2000 Annual Forum
at Glenburn Lodge, Muldersdrift

Wage Premia and Wage Differentials in the South African Labour Market

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Haroon Bhorat[1]

Introduction

Studies of labour demand patterns for the South African economy have indicated clear patterns of preference amongst firms. The studies show that the demand for skilled and highly skilled workers has increased dramatically over the last two and a half decades. This has been matched though by an almost equal decline in the demand for unskilled workers (Bhorat & Hodge,1999; Bhorat,1999). These studies, and others similar to them however, suffer from a key drawback: they fail to account for wages in their analysis. While the methodologies used often assumed constant wages, the key difficulty in including wages in the discussion was a lack of data. Indeed, to date, no time series of wage data by skill exists for South Africa. This study suffers from that same defect. The intention of this study is therefore less ambitious, as is tries to present some of issues that are relevant when considering the role of wages in a skills-constrained, yet high skilled labour growth economy. The picture will be static, utilising household survey data for one year, and concentrates essentially on the degree and extent of wage inequality and the existence of wage premia in the labour market. The study is an attempt then, to take close off the previous employment work done on the South African labour market, in the form of analysing wage data.

Wage Differentials: Descriptive Statistics

The data utilised for this section and the rest of the paper is drawn from the October Household Survey of 1995. While the OHS97 was the latest available survey data set at the time of writing, the wage data in the questionnaire is structured in such a way that individuals who do know or refuse to provide their actual wage income are given the option of coding their earnings according to predefined income bands. The income bands are in turn classified as weekly, monthly or annual categories. This option however seems to have been a fatal mistake, as the data that was eventually captured and made public by Statistics South Africa (SSA) according to actual incomes is applicable to only a portion of the sample. Clearly, for any analysis of wages and wage differentials, this data is inadequate. We are forced therefore to revert to the OHS95, which has actual income figures and noticeably does not have an income band option in the questionnaire.

The earnings data are all in standard monthly figures. The figures were thus not adjusted to derive earnings per month controlled for by hours worked. The reasons for this were that firstly, 92% of the employed worked 35 hours or more in the week preceding the interview[2]. Hence the overwhelming majority of the sample did in fact

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[2] The 35 hour week is used as the cut-off period between full-time and part-time work in the questionnaire.

work full-time. In addition, of those individuals who worked part-time or less than 35 hours, the median hours worked was 25 per week. This means that even for those employed on a part-time basis, the hours worked was quite high. Not surprisingly, the data showed that it was those in the labourer categories, who predominated amongst the part-timers. Yet, even here, the median hours worked was again high, at 21 hours per week. Therefore, given the overwhelming predominance of full-time work amongst the employed, the decision was to present all earnings data as monthly, without recourse to their hourly equivalents.

Using the OHS95 then, the table below presents the first basic cut of wage data amongst the employed. The employed here refers to those both in the formal and informal sector, who number approximately 10 million individuals[3]. Table 1 shows that the median wage for the economy is about R1400 per month. White median wages are the highest amongst the race groups, while that of male workers is higher than females. Interestingly, the median wage of Africans and Coloureds are essentially the same, constituting under a third of the median White income. While the wage for Indians is distinctly above that of Coloureds and Africans, they still remain only about half of the White wage.

Table 1: Median Wages by Race and Gender

Category	**Median**	**% of White/Female**
Race		
White	4000	100.0
Asian	2310	57.8
Coloured	1083	27.1
African	1082	27.1
Gender		
Male	1555	100.0
Female	1200	77.2
Total	1400	35.0/ 90.0

This racial-wage cleavage is not evident when looking at the data by gender. Here, while the male wage is higher, female wages are, at the median, over three-quarters the value of the male wage. This result is picking up the large number of Asian and White females whose wages are in fact higher than many African and Coloured males. Indeed, the data shows that the median wage for White females is R2600 and for Asian females, R1600 per month – both of which are higher than the respective medians for African and Coloured males. This basic wage differential data suggests that while the race-wage gap is still very strong, the gender-wage difference is not as stark. In terms of a wage-driven model of segmentation, there is a decidedly contrasting labour market operating for Africans and Coloureds on the one hand, and Asians and Whites on the other. The gender differentiation though, appears to be less marked.

The table below extends the wage discussion, by examining median wages according to education cohorts. The wage structure is of course monotonically linked to the different education levels, with higher education levels associated with increased

[3] Note that this number utilises the weights within the OHS95 data set. Using the Census 96 weights, the employed number approximately 9.4 million. In either case though, the wage data will not be altered.

median wages. This is of course a result borne out in most earnings function analyses (see Bhorat & Leibbrandt,1999b and Schultz & Mwabu,1996). It is important to note that even though individuals with a tertiary degree earn the most, their median wage is still below that paid to White workers. This would suggest that race, together with education is still an important predictor of earnings in South Africa. Again though, the labour market in wage terms is segmented quite clearly by education levels: individuals with a matric or degree earn significantly more at the median, than those with a Std. 9 qualification or less.

Table 2: Median Wages by Education Levels

Education levels	Median	% of Tertiary
Tertiary	3500	100
Matric	2420	69.14
Std. 6-9	1248	35.66
Sub. A-Std. 5	631	18.03
No education	501	14.31

While the matric median wage is close to 70% of the median degree wage, for those with less than a matric their median income falls by 35 percentage points relative to the highest earner. What is evident is a different labour price attached to those with incomplete secondary education compared to those workers with primary schooling. While incomplete secondary education would yield a median wage return that is 36% of the highest median, this differential increases dramatically when individuals have primary schooling or less. In addition, there is no significant difference in the median wage for these latter two education categories. We are left then with three distinct wage segments in the labour market: one for those workers with a matric or more, those individuals who have some secondary education and finally individuals who have primary schooling or no education.

Labour demand trends for the period 1970-95 indicate very similar patterns to these wage differentials. Hence the demand trends reveal declining demand for workers with primary schooling or no education, and an increase in the demand for those with a Standard 6 education or more. The largest increases in demand were reserved for those with a matric or tertiary education. It is clear therefore that these wage differentials reflect these employment trends. Specifically, the increased demand for those at the top end has resulted in a widening differential between high-education (matric or more) and low-education (primary schooling or less) workers.

Location effects are also important descriptors of wages. Whilst the data is not presented here, urban median wages are of course the highest, followed by peri-urban and then rural wages. The median rural wage is R667 per month, which is approximately 37% of the urban median income. This makes it plain that rural labour markets offer decidedly lower returns than those in urban areas.

The table below presents median wages by nine main sectors, as defined by the SIC system. While the Utilities sector (Electricity, Gas & Water) pays the highest median wage, Financial and Business services, together with Community and Social Services, are essentially at the same median. The lowest paying sector, by quite a large margin, is Agriculture. This is followed by the Construction sector and then Wholesale & Retail Trade.

Table 3: Median Wages by Sector

Sector	Median	% of Utilities
Agriculture	436	17.36
Mining	1500	59.71
Manufacturing	1500	59.71
Utilities	2512	100
Construction	1212	48.25
Wholesale & Retail Trade	1346	53.58
Transport	2177	86.66
Financial & Buss. Services	2500	99.52
Community services	2500	99.52

Noticeably, it is the three key service sectors that yield the highest median wages. The discrepancy between the two primary sectors is partly, though not solely, a function of different union density figures in the two sectors, with the mining industry being highly organised. An interesting switch occurs in the primary sectors when looking at the wage data: while these two sectors are relatively low-paying, White workers in these sectors have the highest median wage across all sectors for all race groups. The race figures also show that across all sectors the median wages of Africans and Coloureds are very similar, while the sector differential for Asians and Whites is smaller. The Community Services sector reflects public sector employees primarily, and this result reinforces the notion of the sector being the largest employer, as well as a relatively high-wage employer.

No descriptive wage statistics would be complete by not examining median wage data by occupations. Occupations here are classified according to the International Standard Occupational Classification (ISOC) system. The usefulness of the OHS95 data set is that we are able to divide the labourer categories into greater detail, hence the existence of six different unskilled categories in the data. The table also presents the wage data by race, as this elicits some interesting comparisons across occupations. Note that domestic helpers, in the language of the survey, refer to domestic helpers and cleaners, helpers and cleaners in offices, hotels and other establishments and hand launderers and pressers. In other words, Domestic Helpers do not encapsulate domestic workers in private households, as these individuals are coded separately.

Looking at the total column, the wage structure is fairly predictable, with the highest median earners being Managers, followed by Professionals and then skilled agricultural workers. The lowest earners are domestic workers, followed by farm workers and then labourers in the Mining industry. Note though that the median wage of unskilled workers in the mining industry is still over twice as much as that earned by farm labourers as well as domestic workers. This yields the well known fact that the two most indigent workers in the labour market are domestic workers and farm labourers (Bhorat & Leibbrandt,1999a; Bhorat,1999).

Table 4: Median Wages by Occupation and Race

Occupation	African	Coloured	Asian	White	Total	*% of Managers (Total)*	*African as % of White*
Managers	1887	2650	N/O	4500	5400	*100*	*41.9*
Professionals	2646	3000	5000	7500	4670	*86.48*	*35.3*
Skilled agriculture	3379	4000	5433	6588	3724	*68.96*	*51.3*
Technicians	2646	3085	3500	4670	3180	*58.89*	*56.7*
Armed forces	1600	1500	2000	2500	2177	*40.31*	*64.0*
Clerks	1249	1200	1600	2500	2000	*37.04*	*50.0*
Craft	755	1100	3333	6612	1625	*30.09*	*11.4*
Services and sales	1200	1346	2000	4500	1438	*26.63*	*26.7*
Machine operators	1280	1200	1500	3283	1323	*24.5*	*39*
Trprt. Labourer	1140	950	900	4667	1115	*20.65*	*24.4*
Manuf labourer	1000	900	1325	2000	1000	*18.51*	*50*
Domestic helpers	975	800	1250	1100	950	*17.59*	*88.6*
Mining labourer	900	800	1520	2600	900	*16.67*	*34.6*
Agric. Labourer	400	464	257	1346	420	*7.78*	*29.7*
Domestic worker	380	360	750	750	380	*7.03*	*50.7*
Unspecified	1150	1900	1500	4057	1399	*25.91*	*28.3*

The race data for the individual occupations do though reveal some interesting trends. Taking the unskilled categories first, there is a strong differentiation in wages by occupation. For example, even though both African and White individuals may be coded as Manufacturing labourers, the median wage of the former is only half that of the latter. In fact, for all the labourer categories, it is clear that African workers are paid significantly less than their White counterparts. While this may be raised as serious evidence of continued discrimination in the labour market, closer inspection of the data reveals that for all these unskilled categories, White workers constitute less than 2% of the employment shares. We are in essence then, talking of a very small share of workers, and it is likely that the discrepancy in wages will be a function of continued discrimination, differing levels of experience, higher number of schooling years and so on. Ultimately though, the apparent stark contrast in median wages at the bottom-end can be ignored, given the insignificant number of white employees being considered.

For the semi-skilled and skilled occupations, the median wage differential between Africans and Whites remains. In this case, the share of African employees is significant, ranging from 35% of the share of professionals to being 76% of the share of machine operators in the economy. Hence, the differential that persists within these semi-skilled and skilled occupations does not pertain to an insignificant share of African workers. The data then delivers an intriguing puzzle: Why is it that while formally coded together as skilled or semi-skilled, African workers earn consistently less than their White counterparts? For example, an African professional will earn a median monthly wage of R2646, while a White professional will earn over twice as much at R7500 per month. We know from work done on earnings functions that ‘observable’ variables such as education, experience and location may account for these differences within the occupations (Bhorat & Leibbrandt,1999b). Descriptive statistics however, cannot be used to effectively account for the contribution of each of these variables in explaining the differentials by occupations. We therefore utilise regression analysis, as contained in the earnings function literature, to explain the precise causes of the wage differentials by occupations.

Modelling Occupation-Level Wage Differences by Race

The approach taken here is to determine in a multivariate framework, what factors may help explain the differing wages of African and White employees within the same occupations. While we know of course that factors such as education and experience are important determinants, the optimal way of measuring the relative simultaneous strengths and contributions of these variables, is to estimate different earnings functions. We estimate two earnings functions for each race group. The first is a skilled worker earnings equation for Africans and Whites, and the second a semi-skilled equation for the same two race groups. Skilled workers here, based on Table 4, refers to workers categorised as managers, professionals and technicians. Semi-skilled workers covers clerks, service & sale workers, machine operators and craft workers. In total then, four regressions are run, two within each skills band.

Following the standard methodology, we estimate the 'observable' determinants of log wages, by including the following variables:

- Gender (where female is the referent variable)
- Location (where urban is the referent variable)
- Province (where the Western Cape is the referent province)
- Sector (where Agriculture is the referent sector)
- Education
- Union Status (where being a union member is the referent)
- Experience
- Hours worked

The education variable is divided into three categories, namely those with Std. 5 or less; those with some secondary schooling (including a matric) and finally individuals with tertiary education. Given that we convert these education categories into splines, there is no need for a referent education level. Experience is calculated as the age of the individual minus the number of years of education, less 6. It assumes that a worker begins working immediately after completing her education, and that the age of school completion will be schooling years plus 6. In essence it is a proxy for experience, rather than reflecting actual years of experience, given that data on actual experience is very hard to collect, and almost always absent in household survey questionnaires. The hours of work variable is important as it acts as an additional controller for using monthly earnings rather than hourly equivalents. In this respect the variable will represent the impact of an additional hour worked on wages earned.

The table below presents the results from the earnings equation estimation on skilled workers. The Heckman selection bias correction was not utilised here or in the semi-skilled regressions, given that the probability of sample bias for very specific segments of labour market individuals as these, was unlikely to induce selection bias. Indeed, regressions run for each of the occupations individually by race, using the Heckman correction technique, yielded an insignificant lambda term throughout, suggesting that no selection bias was present. Standard OLS regressions were therefore run for the four sub-samples above.

Table 5: Earnings Function Results for Skilled Workers

Variable	African	White
Female	-0.151*	-0.491*
Urban	0.055	0.050
None-Std5	0.037**	0.010
Std 6-10	0.122*	-0.004
Tertiary	0.159*	0.256*
E.Cape	-0.040	-0.084
N.Cape	-0.359	-0.150
Free Stat	-0.238**	-0.126
Kwaz/Natl	-0.099	0.080
North-W	0.026	0.081
Gauteng	0.130	0.200*
Mpumal	-0.104	-0.138
N.Prov	0.181	0.015
Mining	-0.176	0.225
Manuf	-0.061	0.436*
Electricity	0.163*	0.348*
Constr	-0.052	0.204
Wholes	-0.044	0.288*
Transport	0.219*	0.374*
Finance	0.331*	0.232*
Comm Serv	0.101	0.343*
Union member	0.036	-0.086**
Experience	0.035*	0.076*
Experience ^{2}	-0.001*	-0.001*
Log of Hours p.m.	0.286*	0.494*
Constant	5.086*	4.777*
No of Observations	2663	2536
F Statistic	29.72	58.23

*: Significant at the 1% Level.

**: Significant at the 5% Level.

Examining the skilled occupation results, it is clear that the important variables are education, experience and hours of work. The education splines for skilled Africans are all significant, with the latter two splines significant at the 1% level. In addition, higher levels of education are associated with higher internal rates of return. Hence a skilled African worker with a tertiary education will earn 16% more from an additional year of education, compared to a return of 4% for those with primary education or less. The difference with White skilled workers is immediately evident though, given that it is only the tertiary education spline here that is significant (at the 1% level). In other words, for White skilled workers, the rate of return to education is only affected, once they attain tertiary levels of education. The rate of return to tertiary education is 26%.

In the first instance then , the significance of the two sets of coefficients make it clear that the educational distributions of African and White skilled workers are different.

White skilled workers appear to be concentrated at the top-end of the education spectrum, while African skilled workers are distributed more evenly across the education levels. Descriptive statistics suggest that while 36% of all white skilled workers have at least a matric, the figure for skilled Africans is 21%. The figures for incomplete secondary education are 14% for Africans and 8% for White workers. It is possible that the inclusion of informal sector operators as managers biased the education levels of Africans downwards, although their sample size is small enough to make little substantive difference to the final results. These results suggest that the first key reason for the wage differentiation between African and White skilled workers, is the higher absolute levels of education amongst White skilled workers, compared to skilled African employees.

A second important deduction from the results, is that the rates of return on the tertiary education variable are higher for Whites than Africans. Hence, while Whites can expect a 26% return on each additional year of tertiary education, for Africans the figure is only 16%. This is surprising given that previous regression results have noted a higher return for Africans instead (Schultz & Mwabu,1998). This higher return for Africans is argued as being due to the lower supply of African high-education workers, resulting in a wage premium on these rationed workers (Schultz & Mwabu,1998). However, these results did not divide the workforce into skills categories, and furthermore did not include any sector or provincial dummies. These two factors may explain, in terms of model specification, the different results obtained. How though, do we explain the higher return on education for skilled White employees in the particular specification used here?

It is possible that there is a quality differential that is actual and also perceived by prospective employers. Hence, the quality of a tertiary degree obtained by African workers may be lower than that obtained by White graduates. The differential in quality would be a function primarily of the contrasting resource allocation between historically white universities (HWUs) on the one hand and historically black universities (HBUs) on the other. With the latter attracting a disproportionate share of the state's annual allocation, the quality of the degrees produced would be higher. These quality differences in turn, translates into a higher return for White workers who are the majority of students at HWUs. The differential may be reinforced at the point of job entry, where employers perceive a HWU degree to be of higher quality than a HBU degree, so perpetuating the skilled wage gap through providing higher returns to White employees.

A further reasoning for the different rates of return, revolves around the notion that the tertiary degree is a heterogenous product. In other words, not all human capital accumulation at the tertiary level will result in the same labour demand responses from firms. Simply put, labour demand trends may indicate a demand for say computer-related or engineering-related degrees above all others. There is a probability that African skilled employees are disproportionately accumulating human capital in areas where labour demand is lower. Such human capital will therefore be rewarded at different rates – as based on firms' labour demand specifications. The table below presents important evidence in this regard. Using the skilled occupations, and breaking them down beyond the categories provided in Table 4 above, the table below illustrates that there has clearly been contrasting patterns of human capital accumulation amongst skilled African and White workers.

Table 6: African and White Skilled Employment: Selected Occupations

African	% of Total Skilled Share	White	% of Total Skilled Share
Primary education teaching professionals	17.55	**General Managers**	16.53
Other teaching associates	14.37	**Finance & Sales Associate Professionals**	10.23
Nursing & midwifery	10.09	**Physical & engineering science technicians**	8.95
Total	100.00	**Total**	100.00

The table presents the three largest skilled occupation shares for Africans and Whites. It is clear that African employees are represented primarily in teaching and nursing occupations. In contrast, white employees are represented in managerial, service professional and scientific professional occupations [4]. Labour demand trends indicate that there has been a significant rise in the contribution of the service sectors to national GDP (Bhorat & Hodge,1999). It is in these sectors primarily, that the three largest white skilled occupations will be located. In contrast, while there is no doubt a need for skilled individuals in the education and health industries, the labour demand trends do not suggest a larger relative increase in the need for these labour types.

The above has made it clear that the educational coefficients for African and White skilled workers underpin some important labour market information. These are firstly, that skilled African workers are on average less educated than skilled White workers. Secondly, that the higher returns to tertiary education are a result of a perceived and actual quality differential in African and White educational qualifications. Finally, more detailed divisions of the skilled band indicates that White workers are found predominantly in occupations which yield much higher wages (and therefore higher rates of return on education), given that these skill types are in high relative demand in the labour market.

The sector dummies support the above education coefficient results. For African skilled workers, it is only individuals in the Transport and Finance sectors, who are likely to earn more than those in Agriculture. Hence, being in the other sectors for skilled Africans, is not in and of itself a significant contributor to earnings. For skilled White workers on the other hand, every sector dummy, barring that of Utilities, is significant. This suggests that skilled White workers are well distributed across all non-agricultural sectors in the economy, and at high enough wage levels, to ensure that their earnings will be increased by being present in that sector.

The experience coefficients are significant at the 1% level for both race groups. This suggests that for each additional year of experience, both skilled groups will see their earnings rise. However, the return on an additional year of experience is greater for

[4] The managerial staff refers to general managers in all nine main sectors of the economy. The Finance and Sales Associate Professionals refers to individuals such as securities and finance dealers and brokers; insurance representatives; estate agents and so on.

White workers than African workers. For each additional year of experience, skilled White workers' wages will increase by about 7.5%, while the figure for Africans is only 3.5%. Given that all we have is a proxy for experience and not actual experience, this would suggest that White workers are on average older than African workers, and hence one would expect the higher unit returns on experience. While not representing overwhelming evidence, the descriptive data does bear this out: while 48% of skilled Africans are 35 or less, the figure for Whites is 40%. The log of hours worked coefficient is also significant at the 1% level for both race groups. Again though, the wage return to working an additional hour is far greater for Whites (49.4%) than Africans (28.6%), with the return to the former being almost twice as large. This may reflect on the different skilled occupations Africans and Whites are found in, with the hourly returns to Whites being greater given the more lucrative occupations they are found in. Hence, an additional hour of work for a nurse is likely to yield a far lower return than an additional hour of work for an engineering technician.

A final interesting result from the skilled regression is the gender dummy. For both race groups, being a female skilled worker reduces the wage earned. However, it is interesting that while being an African female, reduces earnings by about 15.1%, the figure for Whites over three times as large – at 49%. At the margin then, the lower return for White skilled females in fact serves to reduce the overall differential between African and White skilled workers.

When examining the regressions results for semi-skilled workers, it is clear that the same variables are important determinants of the differential wages paid to each of the race groups. In the equations below, the occupation 'skilled agricultural worker' was excluded, given that its categorisation is an odd one, and difficult to define and attach to specific work activities. A detailed look at the category shows for example, that hunters and trappers are combined with dairy and livestock producers.

Table 5: Earnings Function Results for Semi-Skilled Workers

Variable	African	White
Female	-0.309*	-0.373*
Urban	0.128*	0.002
None-Std5	0.039*	-0.074
Std 6-10	0.128*	0.137*
Tertiary	0.017	-0.031
E.Cape	-0.011	-0.064
N.Cape	-0.074	-0.138
Free Stat	-0.165*	0.010
Kwaz/Natl	0.128*	0.050
North-W	0.144*	0.037
Gauteng	0.205*	0.163*
Mpumal	0.139*	0.089
N.Prov	0.205*	-0.004
Mining	-0.835*	-0.047
Manuf	-0.129*	0.249*
Electricity	-0.168*	0.091*
Constr	0.166*	0.106
Wholes	-0.261*	0.144*
Transport	-0.252*	-0.125*
Finance	0.070**	0.088**
Comm Serv	-0.063	-0.033
Union member	0.180*	0.147*
Experience	0.034*	0.056*
Experience ^{2}	-0.000*	-0.001*
Log of Hours p.m.	0.042**	0.516*
Constant	5.896*	4.629*
No of Observations	7396	3179
F Statistic	157.59	72.74

*: Significant at the 1% Level.
**: Significant at the 5% Level.

The results show, in the first instance, that the urban variable is significant at the 1% level for semi-skilled African workers, but not for Whites. In other words, being in an urban area will cause the earnings of African semi-skilled employees to rise (by about 12.8%), while for Whites the location variable is insignificant. This may partly explain some of the differential between these groups: that with Whites being predominantly in urban areas, the wages they earn are on average likely to be higher than those of African workers. The data reveals that amongst the semi-skilled, while 63% of Africans are in urban areas, 93% of Whites work in urban labour markets.

The education variables are different from the skilled earnings equations, in that the tertiary spline is insignificant. Given that we are examining semi-skilled workers, with lower mean levels of education, this is not a surprising result. Again though, it is clear that the mean education levels of African workers is lower than their White counterparts, given that the primary schooling variable is significant for Africans, but not for Whites. Indeed, the data shows that while 23% of semi-skilled Africans have only primary schooling, less than 1% of Whites are in this category. The lower mean education levels of African semi-skilled workers is a key reason then, for the differential semi-skilled median wages reported in Table 4 above.

In terms of secondary education, both coefficients are significant, with African workers reporting a slightly lower rate of return[5]. Hence for each added year of secondary education, African semi-skilled wages increase by 12.8%, while for Whites, the figure is 13.7%. Differential rates of return on education are therefore an important reason again for the higher median wages of White semi-skilled workers, although the differential is not as great as the skilled coefficients. The descriptive statistics indicate that of semi-skilled Africans, 21.2% have a matric, while 54% of White semi-skilled workers have this qualification. In other words, the relatively higher qualifications amongst secondary school Whites, accounts for the education variable's contribution to the overall differential. In other words, firms are simply providing a higher return, because on average the completion rates for secondary schooling is higher amongst semi-skilled Whites. In addition though, the quality of schooling does also play a role in explaining the different returns. As with the discussion for skilled workers, it is also true that there may be actual and perceived quality differences that contribute to the higher White rates of return.

The union variable is significant at the 1% level for both races. The union-wage effect shows a larger increase for unionised Africans than Whites, with the former's wages increasing by 18%, and those of Whites by about 15%. While being a union member does impact on race-based earnings, it in fact assists in marginally reducing the wage gap between the races. The experience coefficient also shows different rates of return. For African semi-skilled workers, every year of experience provides a 3.4% return, while for Whites it is 5.6%. Again, however, the differences are not dramatic. The hours of work coefficients, however are very different. For each additional hour an African semi-skilled individual works, their earnings increase by about 4%, while for Whites, the figure is 52%. This is an extremely large differential, and one that is, at first glance, difficult to explain. The major employment distributions within the semi-skilled band may though provide possible clues. The employment distributions indicate that the largest share of White workers are secretarial staff and keyboard operators. It is possible that this cohort of workers work more on an hourly rate basis, so hiking the returns to hours worked. Hence, the predominance of part-time work amongst this group may be dominating the log of hours coefficient, so explaining the large discrepancy[6].

Finally, as with the skilled regressions, the gender dummy is significant and negative at the 1% level for both races. Again though, the wage reduction for being female is larger for Whites than Africans. White semi-skilled individuals will see their wages drop by 37% if they are female, while for Africans, the figure is 31%. Hence, the lower return for African females serves to reduce the overall wage differential between the two race groups in the semi-skilled cohort.

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[5] It is important to note that for Africans there is an increase in the returns to education when moving from primary to secondary schooling, to the value of about 9 percentage points.

[6] Interestingly, the employment distributions for African and White semi-skilled workers are very similar, with the two of the three largest occupations being the same, namely protective service workers and shop salespersons & demonstrators.

Ultimately, the wage differentials for semi-skilled workers would seem to be a function of both differential rates of return to education and lower absolute levels of human capital amongst African workers. In addition, the larger share of African workers in rural areas, also serves to decrease the median semi-skilled wage. The union variable contributes to narrowing the semi-skilled wage gap, while the experience variable is important, yet not highly significant, in widening the differential. In contrast the log of hours worked is key in explaining the wage gap between the semi-skilled cohorts[7]. The gender and union variables however, combine to reduce the wage gap between the two race groups, although of course the reduction is ultimately marginal.

The above has tried to interrogate the possible causes of wage differentials between Africans and Whites within, what are ostensibly the same skill bands and categories. The results show that for both skilled and semi-skilled categories, education is the key explanatory variable for the wage differential – either in the form of internal rates of return or absolute levels of human capital. In addition, both the levels of experience of White workers and the hourly return rates, contribute to the overall White-African differential. Although less robust, results show that the gender dummy and the union status variable, in certain cases, do contribute to reducing the overall wage gap between the races.

Wage Distribution Patterns

While the above is very useful as a discussion of median wages and wage differentials, we still exclude a picture of the entire wage distribution. The purpose then of this section, is to try and disentangle the wage distribution, at the percentile level, to try and gain a more naunced picture of wage premia and wage differentials in the South African labour market.

Table 6 below calculates a set of log wage percentile differentials by race group. Looking across the race groups, and the total column, clearly the largest wage gap is for the 90-10 differential, as it represents workers at the top-end and bottom-end of the labour market. There are however interesting aspects relating to the other percentiles, specifically the 90-50 and 50-10 differentials. The former would represent those workers at the top-end of the distribution relative to those at the median of the distribution, while the latter compares the median to the bottom-end wage earner. For all race groups, and for the aggregate figures, it is evident that the 90-50 differential is larger than the 50-10 differential. For example, for Africans the 90-50 figure is 3.29 and the 50-10, 2.90. The figures for Whites are 3.84 and 3.42 respectively. In other words, there is greater wage inequality in the top-half relative to the bottom half of the wage distribution. This may indicate the existence of a wage premium for those workers in the 90th percentile, given their scarce supply – a premium that is not operative to the same degree for those at the median, when compared with the 10th percentile earners. Put differently, the scarce supply of highly skilled workers leads to a significant wage premium on their labour, so resulting in a

[7] As is no doubt apparent, the sector dummies are negative in many cases. With Agriculture as the referent sector, this is of course very puzzling particularly in the case of Africans, where most of the coefficients are negative. The only plausible explanation is that outliers in the sample are coded as being in Agriculture, and are earning very high wages.

greater degree of inequality in the top-half of the wage distribution[8]. Note that these contrasting differentials also extend to the figures for the 75-50 and 50-25 percentiles, where the former outweighs the latter across all race groups.

Table 6: Inequality Measures for Log Wages, by Race

Percentile Differentials	Africans	Coloureds	Asian	White	Total
90 - 10	3.44	3.44	3.78	3.98	3.67
75 - 25	3.13	3.10	3.44	3.61	3.34
90 - 50	3.29	3.30	3.66	3.84	3.56
50 - 10	2.90	2.87	3.16	3.42	3.02
75 - 50	2.88	2.86	3.24	3.38	3.16
50 - 25	2.77	2.74	3.00	3.23	2.87
Std. Dev.	3583.404	2691.033	7215.95	18641.71	9678.106
Gini	0.51	0.50	0.55	0.56	0.62

The comparisons of percentiles across race groups, also yields very interesting results. Across all the percentiles, it is clear that the degree of inequality is greatest amongst White workers, followed by Asian workers. The inequality ranking amongst African and Coloured earners varies across the percentiles, but in essence remains smaller than those of Asians and Whites. In terms of wage inequality levels then, there would appear to be greater wage compression amongst Coloured and African workers than Asians and Whites employees. Previous work has alluded to the existence of a segmented labour market, where the characteristics of Coloureds and Africans, were argued to be distinct from those of Asians and Whites (Bhorat & Leibbrandt,1999). This data adds a further supply characteristic that corroborates this evidence. For good measure, the Gini coefficients for the race groups have been calculated. This more concise measure, illustrates the higher levels of wage inequality amongst Asian and White earners, and how they are distinct from the lower Gini measures for Africans and Coloureds. These results suggest that the comparative evidence on increasing and large inequality amongst African households, in fact picks up the significant number of African unemployed in these dwellings. When concentrating on the employed only, these results suggest that there is a more equitable distribution of earnings amongst the African workforce relative to other race groups in the labour market.

The table below disaggregates the percentile measures by gender. Once again of course, the largest differential is by the 90-10 differential. In addition, the 90-50 differential for both males and females is larger than the 50-10 differential. Interestingly though, the degree of difference is greater for males than females. This would suggest that the premium for male wage earners at the top-end is larger than that for female employees. All the same, greater wage compression occurs in the bottom half of the distribution. Combining the race and gender results of Tables 6 and 7 then, there is evidence that overall inequality in the wage distribution is driven more by the differences between the 90th percentile and median worker than between those in the bottom-half of the distribution. Put differently, it is scarcity of high skilled workers, resulting in a significant premia of their wages that explains a

[8] Evidence for the US labour market for example, show that the 90-50 differential is 0.66, while the 50-10 is 0.80 for 1988, indicating a reversal of the comparison here (Juhn, Murphy, Pierce, 1993).

disproportionate share of aggregate wage inequality in the South African labour market.

Table 7: Inequality Measures for Log Wages, by Gender

Percentile Differentials	Female	Male
90 - 10	3.55	3.78
75 - 25	3.27	3.41
90 - 50	3.41	3.69
50 - 10	2.98	3.05
75 - 50	3.06	3.26
50 - 25	2.85	2.88
Std. Dev.	3220.93	12011.69
Gini	0.53	0.64

The differences across genders indicates that there is greater inequality amongst males than females for all percentiles. The fact that the largest differential occurs in the 90-10 and 90-50 percentiles, suggests that it is the high earners amongst males at the top-end of the distribution who are driving this overall gender inequality.

Table 8 below attempts to determine the combined contribution of race and gender to the inequality observed separately above. The table makes it plain the highest degree of inequality amongst the employed, emanates from Asian and White workers of both genders. The figures show that the highest level of wage inequality are for White male workers in the 90-10 and 90-50 percentiles, followed by Asian males in the same percentiles. The next highest level of inequality is found amongst Asian and White females in the 90-10 differentials.

Table 8: Inequality Measures for Log Wages, by Race & Gender

Percentile	**Africans**		**Coloureds**		**Asian**		**White**	
Differentials	***Female***	***Male***	***Female***	***Male***	***Female***	***Male***	***Female***	***Male***
90 - 10	3.41	3.46	3.38	3.49	3.61	3.87	3.64	4.05
75 - 25	3.10	3.15	3.03	3.15	3.28	3.50	3.37	3.66
90 - 50	3.29	3.31	3.24	3.37	3.49	3.76	3.46	3.93
50 - 10	2.81	2.93	2.82	2.88	3.00	3.22	3.17	3.46
75 - 50	2.91	2.90	3.03	2.94	3.15	3.31	3.37	3.49
50 - 25	2.64	2.78	2.70	2.73	2.70	3.06	2.97	3.53
Std. Dev.	1760.74	4315.17	1087.46	3386.35	3128.84	8387.77	5553.62	23263.51
Gini	0.52	0.51	0.46	0.51	0.45	0.56	0.44	0.54

Ultimately, the table suggests that in terms of the race and gender contributions to overall wage inequality, the highest level of within-group differences is found firstly amongst White males, then Asian males, followed by White and Asian females. In other words, the pure race differentials are reinforced and strengthened when cutting the percentiles by gender as well. In contrast, note that at the 90-10, 90-50 and 50-10 differentials, the lowest levels of inequality are found amongst African and Coloured females. The Gini reflects this in aggregate, although note that the Gini for African females is in fact marginally higher than that for African males – a fact that is not easy to explain. Combining the race and gender covariates then, the highest levels of wage inequality are observed amongst White and Asian males, and the lowest amongst African and Coloured females.

A more concrete way of assessing male-female differentials is of course to look at the wage gap between the genders, at the same percentile levels. In other words, examining the 90-90, 50-50 and 10-10 differentials for males versus females will provide detail on the extent of gender wage differences. While the data is not presented here, the evidence shows two very clear trends. Firstly that at every percentile level, the male wage outstrips the female with the inequality measures ranging from 2.21 to 3.44. The second important result, and one which holds true even when holding race constant, is that at higher percentile levels, the degree of inequality between males and females is greater. In other words, inequality levels increase as we move up the wage distribution. The appendix below provides a graphical description of this growing differential at higher levels in the wage distribution.

Wage inequality can also be cut by location. While the figures and table are not shown here, the data reveals again that the upper-end wage inequality is greater than the bottom-end, for both rural and urban labour markets. However, in terms of comparing wage inequality across the regions, there is strong evidence for greater wage compression in rural, relative to urban labour markets.

Table 9 below provides the percentile differentials by education splines. Looking at the 90-10 differences, it is evident that the highest level of wage inequality is found amongst the employed with tertiary education, and a matric. Again, as with the regression results above, this points to the fact that both these education levels are not homogenous. Hence, while individuals may formally have degrees, the type of degree it is, the institution from which the degree was obtained, and discrimination from employers, all serve to segment the returns to this same level of education. Furthermore, relative to other levels of education then, the degree of heterogeneity in these two education splines, outweighs that found in the other schooling categories.

Table 9: Inequality Measures for Log Wages, by Education

Education	90--10	75--50	50--10	90--50	50--25	75--25	*Gini*
No education	3.15	2.70	2.51	3.04	2.30	2.85	*0.55*
Sub A - Std 5	3.18	2.72	2.63	3.04	2.42	2.90	*0.47*
Std 6 - Std 9	3.51	2.88	2.91	3.39	2.70	3.10	*0.53*
Matric	3.76	3.21	3.20	3.62	2.98	3.41	*0.53*
Tertiary	3.95	3.36	3.32	3.84	3.32	3.54	*0.54*

Note that although the 90-10 measures of inequality reflect much higher levels of inequality at the top-end of the education spectrum, the Gini measures show marginally higher levels of inequality amongst those with no schooling. At every percentile differential though, the level of inequality amongst matriculants and degreed persons, is consistently higher than for those in other education cohorts. As with the above tables, there is a greater degree of inequality amongst those in the upper-half of the distribution, relative to those in the 50-10 distribution.

An interesting addition to this differential analysis, is to examine the degree and extent of inequality at the sectoral level. We present three sets of tables in this regard:

the first deals with differentials at the main sector level, the second looks at a set of manufacturing sub-sectors and the final table at 8 sub-sectors within the financial services industry. These two sub-sectors were chosen given that the former contributes the largest percentage share to national GDP, while the latter is of course the fastest growing industry in the domestic economy.

Table 10 below provides the wage differentials at the main sector level. The 90-10 differentials indicate that the highest levels of wage inequality are found in the Financial services sector (3.92), followed by Electricity (3.79) and Construction (3.79). The lowest levels of inequality, as measured by the 90-10 differential are in Manufacturing, Community Services and Agriculture, with the latter yielding the lowest 90-10 differential. Note however, that when using the Gini which weights the entire distribution of earnings, Agriculture is the most unequal sector (0.79), and Electricity the least unequal (0.41). This suggests that in the overall Gini measure for the employed, the largest sectoral-level inequality emanates from Agriculture.

Table 10: Inequality Measures for Log Wages, by Main Sector

Sector	90--10	75--50	50--10	90--50	50--25	75--25	*Gini*
Agriculture	3.04	2.42	2.37	1.60	2.13	2.60	*0.79*
Mining	3.70	3.15	2.87	3.63	2.70	3.28	*0.47*
Manufacturing	3.69	3.15	2.95	3.60	2.70	3.28	*0.56*
Electricity	3.79	3.33	3.21	3.66	3.05	3.51	*0.41*
Construction	3.79	3.20	2.88	3.73	2.61	3.30	*0.63*
Wholesale	3.70	3.10	2.96	3.61	2.74	3.26	*0.67*
Transport	3.71	3.26	3.11	3.58	2.93	3.43	*0.50*
Financial Services	3.92	3.34	3.18	3.84	2.95	3.49	*0.54*
Community services	3.64	3.15	3.11	3.49	2.99	3.38	*0.51*

The data reveals that for all, bar one, of the main sectors, the 90-50 differential is greater than the 50-10 differences. In other words, the wage premium for highly skilled workers is operative in eight of the nine main sectors of the economy. The exception is Agriculture, where the top-end differential is less than the bottom-half differential. This suggests that the earnings of unskilled workers in Agriculture are low enough to generate greater levels of inequality between them and the median earning workers. Higher unionisation rates, and the fact that urban labour markets dominate for the other sectors, ensure that the inequality in the bottom-half of the distribution is not as large for non-agricultural sectors.

The percentile differentials indicate that sectors with high-skill factor proportions, such as Financial services and Electricity are rewarding top-end employees far more than skilled workers in other sectors. This reflects the extreme shortages in the labour market for these skill types, which are manifest then in significant wage premia. In the same vein, the suite of skilled workers demanded by Agriculture and Community services, for example, do not represent supply shortages of the same magnitude. In this case, the wage premia are much lower, and may in fact not be existent. Ultimately, one of the lessons from this analysis is that different sectors demand skilled workers not only in different quantities, but also of different characteristics. This means that sectors will not only reward skilled workers differently, but also reward them according to their shortage in the market. Comparing the Financial services and Community services results, a simple analogy is of a software programmer in the former sector and a nurse in the latter. Both are coded as skilled workers, but the relative shortage of the programmer ensures a much higher return and ultimately a wage premium on her labour.

It is useful though to move beyond the main sector divisions, and to compare wage inequality measures across a set of different sub-sectors. The table below calculates these measures for 10 manufacturing sub-sectors. The categorisation is forced by the detail in the survey. Hence the most disaggregated form that the data is collated is according to these 10 manufacturing sub-sectors. The data and its disaggregation does however convey fairly detailed information about wage inequality within the manufacturing industry. Hence the data shows that the highest 90-10 differentials are in the radio, television & communication and Chemical & Petroleum industries. Both these industries are capital-intensive, meaning that there would a specific need to augment capital with highly skilled workers. In contrast, it is two labour-intensive industries, food, beverages & tobacco and textile, clothing & leather which yield the lowest 90-10 percentile differences – 3.59 and 3.32 respectively. In these sectors then, the lower average levels of technology, translate into a lower demand for specific, high-skilled workers.

Table 11: Inequality Measures for Log Wages, by Manufacturing Sub-Sector

Manufacturing	**90--10**	**75--50**	**50--10**	**90—50**	**50—25**	**75--25**	*Gini*
Food, Beverages & Tobacco	3.59	3.01	2.93	3.49	2.72	3.19	*0.53*
Textile, clothing & leather	3.32	2.60	2.83	3.15	2.49	2.85	*0.41*
Wood, Publishing & printing	3.66	3.20	2.97	3.56	2.74	3.33	*0.64*
Chemical & Petroleum	3.82	3.28	3.07	3.73	2.91	3.43	*0.52*
Glass & non-metallic	3.66	3.00	3.03	3.54	2.78	3.21	*0.47*
Basic metal & Machinery	3.76	3.30	3.06	3.66	2.88	3.44	*0.48*
Electrical machinery & apparatus	3.71	3.25	2.96	3.53	2.66	3.35	*0.61*
Radio, television & communication	3.97	3.35	3.16	3.90	2.91	3.48	*0.78*
Transport Equipment	3.77	3.37	3.11	3.67	2.88	3.49	*0.49*
Furniture & recycling	3.61	3.13	2.91	3.51	2.60	3.24	*0.55*

This trend is reflected in the 90-50 differentials – a proxy for the wage premium. Hence, the differentials here are also greatest for the radio, television & communication and Chemical & Petroleum industries, and lowest for the two labour-intensive industries. Differing levels of technology translate into differing requirements for high skilled workers. It could then be argued that the skilled workers demanded in the capital-intensive industries are in greater shortage, so raising the premium on the required labour, and resulting in the largest 90-50 differentials within the manufacturing industry. If we do not split the sample of earners at points in the distribution, and take the overall Gini measure, the radio, television &

communication sector is still the most unequal, with an extremely high Gini of 0.78 and the textile, clothing and leather sectors are the least unequal, with a Gini of 0.41.

In terms of the percentile differentials though, the data suggests that within the manufacturing industry, wage differentials and wage premia are linked to technology mixes within each of the sub-sectors. Capital-intensive industries engender a demand for high-end workers with very specific skills. The shortage that exists for this labour in turn results in high wage premia, so ensuring that relatively higher levels of wage inequality within these industries. In contrast, labour-intensive industries yield a lower demand for high-end workers, and perhaps even have more of a requirement for general skills at the top-end. The shortages for these worker types are not as significant, meaning that the wage premia are lower, leading to a more truncated wage distribution. Ultimately then, technology choices within the sector are inextricably linked to the wage inequality outcomes observed in each of these sectoral labour markets. The data also suggests that much detail concerning sectoral differences and factor proportions are hidden if we focus solely on aggregate measures of wage inequality.

The main sector that reflected the highest demand for specific, high-skilled labour in Table 10 above, was the financial services. The table below calculates the percentile differentials for 8 sub-sectors within the industry. Once again, we are constrained to using these 8 sub-sectors by the coding provided in the survey. The data shows that the 90-10 differentials are greatest for the research & development and computer & related activities industries. The lowest level of wage inequality is for renting of machinery & equipment. It is possible to argue again, that the demand for very specific, highly specialised skills in the former industries, for which there is a supply shortage, creates the wage differentials observed. Indeed, these two industries – R & D and computer activities are no doubt employers of highly skilled and highly specialised workers, for whom significant premia must exist.

Table 12: Inequality Measures for Log Wages, by Financial Services Sub-Sector

Financial services	90--10	75--50	50--10	90--50	50--25	75--25	*Gini*
Financial intermediation	3.77	3.19	3.06	3.50	2.84	3.35	*0.40*
Insurance & pension funding	3.99	3.43	3.24	3.91	3.00	3.56	*0.53*
Activities auxiliary to intermediation	3.83	3.49	3.34	3.66	3.09	3.64	*0.44*
Real estate	3.92	3.40	3.18	3.83	3.03	3.55	*0.53*
Renting of machinery & equipment	3.72	3.57	2.76	3.67	2.66	3.62	*0.53*
Computer & related activities	4.11	3.53	3.62	3.91	3.50	3.82	*0.50*
Research & Development	4.37	3.95	3.46	4.31	3.29	4.03	*0.56*
Other business activities	3.92	3.29	3.14	3.84	2.97	3.29	*0.60*

In contrast the lower wage inequality industry, rental of machinery and equipment, would in all likelihood not demand highly specialised skills. The demand for skilled workers is probably lower, and the lack of specialist skills demand translates into a lower wage premium, and therefore lower percentile differentials. Indeed, the comparative data on skills demand for the equipment rental relative to R & D is illuminating. The table below shows for example that while the rental industry has no professionals, they dominate the share of employment in R & D, as about 51% of all employees here are professionals. In the rental industry, the largest proportion of workers are clerks and machine operators, thus representing a dominance of semi-skilled workers with more general skills, that are less likely to earn wage premia.

Table 13: Inequality Measures for Log Wages, by Financial Services Sub-Sector and Occupation

Occupation	Renting of machinery & equipment	Research & Development
Managers	6.06	3.53
Professionals	0.00	50.63
Technicians	10.21	14.28
Clerks	39.63	16.1
Service & Sales	2.54	9.83
Craft	7.84	2.83
Machine Operator	23.07	1.88
Labourer	6.26	0.94
Unspecified	4.39	0.00
Total	100	100

It is interesting to note that while the share of managers in the rental industry is larger than that in R & D, 6.06 versus 3.53, the larger inequality within the latter industry arises not because of more skilled individuals generally, but rather due to the specialised nature of these skills. The larger share of managers in the rental of equipment and machinery, while obviously representing skilled workers, is of a generalised enough nature together with having less of a shortage - to reduce the wage premia that such labour can earn.

The sectoral cuts above have suggested, firstly, that high skills-intensive sectors such as financial services and Utilities induce greater levels of wage inequality and also large premia on their skilled workers. Put differently, the proportion of skilled to unskilled workers in a sector is inextricably linked to wage differences and premia in that sector. The detailed sectoral breakdowns suggest that capital-intensive industries within manufacturing, have higher wage inequality and premia relative to labour-intensive manufacturers. Finally though, the sub-sectoral divisions caution against making generalisations about wage inequality either at the economy-wide or main sector level.

Changes in Wage Inequality: 1993-1995

The limitations with the OHS97 and indeed the OHS96 data were noted at the beginning of the paper. The added difficulty that the constraints in these data sets poses, is the inability to do time series estimates of variations in wage inequality. Given these obstacles, an initial and tentative analysis was done on changes in wage inequality between 1993 and 1995. The data for 1993 is of course based on the World Bank/ SALDRU household survey. The latter survey covered a total of 9000 household surveys, and was the first survey of its kind in South Africa.

While the time period of these changes is of course extremely constrictive, some interesting results do emerge. Given also that the period encompasses the transition to a democratic government, certain key labour market and wage alterations would have occurred here, notably in the public sector. Table 14 below looks at these changes by race. The total figures suggest that over the period, wage inequality at all the percentile differentials has increased. For example, the 90-10 differential has risen from 3.61 to 3.67 between the two years, constituting a 1.7% increase. When, examining the racial divisions, the first thing to note about the 1993 data, is that the higher levels of inequality for Asians and Whites relative to Africans and Coloureds found for 1995, is replicated. Thus, the log wage inequality measure for the 90-10 differential for Africans is 3.35 and for Whites it is 3.97. The wage premium of highly skilled workers is also repeated, as the 90-50 differential is higher than the 50-10 differential for all race groups.

Table 14: Inequality Measures for Log Earnings by Race 1993 & 1995

Year	**1993**	**1995**	**1993**	**1995**	**1993**	**1995**	**1993**	**1995**	**1993**	**1995**
Race	*African*	*African*	*Coloured*	*Coloured*	*Asian*	*Asian*	*White*	*White*	*Total*	*Total*
90-10	3.35	3.44	3.49	3.44	3.70	3.78	3.97	3.98	3.61	3.67
75-25	3.02	3.13	3.18	3.10	3.49	3.44	3.58	3.61	3.26	3.34
90-50	3.25	3.29	3.41	3.30	3.55	3.66	3.73	3.84	3.53	3.56
50-10	2.64	2.90	2.75	2.87	3.18	3.16	3.43	3.42	2.83	3.02
75-50	2.86	2.88	3.04	2.86	3.25	3.24	3.32	3.38	3.10	3.16
50-25	2.52	2.77	2.63	2.74	3.11	3.00	3.22	3.23	2.73	2.87

The changes over the period in wage inequality do suggest some interesting trends. Firstly, the 90-10 differential reflects a growing level of wage inequality between 1993 and 1995 for all race groups except Coloured workers. For example, the level of wage inequality for African workers increased by about 3% in this period, while the comparative figure for Asians was 2%. The increase for Whites was marginal. The data then does provide provisional evidence of a growing level of wage inequality in the labour market, particularly amongst African and Asian workers. The growth in inequality amongst African workers would disproportionately represent the large numbers of African employees that entered the public sector at senior positions after 1994. Similarly, the 90-50 differential has grown over the period for all races except Coloured workers. For African workers the growth in inequality has been about 2.3%, while for Asians it has been 3.1% and for Whites it has been 2.9%. In other words, the 1993-95 period has witnessed a rise in the returns to highly skilled workers relative to median skilled workers. Put differently, the wage premium offered to the 90^{th} percentile worker relative to the median employee has risen steadily over these 3 years. Early evidence over what is admittedly a very constrictive time period, suggests that wage inequality has risen since 1993 and furthermore that the premia earned by highly skilled workers has increased.

Table 15 below provides evidence of changing wage inequality by gender. Note that, as with the 1995 data, the level of wage inequality amongst male workers is higher than that found amongst female employees, at all the percentile differentials. Hence, the log wage 90-10 differential for males in 1993 was 3.76, while for females it was 3.58. In terms of male wages, there was a marginal growth in wage inequality between the two periods, in terms of the 90-10 differentials. This appears to have been driven by rising inequality between the median and 10th percentile worker and median versus 25th percentile employee. This may suggest that male workers at the bottom-end of the distribution, who are unskilled, unorganised and often in marginalized sectors such as Agriculture and Mining, have seen their wage returns declining relative to other workers in the distribution.

Table 15: Inequality Measures for Log Earnings by Gender 1993 & 1995

Year	**1993**	**1995**	**1993**	**1995**
Gender	*Male*	*Male*	*Female*	*Female*
90-10	3.76	3.78	3.58	3.55
75-25	3.39	3.41	3.32	3.36
90-50	3.69	3.69	3.49	3.41
50-10	2.94	3.05	2.84	2.98
75-50	3.25	3.26	3.18	3.06
50-25	2.83	2.88	2.75	2.85

Conversely though, female wage inequality actually fell over this period, when measured by the 90-10 differentials. Indeed, while male wage inequality in the 90-10 category increase by about 0.5% for females they fell by just under 1%. For females this decrease was driven by the reduction in wage inequality in the 90-50 and 75-50 wage gaps. This may represent the growing demand for clerical and other administrative staff in the services sectors, so resulting in higher wage returns for women who predominate in these occupations.

While the data is not shown here, wage levels by location suggest firstly that, as with the 1995 data, greater wage inequality exists in urban compared to rural labour markets. The time-series results are very strong, as they show that for all the percentiles, the level of wage inequality in both urban and rural labour markets has increased. For example, in rural labour markets the 90-10 differential has risen by 3%, while in urban labour markets the increase was 2.2%.

Table 16 represents wage inequality data by education cohorts. As with the 1995 data, there is very strong indication that the levels of inequality increase monotonically as we move into higher education groups. Hence, the log wage inequality measure (90-10) for those with no schooling is 3.24, while for those with tertiary education it is 3.91. While higher levels of education then clearly yield higher returns for individuals, this evidence suggests that for both 1993 and 1995, higher levels of education also translate into greater relative inequality.

Table 16: Inequality Measures for Log Earnings by Education 1993 & 1995

Year	**None**		**SubA-Std5**		**Std6-Std9**		**Matric**		**Tertiary**	
Education	***1993***	***1995***	***1993***	***1995***	***1993***	***1995***	***1993***	***1995***	***1993***	***1995***
90-10	3.24	3.15	3.25	3.18	3.47	3.51	3.78	3.76	3.91	3.95
75-25	2.93	2.85	2.85	2.90	3.13	3.10	3.45	3.41	3.56	3.54
90-50	3.15	3.04	3.19	3.04	3.36	3.38	3.62	3.62	3.75	3.84
50-10	2.52	2.51	2.39	2.63	2.82	2.91	3.27	3.20	3.38	3.32
75-50	2.79	2.70	2.73	2.72	2.92	2.88	3.25	3.21	3.32	3.36
50-25	2.30	2.30	2.25	2.42	2.72	2.70	3.03	2.98	3.20	3.08

The changes over time though, yield mixed results. For the 90-10 differentials there is, as would be expected a growing level of inequality for individuals with a tertiary degree. This makes sense in terms of changing labour demand preferences for highly skilled workers with a specific type of tertiary degree, relative to those with a less specific and less sought-after degree. The decrease in inequality for matriculants, is unexpected, although it may suggest that the certification is viewed as being more homogenous by employers, and hence the differential between the lowest and highest earning matriculant has decreased. The lowering of wage inequality in the two lowest education cohorts, may represent the erosion of discriminatory practices amongst firms, as unskilled African workers wages relative to White unskilled workers may have risen over this period.

Ultimately though the above time comparison has suggested firstly that the 1993 data in and of itself, replicates most of the trends observed in the 1995 data, with regard to the race, gender, location and education profiles. In addition, there is a suggestion that wage inequality has risen in the labour market, with the big contributor to this being the higher levels of inequity amongst African and male workers. In addition, the spatial differentials have been exacerbated across all the differentials, while the education cohorts suggest a mixture of declining inequality at the lower end of the education spectrum and increasing differentials for the highly educated, as a reflection of increasing and specific labour demand specifications.

How Large are South African Wage Differentials?: A Tentative International Comparison

International comparisons of wage differentials are a difficult exercise. They of course assume that the country-specific conditions across the sample are all the same with regard to a range of variables. In addition, and perhaps more importantly, they assume that the labour market conditions in each of the economies are similar and therefore comparable. This is the background information then, that has to be considered when accounting for wage differentials across countries. In most cases, it has to be stated, such comparisons belie the significant differences that are present across economies. The differences are particularly magnified when, as is the case below, a developing country such as South Africa is contrasted with larger industrialised economies.

Despite the above caveats, Table 17 below attempts this tentative international comparison, while noting at the outset the assumptions made in doing such an analysis. In addition, the calculations of these differentials differ from the above in two important respects. Firstly, we use hourly and not monthly wages, as most of the sample countries usually report wages on an hourly basis, and these labour markets have a significant share of part-time workers in the formal sector. Secondly, in order to reduce the statistical noise induced when taking all workers in the sample, only male worker differentials are used. This is to avoid picking up the gender bias present in the distribution. In the South African context, race also acts as an important discriminator, and therefore the racial male differentials are also reported here. The developed country figures are all based on data from the mid to late-1980s, and while this is somewhat outdated, there was no comparable later data that could be found, using the percentile differential approach. In addition though, it was felt that the core results would not be affected with the use of more recent wage data.

Table 17: International Comparison of Wage Differentials: Log Hourly Male Wages (Blau & Kahn,1996; OHS,1995)

Country	50-10	90-50	90-10
Germany	0.456	0.539	0.995
Britain	0.594	0.683	1.277
United States	1.040	0.552	1.592
Austria	0.391	0.508	0.899
Switzerland	0.464	0.777	1.241
Sweden	0.382	0.452	0.854
Norway (1982)	0.372	0.382	0.754
Australia	0.755	0.439	1.194
Hungary	0.462	0.661	1.123
Italy	0.478	0.486	0.964
Norway (1989)	0.224	0.525	0.749
Non-US average	0.458	0.545	1.003
South Africa			
Total	***0.85***	***1.43***	***1.53***
White	***1.24***	***1.66***	***1.80***
Asian	***0.96***	***1.49***	***1.60***
Coloured	***0.68***	***1.15***	***1.28***
African	***0.71***	***1.14***	***1.28***

The data shows firstly that in the developed country sample, the USA yields the highest level of wage inequality when measured by the 90-10 differential. Hence, the hourly log wage inequality amongst males in the US labour market stands at 1.592, while in Norway for example, it was 0.749 in 1989. If we include the total male wage inequality for South Africa, we find that the US labour market is still the most unequal, but with South Africa a very close second, at 1.53. The racial wage divisions for male South Africans however, changes the ranking considerably: with these figures, the first and second largest inequality levels are amongst male Whites and Asians, followed then by the US aggregate. The third and fourth ranked 90-10 differentials are again South African, namely for Africans and Coloureds.

Ultimately then, depending on whether we take the racial male cut or the aggregate for South Africa, the ranking does adjust marginally. It is evident however, that the South African labour market, by these comparisons does manifest a very high degree of wage inequality. In turn, it is an inequality that is matched only by the US labour market, with most of the European labour markets revealing significantly lower levels of wage inequality. While the above comparison is fraught with difficulties and constraints, there does appear to be provisional evidence that South Africa has high levels of wage inequality, by international comparisons.

Policy Implications and Conclusions

The above paper has attempted to parallel our fairly good grasp of employment trends and patterns in the labour market, with an intensive examination of the wage trends and patterns that underlay or inform these quantity changes. The results suggest, in the first instance, that when looking at median wages the regular race, gender and education differentials arise. The results show that the racial wage gap is far more severe than the gender wage gap, while the racial wage cleavage is again between Africans and Coloureds on the one hand and Asians and Whites on the other. The education median wage data illustrated the importance of matric or tertiary education in raising worker's earnings.

While the median wage analysis showed that one of the highest paid sectors were financial services and the lowest Agriculture, it was the occupational wage data that was most revealing. The discrepancy in wages of Africans and Whites ostensibly in the same skilled and semi-skilled occupations lead to a more detailed regression analysis. This analysis suggested that one of the key reasons for the wage differential within each of the skill bands, was the higher rates of return on education for White as opposed to African workers. The higher rates reflected White workers accumulating human capital in areas that are in greater demand by firms, as well as the possibility of firms perceiving the a degree from an HWU was of a higher quality than that from an HBU. In addition, unofficial discrimination from firms may also be operative, so reducing the relative wage of African skilled and semi-skilled workers. For both skill bands and both race groups, being a women reduced one's wage while for semi-skilled employees, belonging to a union increased the wage earned.

The remainder of the paper focused on examining wage inequality across the entire wage distribution, splining it at various intervals in the distribution. The results suggested firstly that the levels of wage inequality amongst African and Coloured workers of both genders, was decidedly lower than the inequality found amongst Asians and Whites of both genders. In addition, there was strong evidence for wage significant wage premia operating for skilled workers, as the 90-50 differentials often outweighed the 50-10 differences. This result parallels labour demand trends showing high and increasing demand for skilled workers, in a labour market with severe skills shortages. The education wage differentials suggested that as one moved into higher education cohorts, the level of wage inequality increased. Hence when examining individuals with a tertiary degree for example, the level of inequality within that group was greater than say the inequality amongst primary school workers. This fact displayed once again the heterogeneity in tertiary degrees, and the differential returns that this translated into for workers.

The sectoral wage data reaffirms the above trends as high skills-intensive sectors such as financial services and Utilities, yield the highest levels of wage inequality, combined with 90-50 differentials that are higher than the 50-10 differences. In contrast, a low skills-intensive sector such as Agriculture, revealed much lower levels of wage inequality. The sub-sectoral breakdowns of Manufacturing and financial services showed that there remain contrasting wage differentials and wage premia within the main sector divisions. Particularly in Manufacturing, it was clear that capital-intensive sectors, in demanding labour augmenting high skilled human capital, were more unequal than labour-intensive manufacturers. The limited time-series analysis provides initial evidence that as labour demand trends have become increasingly skewed toward skilled labour, and also as the society shifted to majority rule, levels of wage inequality measured by race increased over the two-year period. Finally, the tentative international comparison revealed that relative to most other developed countries, primarily in Europe, South Africa has high levels of wage inequality, as measured by the 90-10 percentile differentials.

The above results though bear some important policy implications in four areas of labour market policy. These are skills development, employment equity, the notion of an income policy and finally in the long-debated issue of the wage-employment trade-off. Taking the first of these, the data makes it plain that due to a severe skills shortage in the labour market, skilled labour is being paid a premium. Higher than market wages are being offered for skilled workers given their inadequate supply. In another sense, it could be argued that the wage bill is disproportionately skewed to skilled employees, given their shortage. This is of course an inefficient outcome, reflecting a supply-demand mismatch at the top-end of the job ladder. This points to a key lever within the armoury of government, namely skills development. Currently, the South African Department of Labour's skills development programme is legally anchored in the Skills Development Act (SDA), 1998, and administratively run through the Skills Development Policy Unit (SDPU). The purpose of the Sector, Education and Training Authorities (SETAs) is to utilise the levies provided for in the SDA to narrow this gap between demand and supply. Put differently, the brief of the SETAs is to ensure that the supply characteristics of workers is upgraded through the process of education and training, in a manner that meets with firms' labour demand needs. It is only in meeting such needs of firms that the SETAs can be said to have succeeded in their tasks.

While the skills development programme is in its infancy, there does seem to be a realization from government that the most crucial mismatch occurs at the top-end of the job ladder. The results here suggest that through closing such a mismatch, the effect may be to reduce the extent of wage premia, so reducing the skewness that presently exists in the wage bill. An area of immediate weakness though, but one that is more a function of government line department's responsibilities, is that there appears to be little dialogue between the Department of Education (national or provincial) and the National Department of Labour. The very fact that tertiary degrees are so differentially rewarded in the labour market, has immediate policy implications for how the Department of Education needs to conceive of its higher education interventions. It is not clear though, that such thinking has occurred within the department and that it is borrowing sufficient expertise from the DoL to inform and make such policy decisions.

The above leads to a discussion of recent employment equity legislation, contained in the recent Employment Equity Act. Recent proclamations from the Employment Equity Commission (EEC), indicates an intention to examine wage differences and wage differentials more closely, with a view to promoting greater equity in the workplace. The evidence, at all levels in this paper, suggests that a simplistic examination of wage inequality would be foolhardy. The paper indicates that wage differentials are a function generally of supply shortages of highly skilled employees. In addition, they may reflect differing human capital accumulation of individuals, with the contrasts extremely nuanced in the case of degreed workers. Furthermore, race, gender, education, sector and location all combine to form a fairly intricately constructed distribution of wages in the labour market. For the EEC to legislate a reduction in wage differences and inequality without recourse to all these considerations, would be to seriously underestimate the nature and extent of the problem. The current indication is that such a blunt instrument is being used as a guide to reducing wage inequality, and of course the above has shown that such a route could prove to be both extremely disruptive to incentives in the labour market, as well as resulting in highly inefficient outcomes. For example, for the EEC to simply mandate a reduction in race differentials for all professionals, would result in massive distortions on the price of skilled labour, which through the disincentives introduced could lead to an exodus of labour from the domestic market and a rise in shortages.

Another policy intervention that has often been mooted in South Africa is that of a national incomes and employment accord. The idea is essentially that government, labour and business would together attempt to determine a common agenda on employment creation and wage growth. The idea in the latter case is that unions would agree, in return for something tangible from government and business, to keep the growth of real wages in check. All the above analysis has alluded to, is that while there are of course wage pressures induced through unionisation of bottom-end workers, skills shortages in the labour market, have induced similar pressures at the top-end of the job ladder. Any policy discussion around the setting of wages and their growth over time therefore, must take account of the fact that the wage bill is composed not only of earnings of unskilled workers, but also of high-end employees whose returns reflect significant premia through existent skills shortages.

One of the key debates on the South African labour market, has of course been the relationship between wages and employment. An inter-related issue on the wage-employment nexus and one relevant here is how we understand this link in the context of the *wage bill* as a whole. As noted, workers at the top-end are paid a premium, because there is such a supply dearth. In this respect it would be useful to assess the growth of the wage bill over time, and to determine which skills categories have been driving the growth in the wage bill. In this way it will be possible to link wage hikes and employment consequences according to skill levels. It may be possible for example, that a growth in the wage rates of skilled individuals was the primary cause for higher labour costs, and it was this factor that resulted in employment losses. The basic point here is that a rise in labour costs should be carefully apportioned between skilled and unskilled workers. In this way, we can arrive at a more complete analysis of the factors driving a growth in the wage bill, and how this in turn has meant a reduction in employment levels.

Ultimately though, the above paper has attempted to move beyond very basic descriptions of wages and wage differentials in the South African labour market. The central idea of the paper, and one it is hoped that has been achieved, is to display how the quantity supplied and demanded of labour has been and will continue to be very interdependent on the differential prices paid to such labour in the economy.

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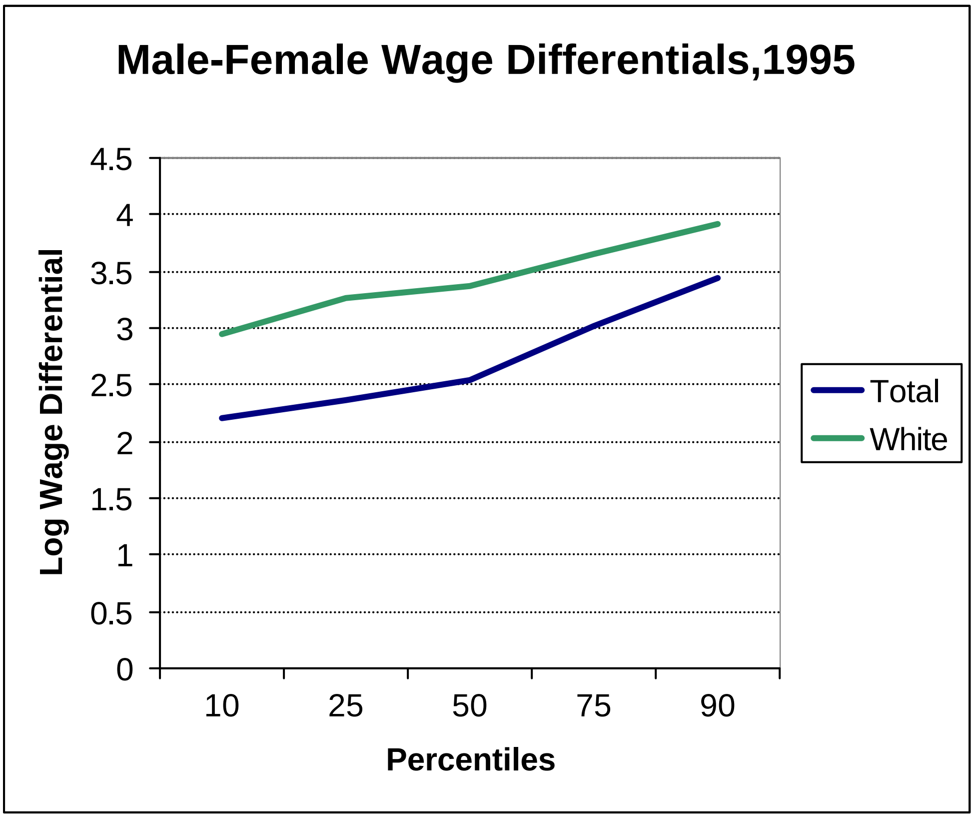
Appendix



Inequality measures for log earnings by Location 1993 & 1995

Year	1993	1995	1993	1995	1993	1995
Location	*Rural*	*Rural*	*Urban*	*Urban*	*Semi-rural*	*Semi-rural*
90-10	3.35	3.45	3.66	3.74	3.80	3.56
75-25	3.00	3.03	3.34	3.38	3.54	3.12
90-50	3.28	3.37	3.54	3.62	3.70	3.46
50-10	2.55	2.66	3.03	3.11	3.13	2.87
75-50	2.85	2.89	3.14	3.21	3.38	2.91
50-25	2.45	2.46	2.92	2.87	3.04	2.70