i: \ln w_i \geq x_i' \beta} \theta |\ln w_i - x_i' \beta_\theta| + \sum_{i: \ln w_i \leq x_i' \beta} (1 - \theta) |\ln w_i - x_i' \beta_\theta| \right\} \quad (\text{iii})$$

The solution to equation (iii) is obtained by linear programming algorithms. To avoid understating the standard errors (since they are heteroscedastic), they are estimated by bootstrap methods¹¹ (Efron, 1979; Buchinsky, 1994; Deaton, 1997). The estimated vector of QR coefficients (β_θ) is interpreted as the marginal change in the conditional quantile θ due to a marginal change in the corresponding element of the vector of coefficients on w_i .

B. Counterfactual Wage Decomposition

¹¹ With 200 replications and accounting for clustering.

The study follows Albrecht *et al's* (2003) adoption of the Machado and Mata (MM)'s (2000 2005) bootstrap method which generalizes the Oaxaca-Blinder (1973) criterion to implement the decomposition directly at each quantile. (see Kee, 2005; de la Rica *et al*, 2005; Albrecht *et al*, 2004). The steps in (MM)'s procedure can be summarized as follows.

- Using a standard uniform distribution, sample a quantile say the θ^{th} quantile.
- With the male database, estimate the coefficient vectors β_{θ}^m at the θ^{th} quantile.
- From the female database take a draw from women's data (x_f), and construct a predicted wage by multiplying the chosen x_f by the estimate of β_{θ}^m . Repeat steps one, two and three N times (e.g. N=5000) and construct a counterfactual male distribution, namely what women would have earned if they were "paid like men".
- Then use the generated wage distribution to construct the counterfactual gap¹² ($\beta_{\theta}^m x_f - \beta_{\theta}^f x_f$) which yields that part of the raw gap explained by different rewards, that is $(\beta_{\theta}^m - \beta_{\theta}^f)x_f$.

Data

The data utilised for the study are obtained from the September (2004) Labour Force Survey (LFS_2) and the (1995, 1999) October Household Surveys (OHS) carried out by Statistics South Africa (Stats SA). The OHS are annual surveys. These surveys are independent cross sections specifically, for each of them different samples were drawn from the population. A large but varying number of households across all provinces of South Africa were sampled allowing a detailed snapshot of labour market conditions and outcomes. For the years 1995 and 1999 in particular, similar sample designs have been applied. 3 000 Enumeration Areas (EAs) were sampled and 10 households within each of them have been interviewed, resulting in a sample size of 30 000 households. The total sample of labour force participants comprises of individuals aged between 15 and 65 and either reported to be employed or were categorised as unemployed using the broad definition¹³.

On the other hand, the LFS_2 is a bi-annual rotating panel household survey. The rotating panel methodology is specifically designed to measure the dynamics of employment and unemployment in the country. The LFS_2 captured information about the labour market situation of approximately 68 000 adults of working age (15-65 years) living in over 30 000 households across the country. Both the OHS, and the LFS_2 have sampling weights and they were considered in the analyses. However, a drawback of both the OHS and the LFS_2 is that the wage information is given in the form of either points or intervals. This

¹² Difference between the female log wage density at various percentiles and the counterfactual density. In line with most of the literature, we chose to evaluate differences in observed characteristics at the men's returns, under the assumption that their market rewards wages are not distorted by discrimination. A positive sign on the gap implies that returns to men's characteristics are higher than the returns to women's characteristics.

¹³ Includes people who although not actively looking for a job would nevertheless like to work.

compromises our analyses as it necessitates employing an indirect method to obtain a wage series compatible with quantile regressions¹⁴.

Data Analysis

Firstly, we dwell on the sample delineation process before describing the variables used in this study. Accordingly, the selected sub-sample comprises of working age Africans (15-65 years) employed in the “formal” sector, provided they availed their wage information. Noteworthy is the fact that our definition of the ‘formal’ sector encompasses the formal and domestic sectors, the latter is included as it employs most African women. Ultimately, the data cleaning exercise engendered the weighted sample statistics presented in Figure 1.2. The available information tallies with the economy’s labour force participation rates since the numbers of employed males constantly outnumber those of women from 1995-2004. The figure also shows that the total sample of African employees who availed their wage information decreased by 7 percent between 1995 and 2004. Quite worryingly, the statistics suggest a wholesale collapse of employment between 1995 and 1999, which is clearly not the case. Probably, the smaller sample sizes for 1999 are due to a sample composition shift or it could be that odd things which we cannot explain happened that year. Nonetheless, the statistics accord with the feminisation of the labour market. While, the sub sample of employed women increased by about 4 percent from 1995-2004 that for men decreased by 13 percent.

Secondly, analyses of empirical wage density functions for the years 1995, 1999 and 2004 were out carried by gender. Incidentally, log real gross monthly wages are used in this study. These real wage series’ were obtained from deflating nominal monthly wages for the years 1995, 1999 and 2004 to the 1995 base (expressed in 2000 prices) using the South African Reserve Bank’s Consumer Price Index (CPI) series (KBP7031J). The density functions were approximated using an Epanechnikov kernel estimator (see Johnston and DiNardo, 1997: 370-375; StataCorp, 2003). Figure 2 shows the resulting density plots.

The three panels in Figure 2 indicate that male and female wage distributions are clearly distinct. In tandem with this, the female wage distributions mainly lie to the left of the male wage distributions, especially at the lower percentiles of the distributions. Also, the latter are characterised by a higher density function around the mode and a relatively lower dispersion. It is also apparent that the advantage that the males enjoy over females at the lower quantiles of the distributions is significantly reduced at the upper quantiles. Thus, if one considers only the raw wage distributions, it appears there is a “sticky floor” and no “glass ceiling” for African women.

Thereafter, a summary of both the dependent and independent variables used by year and gender is provided. The descriptive statistics are presented in Table 1.

Considering the dependent variable, the statistics demonstrate that men’s earnings are on average higher than women’s. The disadvantaged position of women is further highlighted by a 3% decline in their real wages between 1995 and 1999. In contrast, those of men increased by close to 6% in the same period. Despite these differences, both sexes experienced an increase in their incomes between 1995 and 2004. In particular, the wages for men and women concomitantly increased by 12% and 7% respectively.

¹⁴ The derivation of the wage series’ followed ideas discussed in Berger and Yu (2006).

Turning to the covariates, the displayed information conveys some traits of patriarchy in trade union membership. Probably this is due to the relatively higher concentration of women in non-unionised sectors such as the social services (includes domestic workers). Consequently, men's relatively higher wages are partly attributable to the union wage premia.

Furthermore, the data reveals that the distribution of participants among the provinces (by gender) does not significantly differ across the data sets. Perhaps, this implies that the data sets are comparable.

In the case of education, the statistics exhibit that there is a slightly higher proportion of male participants who attained primary level and below than women. Interestingly, both sexes have a higher proportion of participants who attained secondary school than the other levels. In this vein, for both sexes, the ratio of secondary school graduates increased by around 9 percent from 1995-2004. Not surprisingly, the data shows that there are slightly more women with diplomas and degrees than males.

The data also portray some aspects of industrial concentration. In line with this, both genders are concentrated in social services, trade, manufacturing and agriculture. Despite these obvious similarities there are gender disparities in the proportions of participants across these industries. For instance, there is a relatively higher percentage of women in the social services for example, in 1995 the industry accommodated 61% of the female participants and the corresponding proportion of men was 23%. On the other hand, men appear to dominate women in sectors such as agriculture, mining and construction.

Furthermore, the figures expose that there is a higher ratio of participants in elementary and skilled occupational categories irrespective of sex. It is also evident that there is gender based occupational concentration. In this case, there are more male artisans and operators than women. Inversely, women outnumber men in occupations like technicians and clerks.

Lastly, the information given for marriage and fertility harmonises with the stylised facts as both variables are generally declining with time. Subsequent to this data description process, we proceed to analyse the study's estimation results.

V) Estimation results

The outcomes of the quantile regression equations reported at the 10th, 25th, 50th, 75th and 90th percentiles of the wage distributions form the starting point for discussion in this section¹⁵. The results are presented in Tables 2a (for 1995), 2b (for 1999) and 2c (for 2004). For these regressions the omitted (base) variables correspond to an unmarried, non-unionised worker with elementary education, residing in Gauteng province, employed as an operator in the manufacturing industry. The distinct wage models are analysed together and their coefficients provide an indication of whether or not the returns to observable characteristics differ by gender and how these differences change as we move across the wage distributions.

The following findings stand out. The coefficients on age/experience for men are always significant. This means having more experience increases wages up to a certain point of the life cycle but after this peak, an additional year of experience decreases earnings. This

¹⁵ Despite being necessary, the discussion of participation and employment models has been omitted in this essay. However, the outcomes are available on request.

effect slightly decreases as we move up the quantiles of the wage distributions. In contrast to the male equations, these variables do not always feature significantly in the female regressions, although most of the cases conform to the theoretical predictions. Probably, this irregularity in women's returns to the variable in question is due to family related career interruptions.

We also discover that earnings increase with the number of hours worked (if significant). Despite this commonality, some sex disparities in the effects of the variables are perceived. Accordingly, the discrepancies are skewed in favour of women since the coefficients are generally higher in the female regressions. All the same, the returns are higher at the bottom than at the top of the wage distributions.

Besides, being married (proxy for factors such as stability, discipline and motivation) confers some relatively higher returns for men than women. The advantages conferred to workers by this status indicate that it acts as a motivational/productivity signal to employers. Incidentally, the sizes of the 2004 coefficients increase with the percentiles of both sexes' wage distributions, whereas the pattern is not as obvious for females. Conversely, the outcomes for 1999 and 2004 portray that the returns are lower at the upper tails of the male wage distribution, while they are mostly insignificant in the case of females. Interestingly, the findings for 1995 diverge from the above as marriage lowers women's returns. Most likely, the relatively higher fertility rates observed in 1995 made marriage serve as a signal of potential career interruptions to the employers who may have discriminated against married women.

Quite fundamentally, the study establishes that educational attainment yields higher returns as compared to the base level (elementary). The returns tend to increase with the education levels. This upshot contradicts the law of diminishing returns to the formation of human capital. Another observation is that there are gender gaps in these returns. Accordingly, the period from 1995-2004 is distinguished by women who enjoy higher returns at the secondary school echelon and below than men. The gender gap in returns to secondary education declines as we approach the top end of the wage distributions. Also, in contrast to the case for secondary school, men have higher coefficients for degrees than women, except in 1999. Nevertheless, the gender gap in returns to a degree fluctuates along the wage distributions.

In likeness with *inter alia* Butcher and Rouse (2001) and Mwabu and Schultz (1998) union members are found to earn significantly more than non-union members. This outcome highlights the strong bargaining power of South African unions. The union wage premia are higher at the bottom of both male and female wage distributions, except for women in 1999 where the picture is not obvious. The lower returns in the upper quantiles are explainable by the consideration that most wages in the upper market are set by direct contracts as compared to collective bargaining (Bhorat *et al*, 2002). Apparently, some gender disparities in favour of women are evident in the premia. At most the gender gaps tend to increase with the quantiles of the wage distributions.

Furthermore, the outcomes for the industrial sectors showcase that few industries significantly offer higher wages than the manufacturing sector. Overall, this is exemplified by the transport and electricity industrial sectors. Alternatively, industries such as agriculture and trade pay less than manufacturing. Nonetheless, the progression of the

returns along the wage distributions differs by sector and time period. For example, in 2004 there is a decline in men's mining coefficients as we approach the upper tails of the wage distributions, whilst the opposite applies to transport. All the same, gender gaps in industrial returns are difficult to analyse due to perceived inconsistencies in the significance of the variables.

Additionally, the outcomes for the occupational dummies display a wage hierarchy relative to the base category (operator). Accordingly, managers, professionals, technicians and clerks earn significantly more than operators, whereas the opposite applies to employees of the agriculture sector and those in elementary occupations. It is also highlighted that women in higher paying jobs (relative to operators) get larger rewards than men. In most cases, the gender differential in returns to the variable of interest increase with the percentiles of the wage distribution¹⁶.

It is also understood that the estimates for the provincial variables are lower for workers located in any other province than Gauteng. Generally, the magnitudes of the provincial dummies are larger for females implying that women are more likely to earn less compared to men. In principal, the gender disparities in the returns increase with the quantiles of the wage distributions.

Lastly, the female selection bias correction terms featured to be insignificant in most cases. Nevertheless, this finding is not unique as it tallies with that of Winter (1999). Probably, it indicates that selection bias does not generally bind in the formal sector which is the domain of both studies.

In sum, the evidence presented so far points out that returns to observable characteristics differ by gender and that these differences change as we move throughout the distribution. Therefore, the next step is to investigate the sources of the gender gap.

Table 3 presents the raw/observed and the counterfactual gender wage gaps for 1995, 1999 and 2004. The raw wage gaps are defined as the difference between male and female unconditional log wages at the different quantiles of the wage distributions (Albrecht *et al*, 2004). The counterfactual gap shows the disparities between the quantiles of women's log wage distributions and the corresponding quantiles of a counterfactual distribution that arises if women maintained their characteristics but were paid like men.¹⁷

Firstly, we explore the raw gender wage gaps. Table 3 exhibits a monotonically declining gap as we move towards the upper quantiles of the 1995 wage distribution. However, this pattern is not robust across the time periods. For instance, the 1999 gap increases dramatically from the 10th to the 25th percentile and declines thereafter. Typically, the evolution of the 1999 gap identifies females whose wages lie in the 25th percentile as the most disadvantaged¹⁸. Besides, Table 3 displays a gender gap that is generally decreasing as we approach the upper tails of the 2004 wage distribution although the evolution of the gap from the 10th to the 50th percentiles is relatively flat. This tendency for a deceleration

¹⁶ The fact that women have larger coefficients than men in some of the occupations (relative to the reference group of operators) does not imply that they get a higher wage since they may have a lower wage in the reference category. A similar comment pertains to the coefficients on the rest of the dummy variables.

¹⁷ We are unable to compute standard errors for the decomposition due to low computational power as we are using a large sample size.

¹⁸ Probably, the sharp increase from the 10th to the 25th percentiles of the 1999 wage distribution is due to a selection effect as the 1999 sample suggested a wholesale collapse of employment which is clearly not the case when the overall sample of workers is considered.

of the gap as we move up the quantiles of the wage distributions possibly indicates a “sticky floor”. Hence, by focussing only on the mean raw gender wage gap, substantial variations of the gap will be hidden.

Secondly, we investigate the counterfactual wage gaps. A striking feature of these gaps is that they are positive across the data sets. This positive gap implies that men’s returns are greater than women’s. Thus, even if women had the same distribution of characteristics as men, they would still receive lower pay across the wage distribution. The percentage contribution of the counterfactual wage gaps to the raw wage gaps are also presented in Table 3. A percentage value greater than 100 potentially means that women have characteristics that compensate them for any unobservables which may include “discrimination”. In other words, it implies that women have better characteristics than men. However, the very large percentage values found for instance, in the upper quantiles of the 2004 wage distribution merit comment. Possibly, they emerged because the raw wage gap is relatively small.

More importantly, Table 3 shows that the counterfactual wage gap for 1995 decreases from the bottom to the upper tails of the conditional wage distributions. In addition, it exhibits that the 1999 gap strictly declines monotonically from the 25th percentile towards the upper quantiles of the wage distribution. Lastly, Table 3 reveals that the 2004 gap is somewhat flat from the bottom to the middle of the distribution and declines thereafter. In sum, the evidence presented so far unequivocally supports the existence of a “sticky floor” in the “formal” sector of the South African labour market. Thus, low income females are more likely to be disadvantaged, although it is not clear whether the disadvantage is mainly due to “discrimination” or to other unobserved heterogeneity that the model does not control for.

Finally, we probe into the issue of whether the component of the raw gender wage gap attributable to different returns has been increasing or decreasing along the wage distribution over the period 1995-2004. In this case, it is perceptible that the portion of the wage distribution that ranges from the 10th to the 25th percentiles experienced a decline in the returns component of the gap over the period in question (although the case for 1999 merits comment). The decline observed at the bottom tails of the wage distributions could be due to the strengthening of minimum wage policies with time. All the same, the effect of different pay structures on gender wage differentials is still substantial despite the observed decline. On the other hand, the 50th and 75th percentiles saw an increase in the component from 1995-2004. So, we conclude that highly paid women are facing more and more gender based wage inequalities with time.

VI) Conclusion and Policy Recommendations

This paper explored gender wage gaps throughout the wage distribution for African “formal” sector employees in South Africa over the period 1995-2004. The analyses utilised individual data from the 1995 and 1999 October Household Surveys and the 2004 September Labour Force Survey. Quantile regression techniques were used to control for various characteristics at different points of the wage distributions. In addition, the Machado Mata (2005) decomposition method was utilised to estimate the component of the wage gaps not explained by different characteristics (counterfactual gap).

Basing on this methodology, our findings on unconditional wage gaps indicate that the mean gender wage gap conceals some variations in the gap across the wage distribution. In fact, the magnitudes of these gaps slide as we approach the upper tails of the wage distributions. Analogously, the absolute sizes of the counterfactual wage gaps generally decline as we proceed from the bottom to the upper tails of the wage distributions. As it is, both the raw and counterfactual gaps align us towards an existence of a “sticky floor” in the South African labour Market.

Additionally, the study revealed that the counterfactual wage gaps did not generally show a declining tendency along the whole wage distribution between 1995 and 2004. Instead, a slight decline was evident only in the 10th, 25th and 90th percentiles of the wage distribution. If discrimination is the main factor that drove these pay gaps, then female workers in the upper quantiles became more disadvantaged with time, even under the existence of equal opportunity legislation.

On the basis of our findings, it is suggested that if the labour market outcomes for African men and women are to be levelled, considerable efforts should be invested in strengthening the implementation of countervailing clauses on the violation of the gender neutral labour market institutions embedded in new the labour legislation. Quite significantly, it is recommended that mitigatory measures should focus more on women at the bottom end of the wage distribution because they are the most likely to be “discriminated” against. Also, the policymakers should design strategies to curb the widening of the wage gaps in top paying jobs. Furthermore, because discrimination and the subordinate role of women seem to be entrenched at various stages it is essential to get an understanding of the barriers that exist in the labour market and also in the greater society and how they affect African women.

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Appendix

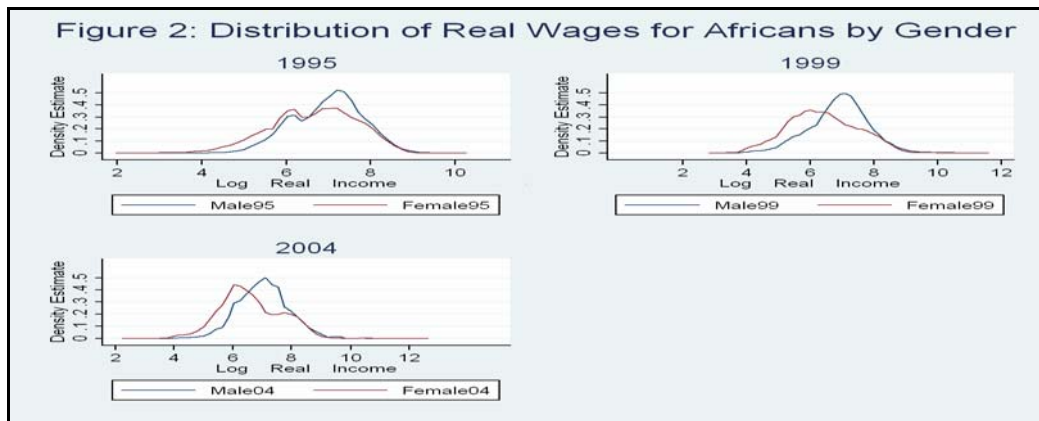
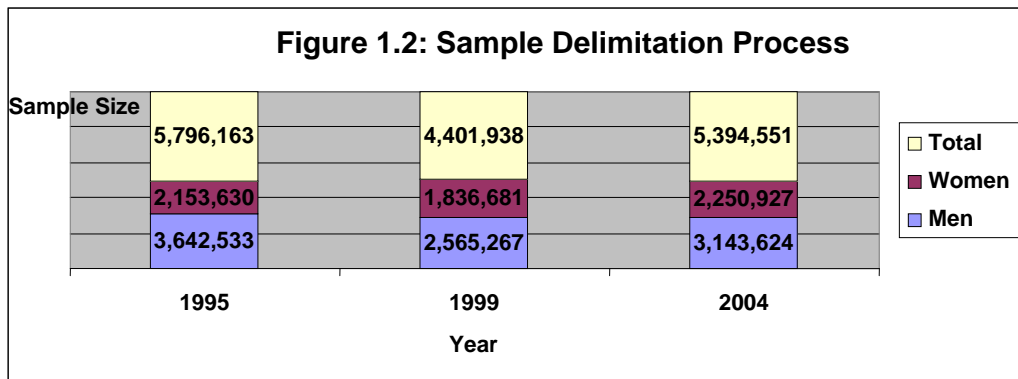
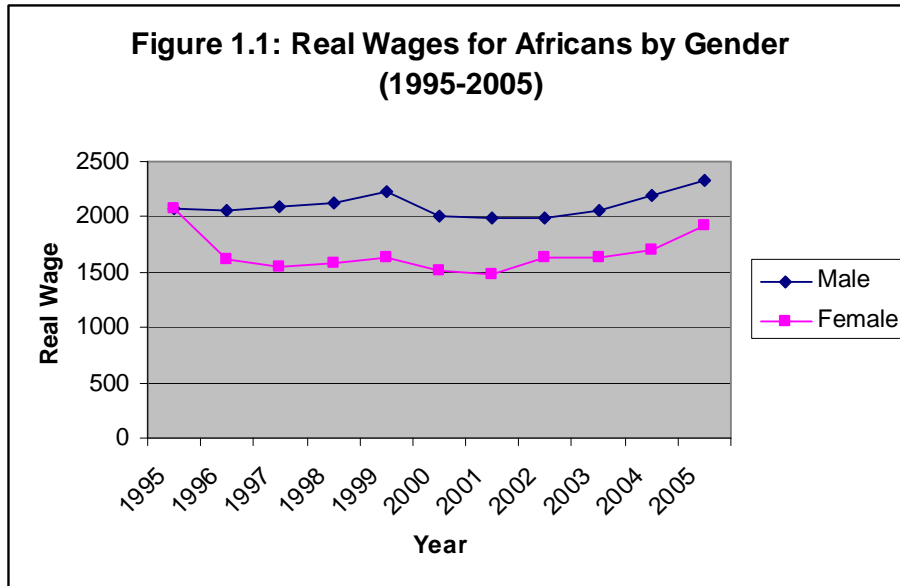


Table 1: Descriptive Statistics for African Employees by Gender (1995, 1999 and 2004)

Gender	1995				1999				2004			
	Females		Males		Females		Males		Females		Males	
Variable	Mean/	S.dev	Prop	S.dev	Mean/	S.dev	Prop	S.dev	Mean/	S.dev	Prop	S.dev
Real Monthly income	1200	27.4	1487	28.39	1164	51.04	1574	50.02	1284	48.2	1667	47.9
Demographic Variables												
Children <15years	0.755	0.009	0.621	0.012	0.678	0.008	0.51	0.008	0.681	0.009	0.487	0.011
Children < 6years	0.452	0.01	0.385	0.01	0.433	0.009	0.35	0.007	0.418	0.009	0.335	0.009
Married	0.453	0.01	0.595	0.007	0.392	0.01	0.54	0.009	0.32	0.009	0.45	0.011
Human Capital												
Age	37.33	0.165	37.52	0.16	37.2	0.19	36.9	0.144	38.2	0.21	37.1	0.21
Age-Squared	1493	12.8	1516	10.5	1484	14.9	1461	11.2	1565	16.5	1486	17.23
Log hours	3.68	0.007	3.76	0.005	3.75	0.007	3.83	0.005	3.7	0.08	3.83	0.005
None	0.078	0.005	0.118	0.005	0.06	0.004	0.09	0.005	0.074	0.004	0.065	0.004
Elementary	0.04	0.003	0.048	0.003	0.024	0.003	0.03	0.003	0.015	0.002	0.019	0.003
Primary	0.24	0.008	0.263	0.007	0.27	0.008	0.28	0.007	0.2	0.008	0.226	0.007
Secondary	0.45	0.011	0.479	0.009	0.45	0.01	0.49	0.008	0.538	0.002	0.57	0.009
College	-	-	-	-	0.026	0.003	0.01	0.002	0.013	0.002	0.014	0.002
Diploma	0.11	0.008	0.061	0.005	0.09	0.004	0.05	0.003	0.114	0.006	0.067	0.004
Degree	0.027	0.004	0.023	0.003	0.04	0.005	0.03	0.003	0.053	0.006	0.038	0.004
Occupations												
Manager	0.006	0.001	0.019	0.002	0.009	0.002	0.03	0.003	0.016	0.002	0.032	0.004
Professional	0.026	0.003	0.018	0.002	0.040	0.005	0.33	0.002	0.039	0.005	0.026	0.003
Technician	0.16	0.009	0.066	0.004	0.124	0.008	0.07	0.003	0.12	0.006	0.063	0.004
Clerk	0.11	0.007	0.071	0.004	0.100	0.006	0.07	0.004	0.123	0.007	0.059	0.004
Skilled	0.12	0.006	0.117	0.005	0.086	0.005	0.13	0.006	0.104	0.006	0.157	0.007
Agriculturalist	0.002	0.001	0.007	0.001	0.010	0.003	0.03	0.003	0.003	0.001	0.006	0.001
Artisan	0.024	0.003	0.133	0.005	0.040	0.005	0.18	0.006	0.035	0.004	0.18	0.008
Operator	0.05	0.005	0.211	0.005	0.035	0.005	0.23	0.007	0.04	0.004	0.178	0.007
Elementary	0.52	0.011	0.361	0.01	0.550	0.008	0.22	0.007	0.513	0.011	0.26	0.009
Industries												
Agriculture	0.08	0.009	0.211	0.011	0.084	0.084	0.13	0.008	0.049	0.004	0.095	0.006
Mining	0.005	0.002	0.094	0.009	0.004	0.002	0.14	0.011	0.002	0.001	0.106	0.012
Manufacturing	0.11	0.009	0.165	0.009	0.096	0.008	0.17	0.007	0.112	0.006	0.174	0.007
Electricity	0.002	0.001	0.013	0.001	0.002	0.001	0.02	0.002	0.005	0.001	0.013	0.002
Construction	0.005	0.001	0.063	0.004	0.008	0.002	0.06	0.005	0.013	0.002	0.097	0.007
Trade	0.16	0.008	0.124	0.005	0.14	0.007	0.13	0.006	0.16	0.008	0.156	0.007
Transport	0.01	0.002	0.063	0.004	0.01	0.001	0.06	0.004	0.02	0.003	0.061	0.004
Finance	0.03	0.003	0.039	0.003	0.049	0.006	0.07	0.004	0.05	0.004	0.107	0.006
Social Services	0.61	0.013	0.232	0.012	0.598	0.01	0.21	0.008	0.59	0.01	0.195	0.008
Provinces												
Western Cape	0.03	0.005	0.045	0.006	0.050	0.006	0.06	0.006	0.054	0.005	0.049	0.005
Eastern Cape	0.146	0.008	0.095	0.004	0.120	0.009	0.07	0.006	0.12	0.006	0.081	0.006
Northern Cape	0.007	0.002	0.012	0.002	0.012	0.002	0.01	0.002	0.01	0.009	0.017	0.002
Free State	0.103	0.005	0.099	0.004	0.098	0.008	0.11	0.008	0.078	0.003	0.182	0.008
Kwazulu/Natal	0.215	0.011	0.185	0.008	0.200	0.014	0.16	0.01	0.223	0.01	0.181	0.013
North West	0.091	0.008	0.111	0.006	0.095	0.007	0.12	0.008	0.085	0.005	0.098	0.008
Gauteng	0.242	0.014	0.282	0.012	0.245	0.011	0.3	0.005	0.26	0.009	0.305	0.011
Mpumalanga	0.068	0.006	0.093	0.004	0.077	0.007	0.09	0.007	0.076	0.004	0.086	0.006
Northern Province	0.098	0.007	0.077	0.004	0.096	0.007	0.08	0.005	0.097	0.001	0.095	0.009
Trade Unionism	0.26	0.011	0.38	0.012	0.32	0.009	0.48	0.01	0.28	0.01	0.382	0.012
N	6734		9964		4949		6470		5121		5918	

Table 2a: Quantile Regressions for African Men and Women's Log Real Wages (1995)

Quantile	Males					Females				
	$\theta_{=10}$	$\theta_{=25}$	$\theta_{=50}$	$\theta_{=75}$	$\theta_{=90}$	$\theta_{=10}$	$\theta_{=25}$	$\theta_{=50}$	$\theta_{=75}$	$\theta_{=90}$
Age	0.052* (0.008)	0.038* (0.006)	0.034* (0.005)	0.026* (0.005)	0.030* (0.007)	0.029** (0.015)	0.016 (0.012)	0.019** (0.008)	0.024** (0.010)	0.027** (0.011)
Age-Squared	-0.001* (0.000)	-0.0004* (0.000)	-0.0003* (0.000)	-0.0003* (0.000)	-0.0003* (0.000)	-0.0035* (0.0002)	-0.0013* (0.0001)	-0.0002*** (0.0001)	-0.0002** (0.0001)	-0.0003** (0.0001)
Log hours	0.112** (0.052)	0.041 (0.033)	0.005 (0.028)	0.013 (0.029)	-0.003 (0.037)	0.202* (0.047)	0.136* (0.041)	0.064*** (0.034)	0.030 (0.032)	-0.044 (0.037)
Married	0.212* (0.029)	0.170* (0.024)	0.132* (0.018)	0.122* (0.018)	0.151* (0.025)	-0.106* (0.033)	-0.114* (0.028)	-0.051** (0.023)	-0.054** (0.022)	-0.002 (0.025)
Education Levels										
Primary	0.137* (0.036)	0.100* (0.029)	0.063* (0.021)	0.072* (0.021)	0.008 (0.032)	0.1758* (0.056)	0.200* (0.043)	0.109** (0.040)	0.064*** (0.038)	0.044 (0.042)
Secondary	0.358* (0.043)	0.299* (0.031)	0.245* (0.024)	0.263* (0.024)	0.207* (0.038)	0.580* (0.059)	0.543* (0.047)	0.403* (0.044)	0.310* (0.037)	0.278* (0.041)
Diploma	0.669* (0.088)	0.546* (0.050)	0.465* (0.050)	0.518* (0.043)	0.498* (0.055)	0.716* (0.102)	0.727* (0.085)	0.493* (0.066)	0.437* (0.070)	0.407* (0.081)
Degree	1.152* (0.116)	0.999* (0.096)	0.906* (0.104)	0.922* (0.095)	0.842* (0.126)	0.900* (0.177)	0.943* (0.126)	0.742* (0.108)	0.640* (0.136)	0.644* (0.130)
Occupations										
Manager	0.375* (0.118)	0.389* (0.080)	0.527* (0.079)	0.648* (0.081)	0.844* (0.131)	0.841** (0.329)	0.693* (0.137)	0.845* (0.212)	1.007* (0.182)	0.818* (0.126)
Professional	0.300* (0.113)	0.306* (0.115)	0.377* (0.112)	0.453* (0.092)	0.459* (0.096)	0.827* (0.200)	0.859* (0.113)	0.840* (0.134)	0.808* (0.128)	0.584* (0.109)
Technician	0.511* (0.090)	0.476* (0.054)	0.527* (0.043)	0.486* (0.039)	0.384* (0.048)	1.000* (0.145)	0.968* (0.085)	0.991* (0.098)	0.957* (0.081)	0.697* (0.084)
Clerk	0.101 (0.071)	0.211* (0.041)	0.219* (0.036)	0.265* (0.042)	0.209* (0.061)	0.389* (0.124)	0.453* (0.076)	0.471* (0.088)	0.527* (0.077)	0.336* (0.077)
Skilled	0.014 (0.052)	0.014 (0.038)	0.133* (0.033)	0.180* (0.031)	0.166* (0.048)	0.027 (0.130)	0.131*** (0.076)	0.233* (0.099)	0.313* (0.080)	0.223** (0.090)
Agric worker	-0.403** (0.172)	-0.386** (0.164)	0.034 (0.169)	0.242** (0.095)	0.153 (0.170)	-0.206 (0.231)	-0.197 (0.261)	-0.139 (0.337)	0.113 (0.279)	-0.314 (0.277)
Artisan	-0.021 (0.047)	-0.008 (0.037)	0.047*** (0.026)	0.113* (0.027)	0.138** (0.045)	-0.234 (0.208)	-0.152 (0.127)	-0.041 (0.067)	-0.036 (0.085)	-0.020 (0.122)
Elementary Jobs	-0.259* (0.039)	-0.274* (0.031)	-0.191* (0.023)	-0.205* (0.023)	-0.280* (0.036)	-0.292** (0.123)	-0.295* (0.064)	-0.234** (0.093)	-0.174** (0.068)	-0.296* (0.077)
Industries										
Agriculture	-0.513* (0.060)	-0.586* (0.047)	-0.720* (0.046)	-0.716* (0.041)	-0.712* (0.057)	-0.326* (0.086)	-0.359* (0.067)	-0.430* (0.107)	-0.473* (0.076)	-0.345* (0.084)
Mining	-0.128*** (0.078)	-0.115** (0.051)	-0.079*** (0.045)	-0.071** (0.036)	-0.111** (0.050)	-0.105 (0.183)	-0.211 (0.201)	-0.152 (0.283)	0.076 (0.199)	0.178 (0.188)
Electricity	0.347* (0.116)	0.232* (0.071)	0.273* (0.072)	0.169** (0.072)	0.164*** (0.091)	0.455 (0.308)	0.626* (0.223)	0.280 (0.199)	0.045 (0.273)	0.102 (0.199)
Construction	-0.184* (0.064)	-0.149* (0.053)	-0.205* (0.044)	-0.209* (0.040)	-0.215* (0.060)	0.192 (0.248)	0.128 (0.278)	0.048 (0.211)	0.106 (0.170)	0.121 (0.230)
Trade	-0.163** (0.066)	-0.181* (0.043)	-0.227* (0.039)	-0.219* (0.034)	-0.204* (0.044)	-0.086 (0.078)	-0.155** (0.061)	-0.152*** (0.086)	-0.240* (0.064)	-0.118** (0.058)
Transport	0.140** (0.057)	0.099** (0.047)	0.018 (0.035)	-0.017 (0.036)	0.032 (0.050)	-0.005 (0.162)	0.039 (0.105)	0.002 (0.140)	0.112 (0.104)	0.306*** (0.160)
Finance	0.083 (0.089)	0.024 (0.052)	-0.051 (0.062)	-0.045 (0.058)	-0.076 (0.067)	0.101 (0.122)	0.130 (0.089)	0.043 (0.101)	-0.028 (0.085)	0.096 (0.094)
Social Service	-0.089 (0.057)	-0.016 (0.047)	-0.023 (0.040)	-0.040 (0.029)	-0.038 (0.049)	-0.191** (0.078)	-0.175** (0.059)	-0.171*** (0.095)	-0.186* (0.055)	-0.089 (0.060)
Unionism	0.346* (0.037)	0.298* (0.023)	0.204* (0.020)	0.168* (0.018)	0.123* (0.024)	0.366* (0.044)	0.331* (0.035)	0.292* (0.029)	0.268* (0.027)	0.206* (0.025)
Provinces										
Western Cape	-0.022 (0.087)	-0.035 (0.059)	-0.081 (0.056)	-0.131** (0.059)	-0.055 (0.091)	-0.005 (0.070)	-0.097 (0.066)	-0.192* (0.054)	-0.218** (0.083)	-0.080 (0.134)
Eastern Cape	-0.377* (0.063)	-0.275* (0.050)	-0.229* (0.044)	-0.159* (0.036)	-0.087*** (0.049)	-0.472* (0.076)	-0.398* (0.050)	-0.368* (0.041)	-0.279* (0.042)	-0.179* (0.042)
Northern Cape	-0.187** (0.079)	-0.209** (0.076)	-0.183** (0.070)	-0.238* (0.065)	-0.257** (0.107)	-0.537* (0.137)	-0.395** (0.150)	-0.367* (0.110)	-0.329* (0.061)	-0.375* (0.088)
Free State	-0.423* (0.061)	-0.381* (0.048)	-0.365* (0.037)	-0.372* (0.035)	-0.351* (0.043)	-1.124* (0.095)	-0.980* (0.070)	-0.848* (0.049)	-0.661* (0.053)	-0.488* (0.049)
Kwazulu/Natal	-0.141** (0.055)	-0.093** (0.045)	-0.059*** (0.032)	-0.027 (0.034)	0.023 (0.052)	-0.265* (0.061)	-0.226* (0.044)	-0.210* (0.037)	-0.158* (0.038)	-0.079** (0.039)
North West	-0.134** (0.063)	-0.107** (0.052)	-0.147* (0.040)	-0.138* (0.037)	-0.064 (0.063)	-0.584* (0.076)	-0.440* (0.078)	-0.362* (0.057)	-0.261* (0.053)	-0.153* (0.042)
Mpumalanga	-0.282* (0.065)	-0.277* (0.053)	-0.193* (0.048)	-0.100** (0.046)	0.007 (0.064)	-0.379* (0.076)	-0.361* (0.057)	-0.254* (0.065)	-0.207* (0.058)	-0.025 (0.080)
Northern Province	-0.237* (0.081)	-0.099 (0.061)	-0.074 (0.053)	0.037 (0.042)	0.096** (0.049)	-0.232* (0.058)	-0.245* (0.067)	-0.107** (0.047)	-0.038 (0.046)	-0.009 (0.048)

Sample Selection Correction Terms										
Lambda1						1.103	2.069	3.427	5.556***	0.549
						(4.139)	(3.389)	(2.455)	(3.078)	(4.282)
Lambda2	-	-	-	-	-	-2.455	-2.851	-4.719	-7.356***	-0.637
						(5.608)	(4.685)	(3.337)	(4.169)	(5.816)
Lambda3	-	-	-	-	-	-0.004	-0.362	-0.408***	-0.666***	-0.175
						(0.368)	(0.272)	(0.215)	(0.284)	(0.372)
Lambda4	-	-	-	-	-	0.031	0.060	0.092**	0.122**	0.050
						(0.060)	(0.042)	(0.032)	(0.043)	(0.063)
Constant	4.609*	5.563*	6.174*	6.595*	6.936*	4.618*	5.092*	5.663*	5.818*	6.737*
	(0.268)	(0.187)	(0.160)	(0.143)	(0.207)	(0.484)	(0.361)	(0.320)	(0.335)	(0.449)
Observations	9964	9964	9964	9964	9964	6734	6734	6734	6734	6734

Bootstrapped Standard errors (200, replications accounting for clustering) in parentheses* significant at 1%; ** significant at 5%; **
*significant at 10%

Table 2b: Quantile Regressions for African Men and Women's Log Real Wages (1999)

Quantile	Males					Females				
	$\theta_{=10}$	$\theta_{=25}$	$\theta_{=50}$	$\theta_{=75}$	$\theta_{=90}$	$\theta_{=10}$	$\theta_{=25}$	$\theta_{=50}$	$\theta_{=75}$	$\theta_{=90}$
Age	0.076* (0.012)	0.050* (0.009)	0.044* (0.007)	0.044* (0.008)	0.062* (0.011)	0.059* (0.015)	0.036* (0.009)	0.034* (0.010)	0.035* (0.010)	0.043* (0.013)
Age-squared	-0.001* (0.0002)	-0.001* (0.0001)	-0.0005* (0.0001)	-0.0004* (0.0001)	-0.001* (0.0001)	-0.007* (0.0001)	-0.0004* (0.0001)	-0.0003* (0.0001)	-0.0004* (0.0001)	-0.0004* (0.0001)
Log Hours	0.232* (0.058)	0.103** (0.051)	0.058 (0.036)	0.064*** (0.035)	0.073 (0.055)	0.425* (0.045)	0.335* (0.035)	0.286* (0.037)	0.254* (0.039)	0.229* (0.056)
Married	0.152* (0.043)	0.144* (0.028)	0.125* (0.022)	0.128* (0.026)	0.123* (0.036)	-0.005 (0.044)	0.013 (0.027)	0.020 (0.028)	0.056*** (0.030)	0.113* (0.042)
Education Levels										
Primary	0.111*** (0.057)	0.020 (0.034)	0.068* (0.026)	0.013 (0.033)	-0.034 (0.042)	0.167** (0.066)	0.139* (0.042)	0.095* (0.036)	-0.019 (0.042)	0.035 (0.055)
Secondary	0.291* (0.058)	0.203* (0.040)	0.248* (0.030)	0.240* (0.034)	0.247* (0.050)	0.387* (0.067)	0.320* (0.042)	0.324* (0.043)	0.229* (0.049)	0.267* (0.056)
Diploma	0.820* (0.091)	0.763* (0.084)	0.716* (0.071)	0.667* (0.068)	0.770* (0.110)	0.971* (0.112)	0.912* (0.083)	0.746* (0.069)	0.589* (0.071)	0.545* (0.102)
Degree	0.897* (0.118)	0.808* (0.090)	0.832* (0.085)	0.883* (0.124)	0.690* (0.134)	1.061* (0.204)	1.013* (0.093)	0.944* (0.100)	0.781* (0.094)	0.818* (0.161)
Occupations										
Manager	0.445* (0.141)	0.484* (0.088)	0.512* (0.104)	0.654* (0.088)	0.857* (0.186)	-0.079 (0.474)	0.794* (0.235)	0.733* (0.150)	0.648* (0.159)	0.565** (0.285)
Professional	0.463* (0.096)	0.349* (0.092)	0.381* (0.081)	0.356* (0.103)	0.535* (0.119)	0.613* (0.210)	0.870* (0.126)	1.002* (0.130)	0.927* (0.132)	0.789* (0.141)
Technician	0.274* (0.084)	0.320* (0.063)	0.377* (0.055)	0.368* (0.069)	0.470 (0.073)	0.577* (0.125)	0.795* (0.105)	0.958* (0.108)	0.861* (0.117)	0.868* (0.113)
Clerk	0.162*** (0.087)	0.219* (0.057)	0.231* (0.043)	0.187* (0.039)	0.332* (0.078)	0.095 (0.124)	0.306* (0.096)	0.422* (0.102)	0.495* (0.116)	0.447* (0.108)
Skilled	0.032 (0.062)	0.030 (0.046)	0.044 (0.033)	0.109* (0.034)	0.225* (0.060)	-0.050 (0.128)	0.114 (0.095)	0.153*** (0.091)	0.160 (0.128)	0.288** (0.123)
Agric worker	-0.292* (0.100)	-0.281* (0.082)	-0.177* (0.053)	-0.061 (0.077)	-0.017 (0.082)	-0.513*** (0.233)	-0.226 (0.168)	-0.062 (0.127)	-0.295 (0.186)	0.055 (0.361)
Artisan	0.087 (0.065)	0.034 (0.037)	-0.004 (0.027)	0.011 (0.032)	0.039 (0.052)	-0.056 (0.144)	0.118 (0.101)	0.147 (0.091)	0.032 (0.116)	-0.004 (0.115)
Elementary Jobs	-0.198* (0.054)	-0.184* (0.037)	-0.194* (0.028)	-0.188* (0.031)	-0.148* (0.047)	-0.408* (0.101)	-0.277* (0.088)	-0.242* (0.087)	-0.326* (0.109)	-0.270* (0.080)
Industries										
Agriculture	-0.563* (0.081)	-0.731* (0.057)	-0.806* (0.045)	-0.792* (0.052)	-0.72* (0.074)	-0.183 (0.131)	-0.294* (0.074)	-0.327* (0.075)	-0.433* (0.078)	-0.460* (0.092)
Mining	0.185** (0.080)	0.031 (0.046)	-0.070** (0.036)	-0.134* (0.043)	-0.133** (0.069)	0.083 (0.447)	0.396 (0.241)	0.230 (0.159)	-0.001 (0.135)	0.568 (0.390)
Electricity	0.171 (0.155)	0.278* (0.092)	0.339* (0.089)	0.285* (0.111)	0.382** (0.156)	0.723* (0.247)	0.440*** (0.236)	0.417 (0.315)	0.755** (0.377)	1.236** (0.549)
Construction	-0.153 (0.100)	-0.195* (0.056)	-0.144* (0.050)	-0.202* (0.057)	-0.178** (0.074)	0.033 (0.655)	0.166 (0.312)	0.299*** (0.161)	0.197 (0.169)	-0.092 (0.348)
Trade	-0.125 (0.085)	-0.193* (0.053)	-0.229* (0.036)	-0.252* (0.040)	-0.274* (0.062)	-0.178 (0.125)	-0.141*** (0.078)	-0.122*** (0.063)	-0.276* (0.081)	-0.183** (0.084)
Transport	-0.002 (0.134)	0.064 (0.061)	0.058 (0.038)	0.038 (0.050)	0.034 (0.082)	0.352 (0.355)	0.234*** (0.140)	0.092 (0.150)	-0.051 (0.167)	0.423** (0.169)
Finance	0.129 (0.078)	-0.004 (0.064)	-0.110** (0.042)	-0.116** (0.055)	-0.154** (0.078)	0.339* (0.121)	0.260* (0.095)	0.229* (0.078)	0.023 (0.080)	0.213 (0.134)
Social Service	0.056 (0.075)	0.090*** (0.051)	0.108* (0.036)	0.079*** (0.046)	0.040 (0.063)	-0.116 (0.107)	-0.174** (0.071)	-0.179* (0.063)	-0.257* (0.064)	-0.179* (0.071)
Unionism	0.441* (0.041)	0.348* (0.030)	0.266* (0.026)	0.216* (0.027)	0.181* (0.035)	0.525* (0.051)	0.483* (0.040)	0.486* (0.035)	0.534* (0.041)	0.536* (0.048)
Provinces										
Western Cape	0.104 (0.086)	0.090*** (0.050)	-0.017 (0.055)	-0.032 (0.052)	-0.067 (0.068)	0.306* (0.084)	0.181* (0.055)	0.090*** (0.049)	0.070 (0.051)	0.012 (0.068)
Eastern Cape	-0.520* (0.081)	-0.447* (0.070)	-0.386* (0.048)	-0.281* (0.061)	-0.326* (0.070)	-0.780* (0.089)	-0.633* (0.058)	-0.662* (0.048)	-0.580* (0.055)	-0.439* (0.071)
Northern Cape	-0.217 (0.149)	-0.117 (0.115)	-0.081 (0.072)	-0.018 (0.084)	0.040 (0.133)	-0.477* (0.138)	-0.416* (0.112)	-0.408* (0.083)	-0.399* (0.078)	-0.413* (0.076)
Free State	-0.412* (0.064)	-0.357* (0.048)	-0.355* (0.042)	-0.361* (0.039)	-0.357* (0.063)	-0.888* (0.084)	-0.867* (0.053)	-0.687* (0.060)	-0.541* (0.065)	-0.394* (0.075)
Kwazulu/Natal	-0.140** (0.066)	-0.130* (0.046)	-0.112* (0.041)	-0.103** (0.047)	-0.083 (0.065)	-0.364* (0.078)	-0.328* (0.044)	-0.355* (0.048)	-0.248* (0.052)	-0.168** (0.069)
North West	-0.255* (0.077)	-0.147* (0.049)	-0.154* (0.037)	-0.114* (0.039)	-0.121* (0.048)	-0.348* (0.079)	-0.325* (0.056)	-0.332* (0.050)	-0.239* (0.046)	-0.197* (0.057)
Mpumalanga	-0.220* (0.076)	-0.141* (0.040)	-0.126* (0.042)	-0.123* (0.042)	-0.105*** (0.062)	-0.379* (0.080)	-0.341* (0.049)	-0.350* (0.047)	-0.268* (0.049)	-0.197* (0.074)

Northern Province	-0.181*	-0.233*	-0.276*	-0.231*	-0.205*	-0.357*	-0.349*	-0.388*	-0.360*	-0.211*
	(0.080)	(0.047)	(0.046)	(0.059)	(0.087)	(0.076)	0.050)	0.042)	0.053)	0.077)
Sample Selection Correction Terms										
lambda1	-	-	-	-	-	-6.141	-5.225	-7.569**	-3.387	1.863
						(6.134)	(3.592)	(3.697)	(5.392)	(6.230)
lambda2	-	-	-	-	-	8.253	6.896	9.894**	4.294	-2.295
						(8.258)	(4.833)	(4.968)	(7.103)	(8.326)
lambda3	-	-	-	-	-	0.406	0.427	0.671**	0.297	-0.272
						(0.540)	(0.327)	(0.327)	(0.520)	(0.579)
lambda4	-	-	-	-	-	-0.052	-0.089	-0.153**	-0.101	0.019
						(0.097)	(0.055)	(0.061)	(0.098)	(0.106)
Constant	3.301*	4.857*	5.598*	5.930*	5.838*	3.409*	4.384*	5.217*	5.542*	5.052*
	(0.314)	(0.269)	(0.195)	(0.203)	(0.303)	(0.685)	(0.417)	(0.407)	(0.559)	(0.598)
Observations	6470	6470	6470	6470	6470	4949	4949	4949	4949	4949

Bootstrapped Standard errors (200, replications accounting for clustering) in parentheses* significant at 1%; ** significant at 5%*; **
*significant at 10%

Table 2c: Quantile Regressions for African Men and Women's Log Real Wages (2004)

Quantile	Males					Females				
	$\theta = 10$	$\theta = 25$	$\theta = 50$	$\theta = 75$	$\theta = 90$	$\theta = 10$	$\theta = 25$	$\theta = 50$	$\theta = 75$	$\theta = 90$
Age	0.047* (0.010)	0.03* (0.006)	0.032* (0.006)	0.035* (0.006)	0.036* (0.011)	0.026** (0.012)	0.041* (0.009)	0.031 (0.008)	0.013 (0.009)	0.018*** (0.011)
Age2	-0.0005* (0.000)	-0.0003* (0.000)	-0.0003* (0.000)	-0.0003* (0.000)	-0.0003** (0.000)	-0.0003** (0.000)	-0.0004** (0.000)	-0.0003* (0.000)	-0.0003* (0.000)	-7E-05 (0.000)
Log hours	0.362* (0.068)	0.192* (0.044)	0.1** (0.048)	0.028 (0.044)	-0.054 (0.071)	0.432* (0.034)	0.4* (0.028)	0.427* (0.030)	0.337* (0.040)	0.287* (0.042)
Married	0.147* (0.034)	0.117* (0.023)	0.11* (0.020)	0.126* (0.024)	0.178* (0.031)	0.07*** (0.037)	0.097* (0.025)	0.094* (0.022)	0.126* (0.023)	0.084* (0.025)
Education levels										
Primary	-0.027 (0.054)	0.004 (0.030)	-0.039 (0.028)	-0.074** (0.031)	-0.116** (0.046)	0.247* (0.072)	0.176* (0.038)	0.088** (0.041)	-0.003 (0.034)	0.001 (0.035)
Secondary	0.154* (0.059)	0.178* (0.032)	0.177* (0.032)	0.17* (0.030)	0.178* (0.047)	0.422* (0.065)	0.422* (0.041)	0.251* (0.043)	0.176* (0.038)	0.276* (0.036)
Diploma	0.716* (0.094)	0.769* (0.062)	0.734* (0.067)	0.637* (0.056)	0.675* (0.079)	0.683* (0.100)	0.861* (0.082)	0.684* (0.069)	0.502* (0.066)	0.493* (0.063)
Degree	0.943* (0.173)	1.01* (0.110)	1.067* (0.121)	1.122* (0.130)	1.104* (0.157)	0.742* (0.166)	0.944* (0.123)	0.611* (0.094)	0.667* (0.117)	0.792* (0.124)
Occupations										
Manager	0.572* (0.139)	0.771* (0.141)	0.754* (0.096)	0.83* (0.082)	0.955* (0.198)	0.903* (0.239)	1.053* (0.157)	1.453* (0.146)	1.463* (0.166)	1.526* (0.159)
Professional	0.451* (0.173)	0.416* (0.092)	0.251** (0.120)	0.259** (0.124)	0.563** (0.220)	0.781* (0.187)	1.027* (0.136)	1.239* (0.110)	1.051* (0.144)	0.984* (0.144)
Technician	0.341* (0.077)	0.252* (0.055)	0.207* (0.068)	0.323* (0.068)	0.504* (0.067)	0.7* (0.139)	0.842* (0.086)	0.957* (0.080)	0.963* (0.102)	0.831* (0.099)
Clerk	0.15 (0.092)	0.176* (0.054)	0.162* (0.056)	0.37* (0.061)	0.52* (0.088)	0.256*** (0.135)	0.393* (0.083)	0.65* (0.080)	0.635* (0.092)	0.602* (0.090)
Skilled	-0.05 (0.059)	-0.011 (0.048)	-0.047 (0.040)	0.001 (0.046)	0.165* (0.057)	-0.02 (0.127)	0.158*** (0.083)	0.329* (0.078)	0.357* (0.102)	0.353* (0.094)
Agricwkr	-0.052 (0.234)	-0.223* (0.074)	-0.327* (0.077)	-0.334* (0.132)	-0.195* (0.093)	0.168 (0.549)	0.149 (0.182)	0.04 (0.137)	-0.013 (0.325)	-0.438 (0.361)
Artisan	-0.013 (0.042)	0.018 (0.034)	-0.029 (0.031)	0.043 (0.032)	0.093*** (0.051)	-0.167 (0.147)	0.005 (0.078)	0.121*** (0.067)	0.106 (0.096)	-0.045 (0.104)
Elementary	-0.227* (0.044)	-0.194* (0.027)	-0.233* (0.027)	-0.2* (0.027)	-0.15* (0.044)	-0.24** (0.105)	-0.096 (0.070)	-0.095 (0.065)	-0.145*** (0.085)	-0.24* (0.085)
Industries										
Agriculture	-0.272* (0.059)	-0.378* (0.040)	-0.504* (0.032)	-0.6* (0.038)	-0.605* (0.064)	0.016 (0.096)	-0.079 (0.063)	-0.191* (0.048)	-0.313* (0.070)	-0.328* (0.069)
Mining	0.281* (0.060)	0.248* (0.040)	0.201* (0.040)	0.113** (0.052)	0.144*** (0.074)	-0.117 (0.358)	0.066 (0.288)	0.044 (0.245)	0.133 (0.350)	1.006* (0.288)
Electricity	0.202 (0.147)	0.028 (0.087)	0.158** (0.061)	-0.039 (0.066)	-0.099 (0.177)	0.632* (0.250)	0.683* (0.208)	0.65* (0.162)	0.386* (0.164)	0.452* (0.160)
Construction	-0.121 (0.075)	-0.143* (0.053)	-0.146* (0.041)	-0.188* (0.043)	-0.189* (0.074)	0.015 (0.131)	0.051 (0.110)	-0.003 (0.083)	0.246 (0.158)	0.278 (0.175)
Trade	-0.255* (0.056)	-0.263* (0.041)	-0.209* (0.037)	-0.198* (0.040)	-0.22* (0.070)	-0.089 (0.107)	-0.179* (0.068)	-0.268* (0.058)	-0.269* (0.073)	-0.213* (0.072)
Transport	-0.008 (0.091)	0.049 (0.057)	0.104*** (0.053)	0.11** (0.053)	0.126*** (0.073)	0.332* (0.127)	0.252* (0.103)	0.258* (0.117)	0.414* (0.127)	0.649* (0.113)
Finance	-0.055 (0.079)	-0.065 (0.056)	-0.114** (0.048)	-0.083 (0.057)	-0.133*** (0.069)	0.251*** (0.131)	0.137*** (0.076)	0.051 (0.063)	0.092 (0.077)	0.073 (0.078)
Social services	-0.075 (0.072)	0.027 (0.049)	0.111** (0.041)	0.108** (0.039)	0.087 (0.062)	-0.057 (0.092)	-0.146* (0.059)	-0.162* (0.044)	-0.193* (0.069)	-0.118*** (0.067)
Unionism	0.513* (0.035)	0.483* (0.027)	0.385* (0.026)	0.344* (0.026)	0.253* (0.034)	0.71* (0.053)	0.654* (0.038)	0.606* (0.036)	0.584* (0.038)	0.603* (0.037)
Provinces										
Western Cape	-0.109*** (0.062)	-0.085 (0.061)	-0.131* (0.037)	-0.115* (0.042)	-0.213* (0.055)	0.164 (0.115)	0.016 (0.049)	-0.034 (0.043)	0.01 (0.051)	0.01 (0.051)
Eastern Cape	-0.354* (0.073)	-0.293* (0.052)	-0.213* (0.044)	-0.129* (0.043)	-0.152* (0.057)	-0.615* (0.065)	-0.57* (0.046)	-0.507* (0.042)	-0.352* (0.048)	-0.4* (0.042)
Northern Cape	-0.438* (0.097)	-0.289* (0.050)	-0.201* (0.052)	-0.049 (0.071)	0.019 (0.104)	-0.253 (0.178)	-0.281* (0.071)	-0.21* (0.060)	-0.191* (0.069)	-0.262* (0.076)
Free State	-0.427* (0.061)	-0.356* (0.040)	-0.351* (0.034)	-0.328* (0.046)	-0.334* (0.055)	-0.669* (0.072)	-0.583* (0.058)	-0.509* (0.038)	-0.458* (0.046)	-0.514* (0.042)
KwaZulu/Natal	-0.171* (0.048)	-0.114* (0.034)	-0.055 (0.034)	0.038 (0.034)	0.005 (0.045)	-0.333* (0.055)	-0.3* (0.040)	-0.277* (0.037)	-0.266* (0.037)	-0.3* (0.033)
North West	-0.193* (0.059)	-0.206* (0.038)	-0.207* (0.040)	-0.183* (0.040)	-0.205* (0.060)	-0.333* (0.072)	-0.323* (0.050)	-0.28* (0.046)	-0.244* (0.042)	-0.287* (0.040)
Mpumalanga	-0.309* (0.063)	-0.254* (0.042)	-0.259* (0.037)	-0.167* (0.051)	-0.051 (0.080)	-0.532* (0.084)	-0.433* (0.057)	-0.404* (0.043)	-0.339* (0.045)	-0.296* (0.047)

Northern Province	-0.315*	-0.226*	-0.216*	-0.149*	-0.185*	-0.517*	-0.545*	-0.435*	-0.337*	-0.311
	(0.080)	(0.042)	(0.044)	(0.050)	(0.056)	(0.070)	(0.051)	(0.040)	(0.047)	(0.043)
Sample Selection Correction Terms										
lambda1	-	-	-	-	-	-3.029	-8.249**	1.175	3.254	0.977
						(3.305)	(3.021)	(2.125)	(2.836)	(2.734)
lambda2	-	-	-	-	-	3.897	11.25**	-1.349	-4.657	-1.632
						(4.460)	(4.047)	(2.903)	(3.803)	(3.676)
lambda3	-	-	-	-	-	0.248	0.73**	-0.215	-0.248	0.028
						(0.303)	(0.278)	(0.186)	(0.262)	(0.254)
lambda4	-	-	-	-	-	0.044	-0.077***	0.042	0.033	-0.001
						(0.046)	(0.047)	(0.028)	(0.043)	(0.041)
Constant	3.755*	4.997*	5.733*	6.188*	6.739*	3.756*	4.029*	3.811*	4.863*	5.405*
	(0.333)	(0.225)	(0.210)	(0.222)	(0.379)	(0.436)	(0.340)	(0.283)	(0.335)	(0.341)
Observations	5918	5918	5918	5918	5918	5121	5121	5121	5121	5121

Bootstrapped Standard errors (200, replications accounting for clustering) in parentheses* significant at 1%; ** significant at 5%; **
*significant at 10%

Table 3: Gender gaps (Observed and Counterfactual) 1995, 1999 and 2004

	$\theta = 10$	$\theta = 25$	$\theta = 50$	$\theta = 75$	$\theta = 90$
Observed	0.56	0.41	0.36	0.16	0.11
Counterfactual	0.60	0.46	0.29	0.14	0.17
1995 % of observed gap due to different returns	107	112	81	88	154
Observed	0.56	0.76	0.55	0.11	0.13
Counterfactual	0.59	0.69	0.51	0.18	0.15
1999 % of observed gap due to different returns	105	91	93	164	115
Observed	0.66	0.61	0.60	0.15	0.05
Counterfactual	0.52	0.44	0.44	0.15	0.13
2004 % of observed gap due to different returns	79	72	73	100	260