Essays in the Economics of Inequality

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Essays in the Economics of Inequality

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to my dad († 2002)

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Chapter 1

Main Introduction

A global human society based on poverty for many and prosperity for a few, characterised by islands of wealth surrounded by a sea of poverty, is unsustainable.

Thabo Mbeki, World Summit for Sustainable Development, 2002

You can easily find people who are ten times as rich at sixty as they were at twenty; but not one of them will tell you that they are ten times as happy.

George Bernard Shaw, 1928

Inequality, rather than want, is the cause of trouble.

Ancient Chinese saying

The relevance of distributional issues in the field of economics becomes evident as the subject has been on the research agenda since many years, even if research intensity varied to some extent in the past. There is of course a well-founded intrinsic motivation to understand the determinants of income distribution, but studies related to the field focus predominantly on the role a given distribution has on other economic phenomena or mechanisms (Atkinson and Bourguignon, 2000).[1] The debate on how income inequality affects economic growth fits well in with this. Especially the 1990s have seen both the development of new theoretical models and comprehensive empirical analyses to gain new insights helping to answer these old questions and to outline the scope for policy (e.g. Aghion, Caroli, and Garcia-Penalosa, 1999; Benabou, 1996; Alesina and Rodrik, 1994; Persson and Tabellini, 1994).

[1] Kuznets (1955) basically started a profound analysis of the secular structure of income distribution.

During the last decade, the interest also centred again on the implications income inequality has on well-being. Not least because of recent discussions of globalisation and its impact on within-country and between-country inequality, these issues come back to the fore (e.g. Wade, 2002; Melchior, Telle, and Wiig, 2000). Theoretical work on inequality and welfare can be traced back to Graaf (1957). Since then, a literature developed convincingly arguing that a more unequal distribution of income, ceteris paribus, reduces aggregate welfare (e.g. Rawls, 1971; Hirsch, 1977; Sen, 1982). Indicators of economic welfare that in addition to the mean income also consider the distribution of it have been proposed by e.g. Atkinson (1970), Sen (1973), and Ahluwalia and Chenery (1974). So far, a few studies have applied some of these inequality-adjusted measures to real data to reassess the welfare level of particular countries (e.g. Klasen, 1994; Jenkins, 1997; Grün and Klasen, 2001).

Part I of the present work belongs to this field of study. In contrast to previous studies, the scope of analysis comprises not only particular countries, but aims at international and intertemporal comparisons as well as a global assessment of well-being.[2] As today rich data sets on both average incomes and income inequality are available, it seems natural to apply these data to welfare measures that combine mean income and its distribution. Theory suggests several ways how inequality can be incorporated into a measure of welfare. As the empirical analysis will show, the resulting levels of welfare respond to these differences. Furthermore, some measures allow to vary the penalty associated with a given unequal distribution of income. This way, it is possible to detect how different degrees of inequality aversion affect the level of aggregate welfare.

Cross-country comparisons of well-being are still almost exclusively based on a measure of average income, like GNP per capita. In the context of utilitarian welfare economics, strong assumptions are necessary to justify this approach. Income inequality is either 'assumed away' or an optimal distribution of income is supposed. To prove that these assumptions entail a misleading view of aggregate welfare is the aim of the *international analysis*. A comparison between inequality-adjusted measures and unadjusted average incomes will demonstrate what impact the inclusion of income inequality has on the assessment of a country's welfare level.

The question whether income inequality systematically changes over time also attracts attention from time to time. In the context discussed here, it corresponds to whether the impression of welfare changes would be different once the change in inequality is also taken into account. To arrive at assured results, the *intertemporal analysis* will investigate the subject via econometric methods applied to the total sample of countries as well as detailed analysis of selected countries.

[2]Please note that I will be concerned with the economic dimension of inequality and well-being only. Furthermore, only the dispersion of income and not wealth will be considered.

Such welfare comparisons across time are focused on conditions prevailing within particular countries. It is, however, well-known that income inequality between countries is considerably larger. Abstracting from regional boundaries leads to the concept of global inequality which refers to income inequality between all people regardless where they live (Lundberg and Milanovic, 2000). In the concluding *global analysis* I try to explore how global welfare changed during the last 30 years and what role the change of global inequality played.

Going back to the concept of within-country inequality, the distribution of income in South Africa is found to be exceptionally dispersed. Apartheid ruled for more than 40 years and left the country in a socially and economically segmented state. During Apartheid, the labour market - normally a major source of acquiring means - was heavily regulated in favour of Whites and contributed to the emergence and establishment of a racial wage hierarchy which persists until today. Part II of this work is devoted to a comprehensive analysis of labour market outcomes in the post-Apartheid period. In contrast to previous studies which determined the extent of labour market discrimination using the standard decomposition approach (Oaxaca, 1973; Blinder, 1973), I will apply a decomposition technique suggested by Mavromaras (2003) and Neuman and Oaxaca (1998). By jointly considering the probability of finding employment and the wage determination process, it is possible to determine indirect effects of wage discrimination in addition. These effects already arise at the hiring stage but also influence the wage rate. A comparison between the standard decomposition approach, detecting only direct wage discrimination, and the selectivity corrected approach allows to assess, whether the appearance of wage discrimination changed over time and whether different population groups have to contend with different kinds of discrimination.

Since 1994, the need to reduce disparities in earnings, employment, and occupations has been addressed explicitly by the new South African legislation. In the context of the South African labour market the focus of the public is predominantly on racial inequality, I will also examine gender differentials. As the results will show, women also suffer from a substantial extent of direct wage discrimination, but partly face indirect effects as well.

Results on the extent of labour market discrimination obtained from both the standard method and the selectivity corrected approach are derived from a decomposition of mean wage differentials. Any heterogeneity among individuals is thereby disregarded. Furthermore, the data used in the decomposition analysis are repeated cross sections, allowing a detailed snapshot of labour market conditions and outcomes but the study of temporal changes at an individual level is not possible. The analysis in Part III tries to overcome the static nature of cross sectional data. With the help of cohort techniques, several survey years can be linked to follow not individuals but birth cohorts over time.

This allows to break down some of the findings of Part II to a disaggregated level using substantially more information that is provided by the data. In particular, group specific mean wages can be split up into several age groups revealing their contribution to the overall average. Inspecting socioeconomic characteristics related to the studies on labour market outcomes point out important differences both between race and gender and young and old people. Wage differentials determined in Part II can also be analysed at a cohort level. As cohorts are followed over time, it is furthermore possible to watch their earnings mobility. The comparison of within cohort changes will show whether young and old cohorts develop alongside similar paths. Finally, as different birth cohorts are observed at the same age, I will attempt to separate life-cycle from generational effects regarding the earnings of African workers. The results regarding the cohort effects are partly unexpected, but particular labour market conditions as well as the overall performance of the South African economy might help to explain it. However, to arrive at assured results, further investigation is needed.

Part I

Growth, Income Distribution, and Well-Being: Comparisons across Time and Space

Chapter 2

The Theory of Well-Being and Real-Income Comparisons

2.1 Introductory Remarks

Despite its well-known short-comings, GNP per capita is still the most widely used indicator for comparisons of well-being across countries; and the per capita growth rate is still the most common indicator of changes in well-being.[1]

The exclusive reliance on this measure is largely due to pragmatic grounds. GNP as well as GDP are important measures of production possibility and business cycles. Hence, great efforts are made to measure them timely, accurately, and according to internationally agreed standards. With these data readily available, it is tempting to rely on them for international and intertemporal comparisons of well-being. Moreover, it is argued by many that GNP per capita and growth of per capita income is still the best available proxy for changes in well-being as it is highly correlated with more complete or more broad-based measures of well-being (e.g. Dollar and Kraay, 2002; Ravallion, 1997).

Nevertheless, it continues to be the case that its neglect of income distribution is one of the most serious short-comings of GNP as an indicator of welfare. In particular, a broad range of philosophical approaches to the measurement of welfare (ranging from utilitarianism with some very reasonable assumptions about utility functions to Rawlsian reasoning or Sen's capability approach) would suggest that, ceteris paribus, high economic inequality reduces aggregate well-being. In fact, there exists a range of measures for well-being that make use of this insight and combine mean income with some measure of income inequality to arrive at better measures of welfare than average income alone (e.g. Atkinson, 1970; Sen, 1973; Dagum, 1990; Ahluwalia and Chenery, 1974).

[1] There are other indicators, such as the Human Development Index and related measures, that have attempted to generate alternatives to this exclusive reliance on income, but they have been criticised for their choice of indicators, aggregation rules, and their neglect of distribution of the achievements considered (see Srinivasan, 1994; Ravallion, 1997).

In the past the application of those measures was limited, mainly because of lack of data on income distribution. Recent years, however, have seen great advances being made in the generation of data on income inequality (e.g. Deininger and Squire, 1996; Gottschalk and Smeeding, 1997; WIID, 2000). Thus it seems natural to apply well-being measures that combine GNP per capita and income distribution to these new data and investigate to what extent these measures will generate comparisons of well-being across space and time that are substantially different from pure per capita income comparisons. This exercise is the purpose of Part I.

The following analysis itself consists of three major parts. As a preliminary step, income inequality-adjusted welfare levels are calculated using various measures for as many countries as possible in 1960, 1970, 1980, 1990, and 1998. In the *international analysis* countries are ranked according to their welfare level in both pure income based measures and inequality-adjusted welfare indicators. A comparison of country specific levels of well-being will demonstrate by how much aggregate welfare in a particular country is reduced once the unequal distribution of its income is taken into account. Looking at the welfare ranks, winners and losers can be detected, i.e. some countries will reach a higher welfare rank than their income rank and vice versa. As a time span of almost 40 years is covered, it is also possible to assess changes in well-being. The *intertemporal analysis* addresses the question whether or not the received impression of welfare changes differs across the various measures. Finally, the *global analysis* tries to find out how global welfare changed during the last 30 years.

It should be pointed out at the start that this study presents results of an exercise that, to some degree, is still speculative. On the theoretical side, I am not aiming to propose definitive measures of well-being. Instead, I merely wish to illustrate how reasonable ways of incorporating inequality in an assessment of well-being will change the impression of well-being across space and time. On the empirical front, the conclusions should be seen as similarly tentative. While today many more data on income inequality across space and time are available, the accuracy and comparability of many of them remains a huge problem (see Atkinson and Brandolini, 2001; Deininger and Squire, 1996). The robustness of the results will be verified by some sensitivity analyses, i.e. using possibly better data available for some points in time in a limited number of countries and using regression-based adjustments. None of this can substitute for long consistent time series of internationally standardised and comparable data which are at present not available. Moreover, the international comparisons of inequality are limited to a small number of countries in the early years considered (1960, 1970) so that it is difficult to say much about temporal trends in inequality and well-being in many countries. And even for these countries only very irregular data points on inequality are available so it is hardly possible to talk about consistent time series. Finally, the 'global' analysis is restricted to some 80 per cent of the world's population, and the 20 per cent excluded are clearly not a random sample. To achieve such good coverage and include the most populous African countries as well, somewhat heroic assumptions were necessary in addition, as reasonable data were only available for circa 76 per cent of the world's population in 1998. Despite these shortcomings, the analysis generates a number of important and usable findings that should be fairly robust to most of the many data problems I encountered.

2.2 The Theoretical Approach

Despite a long history, the theory of welfare judgements across space and time continues to be beset with conceptual and practical problems. Ever since it became evident that social choice theory was not yielding acceptable[2] procedures for making social welfare judgements, such judgements have been based on axiomatic approaches to welfare measurement. Those are based on a conceptualisation of what constitutes welfare and then the derivation of an indicator that, under certain stated assumptions, can adequately measure the chosen concept.

Applying such measures to welfare comparisons across space and time generate additional problems. Those are discussed in detail in Sen (1982, 1984) and will only be summarised here. In particular, the theory of welfare comparisons is based on situational comparisons, i.e. whether a person would hypothetically prefer situation A to B. This comparison thus takes place at the same time and is done by the same person. Intertemporal or international welfare comparisons, however, address different questions. Intertemporal comparisons have to contend with the problem that the persons are not evaluating the welfare of two situations simultaneously, but sequentially. This may generate problems if overall perceptions of welfare or tastes have changed over time (in addition to the problem that not all the people are alive in both periods). Comparisons across space, as done in inter-country comparisons, are even more difficult as now the persons differ whose welfare is being compared.[3] The comparison could be made using the price (or other welfare weight) vectors of either country, which would not necessarily generate the same result. In addition to this theoretical problem, the comparability of prices poses another problem, namely the appropriate exchange rate for international comparisons. In the past, most real income comparisons were based on official exchange rates despite the knowledge that

[2]Acceptable is meant in the sense of obeying minimal requirements such as the four conditions stated by Arrow in his famous impossibility result (Arrow, 1963). See also Sen (1973, 1999) for a discussion.

[3]One could try to translate an international comparison into a situational comparison, i.e. asking the British whether they would prefer to live in Britain this year or in France this year. But this also leads to considerable problems, as it is not clear which British person should compare themselves to which French person, or whose welfare function should be used. For a discussion of those issues, see Sen (1982, 1984).

they are often distorted as a result of speculation and currency restrictions, and that they imply a systematic undervaluation of the non-traded sector in poorer countries. In recent years, the International Comparison Programme (ICP)[4] has generated purchasing power parity estimates of GDP and GNP based on international prices that try to address these particular short-comings.[5]

Thus, there are some important conceptual questions that relate to such comparisons. Only if one places restrictions on intertemporal changes and international differences in preferences, these comparisons can yield meaningful outcomes. Given the ubiquity of such comparisons, it appears that most analysts are willing to make such assumptions.

The most commonly used indicator for welfare comparisons across space and time is real per capita income.[6] It can be derived from utilitarian welfare economics using three alternative sets of assumptions. One set would demand everyone to have identical unchanging cardinal utility functions where income (or consumption)[7] enters the utility function linearly (e.g. in the simplest form, every unit of consumption generates one unit of utility). An alternative set of assumptions could allow for more realistic concave utility functions, but would still require identical utility functions and require in addition that everyone is earning the per capita income and thus consumes the mean commodity bundle (Sen, 1984). A third set is based on Samuelson (1947) and takes an 'individualistic approach' to welfare measurement. Under this approach, social welfare is recovered from individual welfare based on revealed preferences using the Pareto principle. If preferences are complete, convex, and monotonically increasing, if each person's welfare only depends on her purchases (i.e. no externalities and public goods), if there are no market imperfections on the buyer's side, and if each person is rational in the sense that her choices reflect her welfare ranking, then the ratio of market prices should equal the ratio of intra-personal weights (marginal rates of substitution) attached to these goods. These assumptions are not sufficient, however, to ensure that the market prices say anything about the valuation of a good going to two different people, as this requires interpersonal comparisons. To

[4]The ICP produces estimates of the economies' main aggregates which are comparable across countries. Purchasing power parities are generated and used for converting the data into a common currency (UN, 1992). Unfortunately, not all countries participate in the project. Most notably, the lack of reliable PPP conversion factor for China that never took part and India with the latest PPP estimates stemming from 1985 may limit international comparability.

[5]While the data generated by these methods are widely used, they are not beyond question. In particular, the resulting adjusted per capita incomes are sensitive to the choice of 'international prices' which is closer to the prices prevailing in rich countries (Berry, Bourguignon, and Morrison, 1991; Hill, 2000). Moreover, as chapter 3.2 reveals, PPP adjustments can differ in their outcomes as the differences between the World Bank estimates and the Penn World Tables demonstrate. For a critical assessment of the concept and current use of PPP in the context of poverty measurement see Reddy and Pogge (2002).

[6]There are well-known omissions and distortions of GNP as a measure of the value created in an economy. These issues will not be discussed further here.

[7]I abstract from the difficulties associated with the treatment of saving in an indicator of welfare. For a discussion, see Osberg and Sharpe (2002).

be able to make such interpersonal comparisons, which are necessary for all real income comparisons, one has to assume in addition that the income distribution is 'optimal' in the sense that the ethical worth of each person's marginal dollar is equal (Samuelson, 1947).

All three sets of assumptions are problematic. While many aspects of the various approaches appear unrealistic, the need to *explicitly* ignore the distribution of income in a welfare comparison is particularly unpalatable. Ignoring income distribution through the assumption of linear utility functions, through the assumption of everyone having the same income, or through the assumption of income distribution being 'optimal' from a welfare point of view is all equally debatable. In fact, both theoretical considerations (e.g. declining marginal utility of income derived from convex preferences) as well as empirical observations (e.g. about risk aversion and insurance as well as subjective well-being) clearly suggest that neither utility functions are linear in income or consumption, nor that the existing distribution of incomes is 'optimal' from a social welfare point of view.[8] Instead, these theoretical and empirical considerations point to concave utility functions, i.e. inequality reduces aggregate welfare as the marginal utility of income among the poor is much higher than among the rich.[9]

Non-utilitarian views of welfare would also suggest that income inequality reduces aggregate well-being. For example, Sen's capability approach (Sen, 1987) which calls for a maximisation of people's capability to function (e.g. the capability to be healthy, well-nourished, adequately housed, etc.) also exhibits declining marginal returns in the income space.[10] Similarly, application of Rawlsian principles would also suggest that welfare is higher in societies where inequality is lower (Rawls, 1971).[11]

One approach to improve upon the welfare content of real income comparisons is therefore to jettison this neglect of income distribution and incorporate the notion of declining marginal welfare returns of income. Each of the measures proposed in the next chapter does precisely this in slightly different ways.

[8]See for example Alesina, Di Tella, and MacCulloch (2002) who show with the help of U.S. happiness data and the Euro-Barometer Survey Series that income inequality negatively affects the utility level of individuals, even though personal characteristics like individual income are controlled for. They also point to unexpected differences across population groups and regions. For example, the poor in Europe and the rich in America exhibit greater aversion to inequality than other income groups. The authors argue that the different degree of social mobility contributes to this outcome, though these differences may be rather perceived than realistic.

[9]This is inherent also in the approach by Graaf (1957) and Sen (1982) who treat the same good going to two different people as two different goods and thus explicitly do away with the distinction between size and distribution of income as the 'welfare depends on them both' (Sen, 1982).

[10]For example, there appears to be a concave relationship between income and life expectancy, and income and educational achievement. For a discussion, see Klasen (1994).

[11]In the lexicographic version of the maximin principle, only the position of the worst off is relevant; if one generalises a bit, one would get a more continuous declining marginal valuation of income. Similarly, Hirsch's views on the social limits to growth also imply declining aggregate well-being as a result of inequality. For details see Hirsch (1977) and Klasen (1994).

Before turning to this issue, however, it seems useful to consider one explicit objection to the incorporation of distributional issues in an assessment of well-being. It could be argued that higher inequality will lead to higher growth rates.[12] Redistributive policies may then distort incentives to invest as they are often realised in terms of disproportionate taxation of property growth. This would suggest that there is a trade-off between higher well-being associated with today's lower inequality and lower well-being associated with the subsequently reduced economic growth. While such dynamic considerations go beyond the scope of this analysis and would, in any case, require the inclusion of other dynamic issues (e.g. the role of savings and of depreciation of human, natural, and physical capital in long-term well-being of nations)[13], there is a growing consensus that this trade-off between distribution and growth does not exist. In fact, if anything, the debate has recently shifted in the opposite direction suggesting that initial inequality lowers subsequent growth prospects rather than increases them (e.g. Deininger and Squire, 1998; Alesina and Rodrik, 1994; Clarke, 1995; Persson and Tabellini, 1994; Klasen, 2002). While these findings are still tentative and subject to some debate[14], they suggest that the older claim, that high inequality is necessary for growth, does not seem to be born out by the facts (see also Klasen, 1994).

2.3 The Well-Being Measures Used

This section describes some measures that jointly consider per capita income and its distribution and therefore avoid the particularly problematic neglect of income distribution in a consideration of welfare. Most are well-known in the inequality literature although not all of them have been used explicitly for aggregate welfare comparisons. All share the feature that they can be summarised by the following formula:

$$W = \mu(1 - I), \qquad 0 \leq I \leq 1. \tag{2.1}$$

Welfare W is a function of mean income μ, reduced by a measure of inequality I. Thus, the existing degree of inequality adjusts mean income downward to reflect the welfare loss

[12] Assuming a Keynesian consumption function, a more unequal distribution of income leads to higher aggregate savings which is one of the main determinants in any growth model.

[13] One might also want to consider longevity in conjunction with income and income inequality to measure how long people are able to enjoy their incomes. For a discussion, see Berry, Bourguignon, and Morrison (1991).

[14] See, for example, Forbes (2000) and Lundberg and Squire (1999). The last-named regard growth and income inequality as jointly determined rather than one causing the other; they also find that inequality is particularly bad for income growth among the poor, while it has a different effect for income growth among the rich.

associated with the (unequal) distribution of that mean income. Several measures will be considered because there are on the one hand differences with respect to the intensity of 'welfare penalty' that is imposed. On the other hand the measures vary in the way they penalise different types of inequality.

The first measure considered here was proposed by Sen (1982) and incorporates inequality by using the Gini coefficient G:

$$S = \mu(1 - G). \tag{2.2}$$

The Sen measure can be derived by replacing Samuelson's problematic 'optimal distribution' assumption by the assumption of 'rank order weighting' (Sen, 1973). Individual incomes will be weighted according to their rank in the income distribution (with the richest person receiving rank 1 and thus the lowest weight for her income). It can also be derived from a utility function where individuals consider not only their own income, but the entire income distribution, with particular emphasis on the number of people with incomes below or above one's own (Dagum, 1990). Thus, preferences are assumed to be interdependent which accords well with recent empirical findings (e.g. Easterlin, 1995; Banerjee, 1997).

A variant of this measure was proposed by Dagum (1990):

$$D = \frac{\mu(1 - G)}{1 + G} = \mu(1 - \frac{2G}{1 + G}). \tag{2.3}$$

Clearly, the Dagum measure is a more extreme version of the Sen measure as it results in a higher penalty because of the denominator which imposes an additional punishment for inequality. The Dagum measure is also based on interdependent preferences and implies that people receive a further welfare penalty from the people ahead of them in the income distribution which also appears to be a reasonable assumption.[15]

In addition, two versions of the Atkinson welfare measure are presented. The Atkinson measure was developed as an indicator of inequality that explicitly considers the welfare loss associated with inequality in the measure (Atkinson, 1970). But one can equally well just use the way the welfare loss is calculated, the *equally distributed equivalent income*, as the welfare measure itself.[16] This equally distributed equivalent income is the amount of income that, if distributed equally, would yield the same welfare as the actual mean income and its present (unequal) distribution (Deaton, 1997). The general form of this

[15] See Dagum (1990) for a derivation and justification of this measure.

[16] This has been done, for example, for Britain by Jenkins (1997) and also by UNDP in deriving the gender-related development index (UNDP, 1995). For a discussion of this index, see Bardhan and Klasen (1999).

measure is given in equation (2.4):[17]

$$A2 = \left[\frac{1}{N}\sum_{i=1}^{N} x_i^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}. \tag{2.4}$$

The measure depends crucially on the exponent ε, the *aversion to inequality factor*. The higher ε, the higher the penalty for inequality. Two cases are studied explicitly, $\varepsilon = 2$, denoted as $A2$, and $\varepsilon = 1$ ($A1$). In the latter case, the general form of the Atkinson measure is not defined and changes to:

$$ln(A1) = \frac{1}{N}\sum_{i=1}^{N} ln(x_i). \tag{2.5}$$

The Atkinson measures can be derived from social welfare functions that are additively separable functions of individual incomes. Thus they are based on individualistic utility functions where people only care about their own incomes. Inequality reduces welfare in this formulation as the utility functions considered are concave for all $\varepsilon > 0$. All the measures exhibit constant relative risk aversion. The $\varepsilon = 1$ has the additional property of being based on a constant elasticity utility function, suggesting that a percentage increase in income is valued the same regardless of its recipient. Such an assumption has quite a lot of intuitive appeal. While clearly $\varepsilon = 2$ penalises inequality more than $\varepsilon = 1$ and is thus based on declining elasticity of income, the underlying assumption, that at twice the level of income, a percentage increase in income is valued half as much as at the lower level of income, also appears to be within the range of reasonable presumptions (see Deaton, 1997; UNDP, 1995). Such penalties of inequality are still consistent with findings from the micro literature on utility and risk.[18] Most of the non-utilitarian theories suggested above would, in fact, require considerably higher inequality aversion.[19]

A third set of measures were proposed by Ahluwalia and Chenery (1974) which presented measures that combine income growth with redistribution. In particular, they suggested a measure which they called a population-weighted or equal-weighted growth rate which is simply the arithmetic average of the growth rates of each individual. Instead

[17] This measure also satisfies the general form of the well-being measure $W = \mu(1-I)$ where $I = \frac{1-A}{\mu}$. See Atkinson (1970) for discussion.

[18] Using data from Poland and the Soviet Union, Stodder (1991) estimates upper and lower bounds of the aversion to inequality parameter and arrives at $1 < \varepsilon < 3$. A recent study on measuring inequality aversion of individuals was conducted by Amiel, Creedy, and Hurn (1999). With the help of the *leaky-bucket* experiment they examine to what extent students from Australia and Israel tolerate income inequality. They found surprisingly low aversion to inequality factors ($\varepsilon \approx 0.25$), but also regional differences. Furthermore, they acknowledge that the results may not be applicable to other population groups.

[19] A strict interpretation of Rawls lexicographic maximin principle would require ε to be infinite (see also Atkinson, 1970).

of treating a dollar increase the same regardless of its recipient, this measure treats a percentage increase the same, thus also allowing for declining marginal utility of income and exhibiting what they called the 'one person, one vote' principle of growth measurement. It turns out that this measure is a small-number approximation of the Atkinson $\varepsilon = 1$ measure, which also weights a percentage increase the same regardless of its recipient.[20] Thus, it will not be reported separately here. But the similarity between this measure and the Atkinson measure gives another justification for the Atkinson measure.

Similarly, their second growth measure, the welfare or poverty-weighted growth rate (which gives greater weight to income increases of the poor than the rich) is a discrete approximation of a version of the Atkinson with $\varepsilon > 1$. The Atkinson measure with $\varepsilon = 2$ measure will therefore yield very similar results.

Before turning to the data and the results, it is important to briefly discuss the most important differences between the measures.[21] Apart from the penalty applied to inequality, the two Gini-based measures differ quite fundamentally from the two Atkinson measures (and thus the Ahluwalia and Chenery measures) in ways that are important to consider. Firstly, the two sets of measures respond differently to equal-sized income transfers at different points in the income distribution. While all measures are consistent with the Dalton principle of transfers[22], the Atkinson measures obey what has been called transfer sensitivity. An equal-sized transfer will have a larger impact on inequality (and thus on welfare) if it happens among the poorer sections of the income distribution than if it happens among richer sections (Sen, 1997). Most would agree that this is a desirable property. In contrast, the largest impact of an equal-sized transfer using the Gini coefficient will be among the mode of the income distribution, i.e. among middle income groups. The difference occurs as these transfers will have the largest impact on the rank of the people affected by the transfer and thus the weights attached to their incomes (see Atkinson, 1970; Blackorby and Donaldson, 1978). Given, income comparisons with others are very important, shifts in income which have a large impact on the ranking should clearly be weighed heavily.[23] But it seems that many analysts see this as a rather

[20] It can be shown that the growth in the Atkinson measure with $\varepsilon = 1$ is simply the geometric mean of the growth rates of individuals (or quintiles, depending on the unit of disaggregation), while the population or equal weights measure is the arithmetic mean of the growth rates. For small numbers, one is an approximation of the other. See Klasen (1994) for a discussion and application of the Ahluwalia and Chenery measures.

[21] For a more extensive discussion of these issues, refer to Atkinson (1970), Blackorby and Donaldson (1978), and Dagum (1990).

[22] The Dalton principle of transfers says that the value of an inequality measure must fall by a transfer from a richer person to a poorer person which does not reverse their position in the income ranking.

[23] For a recent study on these issues, see for example Graham and Pettinato (2002). Analysing data from Peru (covering the period 1985-2000) and Russia (1995-1998), they found that relative income differences seem to matter more for those in the middle of the distribution than for other income groups.

undesirably attribute of the Gini-based measures (e.g. Atkinson, 1970).[24]

The second major difference relates to the behaviour of the overall measure if only parts of the population are affected by any changes. The Atkinson measures are subgroup consistent and thus imply that any increase in the income of a sub-group (or a reduction in inequality of that sub-group) will, ceteris paribus, raise aggregate welfare. In contrast, an increase of income accruing to the richest could actually lower aggregate welfare in the Gini-based measures as the increase in mean income can be more than off-set by the increase in inequality.[25] Some see this as an argument in favour of the Gini-based measures (e.g. Sen, 1997; Dagum, 1990), others see subgroup consistency as a valuable criterion. In the context of this work, it will suffice to note that the Gini-based measures penalise inequality more if middle income groups are hurt the most, while the Atkinson measure will penalise more if the poorest are hurt the most by it.

[24]Amiel, Creedy, and Hurn (1999) compare alternative specifications of a social welfare function and conclude that a Gini based function yields a better fit of the regression.

[25]See Dagum (1990) for examples. This difference only appears if inequality is much more extreme than the types of inequality existing in today's world.

Chapter 3

The Comparison of Well-Being across Time and Space

3.1 Description of Data Sources

For both components of the measures, data on mean income and inequality, there are several options. For the following analysis, the main source of data on inequality is the World Income Inequality Database version 1.0 (WIID, 2000), which provides more than 5.000 Gini coefficients and associated distributions for 151 countries. The main sources used for assembling the data set were the Deininger-Squire data (Deininger and Squire, 1996), the Luxembourg Income Study (LIS, 2000), the TransMonee Project (TransMonee, 1999) as well as other research studies and information provided by various Central Statistical Offices. To get recent data for developing countries as well as some OECD countries, Gini coefficients and income shares published by the World Bank's Poverty Monitor (World Bank, 2002) and directly provided by LIS are added.[1] In WIID all observations are classified as either 'reliable' or 'less reliable'. Only observations which are categorised as 'reliable' and represent the entire population of a country are considered.[2] With respect to the underlying income concept, inequality data must be based on gross or net income, or on expenditures. Regarding the unit of income recipient, data based on person (or household per capita), or households are chosen. Only for few countries the analysis

[1] My special thanks go to David Jesuit and Tim Smeeding for kindly providing the most recent data of several OECD countries.

[2] The quality of income inequality data provided by Deininger and Squire (1996) was already evaluated by them. If the data satisfy a minimum standard, i.e. they are based on household surveys, representative of the entire country, and a comprehensive concept of income (or expenditure) is used, they are included in the so-called 'high quality' set. Atkinson and Brandolini (2001), however, warn of the 'mechanical use' of the data. In WIID, data have been scrutinised one by one once again and the quality of the data was sometimes rated differently. Therefore, it happens that data classified as 'not accepted' and therefore not contained in the quality subset of Deininger-Squire are part of the 'reliable data set' in WIID. The opposite, that data belonging to the quality set but are categorised as 'not reliable' in WIID, is also possible.

has to rely on data that either have been adjusted for household composition using an equivalence scale or where the income concept used and the reference unit are unknown.[3] In the case where several Gini coefficients with associated distributions were available for a particular country at a particular point in time, that observation allowing to base inequality data on the same or similar specification across time was chosen.

Ideally, one would want to at least ensure that the indicators used are based on a consistent definition of income and reference unit both across countries and time.[4] Pursuing this strategy would result in only a small number of countries and not allow a meaningful international analysis. While the main analysis deals with differing income concepts and reference units, in the sensitivity analysis, I try to generate consistent data by making suitable adjustments to base all data on unequivalized gross income per person.

Although WIID is probably the most comprehensive source on data on inequality, data for the early years in the analysis are rare and some adjustments were necessary. In case there is no Gini coefficient and associated income shares for the particular point in time, the nearest available data is used for calculation. Despite these adjustments the samples of countries to which all measures can be applied are still quite limited. Table 3.1 shows the different years of available data on income distribution that have been chosen for the years 1960-1998. The greatest concessions had to be made for less developed countries like Pakistan, Panama and Chile in 1960, or for Nepal, Indonesia and Singapore in 1970. But also in case of developed countries like Finland in 1960 and 1970, or Belgium and Italy in 1970 the inequality data come from considerably later periods. For 1998, the latest available income distribution estimate has been applied which in a few cases date as far back as 1990 or 1991, but in most cases comes from the period 1993 to 1997.[5]

Regarding income data one could consider per capita income, per capita disposable income, or per capita consumption. To make the analysis comparable to international comparisons of per capita income and to get the largest possible sample, I rely on per capita gross national product[6] as presented in the national accounts as the income concept used.[7] The calculation of the well-being measures is based on purchasing power adjusted

[3]For a discussion of the use of equivalence scales in the context of welfare measurement, please refer to Atkinson, Rainwater, and Smeeding (1995), Deaton (1997), and Ayala, Martinez, and Ruiz-Huerta (2001).

[4]Even if Gini coefficients are based on the same definition of income and economic unit they might not be comparable across countries, because of differences in sample methods, quality of surveys etc. (see WIID, 2000).

[5]In nearly all cases, the exact year for the income estimate is used under the (implicit) assumption that changes in income distribution between adjacent years are typically smaller than changes in mean income. Given positive average real income growth present in almost all countries which would bias income comparisons from different years, this assumption appears reasonable.

[6]Gross national product should better capture welfare of the population than gross domestic product as the former includes earnings from abroad and excludes earnings by foreigners.

[7]There are basically two reasons why national account data instead of survey means are used. Firstly,

income data provided by the Penn World Table (PWT), versions 6.0 and 5.6 (Heston, Summers, and Aten, 2001; Summers and Heston, 1991).[8] In addition, data on GNP per capita based on official exchange rates from the World Bank for all years as well as the World Bank's purchasing power adjusted income data[9] for the years 1980, 1990, and 1998 (WDI, 1999, 2001, 2002) will be presented for comparison.

In the sensitivity analyses, the data used will be replaced with alternative estimates which either differ in the definition of income and/or reference unit or were provided by another data source. Moreover, I estimate fixed effects panel regressions to try to address the inconsistent treatment of the reference unit and the income concept, applying similar procedures as used by Dollar and Kraay (2002) and Lundberg and Squire (1999). Using the regression-based adjustments, all observations are based on gross income per person.

For the calculation of global well-being and changes thereof between 1970 and 1998, I start by using a sub sample which consists of 72 countries representing 81 per cent percent of the world population in 1998. In order to reach such coverage and include some of the populous and high population growth African and Middle Eastern countries, it was necessary to assume in some cases that income inequality remained stable throughout the period studied and only income growth changed, as more data are available on the latter than the former.[10] However, the main analysis disregards many of the formerly socialist countries since the PWT do not provide sufficient information to calculate PPP adjusted per capita income for this group of countries in the given period. Since many

the latter are only available for recent years, hence, neither allowing the time frame nor the regional coverage of the present analysis. Secondly, the inequality-adjusted measures will be placed alongside the income per capita figures to reveal the existent differences. The drawback of relying on national account data is that the results obtained here are not comparable to those of similar studies based on survey data (e.g. Milanovic, 2002; Ayala, Martinez, and Ruiz-Huerta, 2001).

[8]The PWT 6.0 series dealt with is real per capita GDP, chain method (1996 prices) which is turned to GNP per capita using a series that relates current GNP to GDP (CGNP series). This series is only included in version 5.6 and covers the period 1970-1992 for most countries. For the years 1960 and 1998, numbers reported for the most adjacent years are adopted. Since for the vast majority of countries, GNP and GDP are of similar magnitude and country specific ratios of both income measures are relatively constant over time, these manipulations should not cause major problems. A comparison with the latest release of PWT 6.1 which includes an update of the CGNP series covering the time span 1960-2000, 'justifies' this approach as well.

[9]The series used is GNI per capita, PPP in current international dollars. Gross national income is the "sum of value added by all resident producers plus any product taxes (less subsidies) not included in the valuation of output plus net receipts of primary income [...] from abroad" (WDI, 2002). All data taken from the World Bank were deflated to 1996 prices using the US GDP deflator (WDI, 2002) as this is the base year in PWT 6.0.

[10]This way, all countries shown in Table 3.1 with at least two observations on inequality between 1970 and 1998 are included, except for Bulgaria (no income data in 1970 and 1980 available) and Sierra Leone (civil war in the early 1990's). The assumption of stability of income distribution is, especially when compared to huge variations and changes in income growth levels, reasonable as will be shown below and as has been found by others (e.g. Deininger and Squire, 1998; Lundberg and Squire, 1999). Of the world's 40 most populous countries in 1998 all except Russia, Germany, Vietnam, Iran, Ukraine, Democratic Republic of Congo, Myanmar, Argentina, Sudan, Afghanistan, and Uzbekistan are considered.

of them experienced a considerable worsening in income inequality during the transition period (Milanovic, 1998; Grün and Klasen, 2001), ignoring them in a global analysis of well-being may yield flawed results. Therefore, I expand the sample by 15 Eastern European countries and successor states of the Soviet Union, covering now 86 per cent of the world population, and make a second analysis of global well-being for the years 1988 and 1998 by using GNI per capita in PPP terms provided by WDI (2002).[11] For both samples I calculated average income per quintile for each country, sorted them in ascending order to generate global income quintiles, and then calculated average incomes of these world quintiles based on the population-weighted country quintiles contained in each world quintile.[12] These computations result in average incomes per 'world quintile' which are applied to the Atkinson measure with $\varepsilon = 1$ and $\varepsilon = 2$.

3.2 Well-Being Comparisons

3.2.1 International Analysis

Table 3.2 presents the analysis for 1960 based on the six measures used. The first two measures are per capita income, using exchange rates and PPP, respectively. The next two are the Atkinson measure with $\varepsilon = 1$ and the Sen measure, exhibiting a comparatively 'mild' well-being penalty for inequality. The last two are the Atkinson ($\varepsilon = 2$) and the Dagum measures with a more heavy implied well-being penalty for inequality. The analysis is restricted to only 43 countries. Since they cover a wide spectrum of incomes, big changes in ranks can only happen when there are very drastic differences between the measures.

Well-being, as estimated by the various measures, falls drastically when considering inequality. Using the Atkinson ($\varepsilon = 1$) or Sen measure, well-being falls by about 10-65 per cent, and by 70 (Brazil and Mexico) to nearly 80 per cent (Gabon) in the Atkinson ($\varepsilon = 2$) and Dagum measure. Compared to pure income per capita measures, existing inequality leads to major reductions in measured well-being in all the countries considered.

As expected from the discussion of inequality-adjusted measures above, there are some differences in the extent of 'penalty' for inequality, depending on the measure used. For example, Pakistan gets penalised less by the Atkinson ($\varepsilon = 2$) measure than the Sen measure, while the reverse is the case for the Philippines. The reason is that in the

[11] In particular, I include Belarus, Bulgaria, Czech Republic, Estonia, Kazakhstan, Kyrgyzstan, Lithuania, Moldova, Russia, Slovak Republic, Slovenia, Turkmenistan, Ukraine, and Uzbekistan. Data on income inequality for the pre-transition period are mainly taken from Milanovic (1998); for the year 1998 I again rely on WIID (2000).

[12] When a country quintile straddles the line between two world quintiles, the country quintile was proportionately allocated to ensure that the world quintiles contain equal population numbers.

Philippines the poorest do particularly badly corresponding to a heavy penalty in the Atkinson measure, while in Pakistan the middle income groups do relatively worse, which attracts the higher penalty in the Gini-based measure.

In 1960, no assessment of inequality can dislodge the US from the highest rank in all measures, and nothing can prevent Tanzania from being at the bottom of the list for those indicators with data being available. But there are also a number of rank changes. Firstly, there is a considerable difference between the ranks using exchange rate and PPP, suggesting the presence of over- and undervalued exchange rates. As expected, the discrepancy is larger among poorer countries, related to the undervaluation of the non-traded sectors. Secondly, there are a number of remarkable rank reversals when inequality is progressively being considered. For example, Bangladesh and Madagascar trade places between the pure income and the broader well-being measures. In the two income measures Madagascar is four ranks ahead; in the last two columns, Bangladesh is five ranks ahead.[13] A similar reversal occurs, somewhat surprisingly, between Britain and Sweden. Sweden is ahead in the pure income measures, while Britain is ahead in measures that also consider distribution; in fact, it mostly occupies the second highest spot in this list. This suggests that the very low inequality in Sweden was not already present in the 1960s, and the rise of Britain reminds us that Britain was among the more equal countries in Europe in 1960.[14]

Table 3.3 shows the rankings for 48 countries in 1970. Again, there are large differences between exchange rate based estimates of real incomes and PPP estimates, with the discrepancy being largest among poorer countries. Considering inequality continues to reduce well-being drastically. Once again, Brazil is one of the countries that lose most: Well-being using the Dagum measure is 73 per cent below the level it would be if its per capita income were equally distributed. The US remains on top in all measures except the exchange rate adjusted income per capita measure, arguably the least reliable indicator of well-being. At the bottom Nepal, Indonesia, and Sierra Leone vie for the worst spot. Some more dramatic reversals in rank occur. Panama falls from number 25 in the exchange rate list to number 41 in Atkinson ($\varepsilon = 2$) measure. Conversely, Sri Lanka rises from 16 ranks below in the first column to one rank above Panama once inequality is considered in the Atkinson ($\varepsilon = 2$) measure. Unequal Brazil trades places with more equal Korea, and now Sweden maintains its rank when inequality is being considered, while Britain's fall in the income rank cannot be completely compensated by its still comparatively low inequality.

[13] Colombia is another country that also falls considerably, once PPP and inequality is considered.

[14] Gottschalk and Smeeding (2000) also report fairly high income inequality in Sweden in the 1960s. In the LIS, Sweden is found to be considerably more equal than Britain. Since the LIS does not go back that far, it is hard to tell whether the reported higher inequality in the 1960s is due to measurement error or true effects. See also the sensitivity analysis in the next chapter and Atkinson and Brandolini (2001).

Table 3.4 examines 57 countries for 1980. There is one more indicator, PPP adjusted income per capita from the World Bank (WDI, 2002), which is placed alongside the data from the Penn World Tables. The comparison suggests that the PPP adjustment is subject to some margin of error. For example, China, India, Pakistan, Bangladesh, Indonesia, Malaysia, Thailand look somewhat richer in the PPP adjustment from the Penn World Tables than in the adjustment done by the World Bank while the reverse appears to be the case for several Latin American countries. Several rank changes happen as a result of these differences in the PPP adjustments.

The inequality-adjusted measures continue to be much lower than the income measures. Brazil and Colombia continue to suffer from the largest reductions in well-being which are also now larger than previously, suggesting not only high but worsening inequality. Due to rising inequality and catch-up growth, the US loses its top spot to Belgium in the Atkinson ($\varepsilon = 2$) measure.[15] Britain still rises in the ranks when inequality is considered. Unequal Brazil and more equal Costa Rica now trade places; Brazil is two ranks ahead in PWT PPP income (column 3), and Costa Rica is one to three places ahead in the inequality-adjusted measures. Bangladesh, on the other hand, no longer improves its position as much as before.[16]

Table 3.5 examines the per capita income and well-being in 70 countries in 1990. The differences between the PWT and the World Bank PPP adjustments still exist, but remain consistent in the sense that the differences in assessment in 1990 are largely the same as for 1980. Well-being continues to be much lower than before; by and large, the reduction appears to be similar to previous decades suggesting no general worsening (or improvement) in income distribution.

Regarding rank reversals, Brazil and South Africa, two of the world's most unequal countries, get surpassed in the Atkinson measure ($\varepsilon = 2$) by Indonesia, a country 25 and 30 ranks, respectively, below in the income ranking with less than half the PPP income per capita when compared to Brazil. That is to say, Brazil could generate the same level of well-being with only half the income, if that income was as evenly distributed as it is in Indonesia.

Low levels of income and sizeable income inequality assure that many African countries land at the bottom end in all measures. At the other end of the spectrum, the US only retains the second spot in the PPP-adjusted income measures and the mildly penalizing inequality-adjusted measures. In the Dagum measure it is surpassed by Canada and Luxembourg and, in the Atkinson ($\varepsilon = 2$) measure, additionally by Belgium and the

[15]The US loses especially in the Atkinson ($\varepsilon = 2$) measure as the poorest are particularly badly off in the US. See also Gottschalk and Smeeding (2000).

[16]This is due to somewhat higher observed inequality in 1980, which falls again in the late 1980s and early 1990s. To what extent this data point is an aberration, is difficult to tell.

Netherlands. This fall in ranks of the US is mostly due to rising inequality there, compared to the other countries (rather than differences in average income growth). Clearly, people in the US are paying a price in terms of well-being due to the higher inequality there and other countries do not suffer from the same problem (see Klasen, 1994).[17] Similarly, higher inequality in Britain ensures that the country no longer rises in ranks and even falls in some measures once inequality is considered.

Table 3.6 shows the well-being measures for 72 countries in 1998. At the bottom end, we again find mostly African countries. Indonesia still improves in ranks and is ahead of Peru in the Dagum and Atkinson ($\varepsilon = 2$) measures. Likewise, poorer Bulgaria and richer Mexico trade places in two measures which also consider inequality. At the top end, Luxembourg but also again the US lead the pack in most indicators. The US gained strength since they experienced a substantial increase in income per capita and a comparatively small change in income inequality compared with 1990. Rising inequality in Canada is ensuring that it is falling further behind, being surpassed by some other OECD countries in the Atkinson ($\varepsilon = 2$) and Dagum measures.

It is hard to summarise the many particular findings from this discussion. But a few points are worth noting. Firstly, as expected real income comparisons based on official exchange rates give a very misleading impression of well-being. In particular, they systematically understate well-being in developing countries. At the same time, there are discrepancies between the two sets of available PPP estimates. Secondly, the consideration of the income distribution has a large impact on well-being. Well-being falls by 15-75 per cent once inequality is taken into account. The comparison of welfare levels between Indonesia and Brazil in Figure 3.1 is informative here. Relying on unadjusted income measures, Brazil is far ahead of Indonesia in all years. But once inequality is considered as well, Brazil's welfare levels drop sharply and in 1998 Indonesia has not only closed the gap but, according to the newly introduced Atkinson measure with $\varepsilon = 5$ reached a slightly higher welfare level than Brazil. Thirdly, large differences in inequality between countries lead to very large changes in rank. Brazil's drop in rank is a very dramatic illustration of this. Fourthly, changes in inequality have an important impact in some countries, most notably the US and Britain. This is also illustrated in Figure 3.2 which examines the welfare levels for the US and Canada between 1970 and 1990. While the slopes of the curves for the US become steeper when going from 1970 to 1990 thereby

[17] Please note that these results differ from Ayala, Martinez, and Ruiz-Huerta (2001) who, based on micro data, find that the US is surpassed only by Belgium in the Atkinson ($\varepsilon = 2$) measure, while Canada and Sweden remain considerably worse off. The difference in findings is probably due to the fact that the present analysis uses the mean (gross) income variable based on national accounts, while in Ayala, Martinez, and Ruiz-Huerta (2001) mean income refers to disposable income based on adjusted micro data. Other sources of differences could be the different PPP adjustments (PWT versus OECD PPP adjustments), and differences in the Gini coefficients.

indicating rising inequality which leads to lower welfare levels, Canada experiences declining inequality and is thus able, according to some measures, to reach a higher welfare level than the US in 1990.[18] Fifthly, the combination of income growth as well as levels and changes in inequality together can lead to very large differences in changes in well-being. The comparison between Sri Lanka and Peru is instructive here (see Figure 3.3). Sri Lanka combines comparatively low inequality with steady growth, Peru experienced considerable fluctuations in its mean income with relatively high inequality. In 1998, despite being still poorer in income than Peru, Sri Lanka has already a higher welfare level in the Atkinson ($\varepsilon = 2$) measure and adds to this lead if $\varepsilon = 5$ is assumed. To assess whether these findings are due to peculiarities and inconsistencies of the data chosen, a sensitivity analysis is presented in the following.

3.2.2 Sensitivity Analysis

The robustness of the results is verified with the help of two different approaches. Firstly, I simply replace the data on income distribution used in the original analysis. Alternative data which are either based on different income concepts and/or reference units or come from a different data source are considered.[19] For countries with such alternatives available, I replace the Gini coefficients and income shares, calculate the measures, rank the countries again and compare the results with those obtained from the original analysis.

Table 3.7 shows the Gini coefficients and their alternatives, what income concepts and recipient units they are based upon as well as the resulting changes in rankings. The simultaneous replacement approach leads mainly to no or only small changes in ranking. However, in some cases major changes take place. The alternative Gini coefficient used for Jamaica in 1960 exceeds the one originally used by only 1.7 percentage points, which leads to only little changes in ranking when focussing on the Gini based measures. However, the income shares (which are not reported here) partly change dramatically, leaving the poorest 20 per cent with only half the income and increasing the share of income going to the richest 20 per cent of population considerably. The Atkinson measures answer these dramatic changes with notably lower ranks.[20]

Turning to the year 1980, Canada and Norway experienced significant changes in ranking. For both countries the alternative Gini coefficients were taken from LIS (2000)

[18]Interestingly, Canada, despite its smaller income, also regularly surpasses the US in the Human Development Index calculated by the United Nations Development Programme UNDP (2002).

[19]In addition, this replacing approach is restricted to alternative data which are based on the same year (plus/minus one year) as used in the main analysis. The source of alternative data is given in Table 3.7.

[20]One may doubt these rather extreme changes in the income shares. I nevertheless used the data as both the 'original' source (Deininger and Squire, 1996) and WIID classified them as reliable.

and are based on the same specifications as the ones used in the original analysis. However, the Gini coefficients itself differ considerably, thereby leading to changes up to 8 ranks. Data on inequality provided by the Luxembourg Income Study are derived from micro data sets and undergo different strategies of top and bottom coding - both may contribute to the existing differences.

Mexico in 1990 is another example of the bandwidth of inequality data available for one particular point in time. Both Gini coefficients were provided by Deininger and Squire (1996) but belong to different quality classifications. The main difference between the two indices is the income share going to the richest 20 per cent of population, which amounts to 59.3 per cent in the first distribution but is declining to 53.6 per cent in the one used alternatively. Consequently, distribution of income is more equal according to the alternative data and especially the measures that penalise the existing degree of inequality more rank Mexico up to 6 positions higher.

In a second kind of sensitivity analysis, I use a regression-based approach to deal with the inconsistencies in terms of the income concepts and reference units used. The sample is expanded by adding data of countries not considered in the main analysis but which are part of the reliable set in WIID (2000). This enables us to get several observations per country at the same time which should enhance our ability to identify the reference unit and income definition effects. In particular, I regress the Gini coefficients available on the income definition (expenditure, net income, unknown income, or gross income, the excluded category), and the reference unit considered (household, family, unknown, equivalized, or person, the excluded category). Following suggestions from Atkinson and Brandolini (2001), dummy variables for Deininger-Squire data labelled as 'cs' (no consistent source) and 'ps' (primary source unknown) are included.

Regression 1 in Table 3.8 shows that indeed the income definition and the choice of reference unit do matter. Expenditure-based and net-income or equivalized Gini coefficients are typically lower, while household-based Gini coefficients appear to be higher.[21] The interaction term net income and OECD countries in the second regression shows that the difference between gross and net income is largely a phenomenon of OECD countries, as one would expect (Atkinson and Brandolini, 2001).

As a next step, the Gini coefficients are adjusted according to the regression results from the first estimation. All the Gini coefficients are thereby based on the omitted categories, i.e. gross income per person. This way I hope to have dealt with the most glaring

[21]The somewhat surprising result about household-based Gini coefficients was also found by Lundberg and Squire (1999). Note that the regressions here have considerably higher explanatory power (as measured by the R-squared) as the ones used by Dollar and Kraay (2002) and Lundberg and Squire (1999).

inconsistencies, although further adjustments are surely possible (Atkinson and Brandolini, 2001).

How do the results change if one uses these adjusted Gini coefficients for the calculation of the Gini based measures? Table 3.9 shows that generally the results do not change greatly. Using the Sen measure, the vast majority of rankings remain the same or change only by one position. Regarding the Dagum measure, more significant variations happen, but again there is more persistence than change. The year 1990 marks some kind of outlier with almost 40 per cent of the rank changes happened to be by two positions. Moreover, most of the dramatic rank reversals and changes discussed earlier still hold.[22]

These sensitivity analyses suggest that few of the basic results on the large absolute impact of income inequality and the change in ranks as a result of it are seriously affected by using different data sets. However, quite a number of individual rankings are concerned so that analyses focussing on smaller differences, particularly among OECD countries, should be based upon more consistent data sources rather than rely on the somewhat heterogeneous information used here (e.g. Ayala, Martinez, and Ruiz-Huerta, 2001).

3.2.3 Comparisons across Time

The previous discussion has already suggested that in some countries inequality has changed considerably. At the same time, it appears that there is also a great deal of stability in income inequality measures. Most countries either seem to improve or worsen in rank at a point in time when inequality is considered, with this relationship not changing much over time. This question is examined a bit more closely now.

A first impression can be gleaned from Table 3.10 which shows average Gini coefficients from the 1960s to the 1990s. What emerges is a great deal of stability. The average Gini coefficient, whether raw or adjusted based on regression 1 in Table 3.8, does not appear to have changed a lot (see also Deininger and Squire, 1998; Lundberg and Squire, 1999).[23] This average could, however, mask some variation. To arrive at a better understanding, a regression based approach is chosen. As a first step, it would be helpful to see whether, controlling for country-specific fixed and random effects, there are temporal trends in inequality. In Table 3.11 specifications (1) and (2) show the results from the fixed and

[22]For example, while Brazil and Indonesia still move towards similar welfare levels once inequality is considered in the measurement, Brazil remains more ranks ahead in the inequality-adjusted welfare measures. This is mostly due to the fact that the Indonesian data are based on expenditures while the Brazil data are based on gross incomes. Similarly, Britain rises less in the early years considered and it falls more in the later years once the adjusted Gini is used, since an equivalence scale was applied to calculate the original data.

[23]The small observed changes could be due to compositional changes.

random effects regressions.[24] While the general impression of great stability is supported, it is suggested that, when compared to the 1990s, inequality was significantly higher in the 1960s, and significantly lower in the 1980s, but the average differences were not very large in magnitude.[25]

The last two specifications in Table 3.11 are fixed effects regressions testing for an intertemporal Kuznets curve, i.e. the hypothesis that as countries go through the process of development, inequality first worsens and then improves again. The results are quite clear here. There is not even the smallest hint for such an inverse U relationship that would hold systematically across all countries (see also Deininger and Squire, 1998; Lundberg and Squire, 1999). In fact, specification (4) rather suggests the opposite, namely a U shaped relationship, even though it is not a very distinct curve. Thus, on average, systematic trends in income distribution that relate either to temporal trends or to trends in income could not be detected. It does not appear that inequality within countries is rising or falling systematically. For the study of well-being, this is a significant finding since it basically means that assessments of *changes* in well-being will not differ much for most countries if one switches from an income growth rate to a measure that evaluates the observed growth in the distribution-sensitive measures.

Figures 3.4 and 3.5 plot two typical examples. While Brazil and Indonesia differ greatly with respect to the degree of existing inequality, the income distributions itself did, in a relative sense, not vary a lot in the last decades. This results in comparatively small differences between an income growth rate and the growth rate of the distribution-adjusted income measures (illustrated by similar height of the first columns of each measure). At the same time, this general stability masks some apparent rises and declines in inequality in those countries. For example, in Brazil income distribution appears to have become notably more unequal between 1961 and 1990. In the sub-period 1981-1989, this trend was accompanied by only moderate income growth leading not only to smaller, but negative growth rates in the inequality-adjusted welfare measures. In 1997, income inequality was at an all-time low and positive growth rates are reported for all measures for the period 1990-1997. Thus, one should not interpret longer-term stability as the absence of any developments in sub-periods (see also Atkinson and Brandolini, 2001). Canada and Finland are two other examples where changes in inequality differed in different time periods (Figures 3.6 and 3.7). Finland is particularly notable for the fact that inequality appears to have declined considerably since the 1980s leading to higher changes in well-being once inequality is considered. Finally, the case of China (Figure 3.8) illustrates that considerable income growth is not automatically associated with a worsening income distribution,

[24] A Hausman test suggests that random effects would be preferable to use, although the results do not differ much.

[25] These results are robust to using the adjusted Gini coefficients.

although higher inequality in the 1990s let the inequality-adjusted growth rates become smaller.

It thus appears that increasing income inequality observed in some rich countries are not global processes.[26] It seems not to be the case that all industrialised countries are condemned by global forces or other factors to face ever-rising inequality. Although a careful investigation of this issue goes beyond the scope of the present work, the differences in experience suggest that the role of economic policy in generating and combating income inequality is quite considerable (see also Atkinson, 1997; Aghion and Williamson, 1999).

Despite this general rule, there are some notable exceptions and it is important to emphasise that in some countries the assessment of income growth seriously bias our view of changes in well-being. In particular, Britain and the US will be studied now.[27] The impact of inequality on changes in well-being in the US was already examined in Klasen (1994). Here, the analysis is extended to the year 2000 and some additional measures are presented. Data on income and inequality are taken from the Historical Income Tables provided by the U.S. Census Bureau (U.S. Census, 2002).[28] The reported Gini coefficients are somewhat higher, but follow a similar trend as the ones used in the previous analysis. Figure 3.9 shows the basic results. During the 1950s and the 1960s, high annual growth was accompanied by falling inequality which ensures that increases in well-being were considerably above the income growth rate. In contrast, in the 1970s, 1980s, and 1990s, low to moderate income growth was accompanied by sharply rising inequality so that well-being grew by negligible amounts. In fact, it shrank in the 1980s, depending on the measure.[29]

Since economic growth has picked up since 1993 and unemployment is/was at a 30 years low, one may wonder how well-being changed in the so-called 'new economy.' Figure 3.10 gives an impression. Since 1993, income growth has been still somewhat below the high growth rates of the 1960s, and inequality continues to worsen (although at a much slower pace) in the 1990s. This time, it is more due to greater income increases among the rich, rather than deteriorations among the poor which was the case in the 1980s. This rising inequality means that well-being in the 'New Economy' was growing considerably

[26] Based on the LIS, Gottschalk and Smeeding (2000) find that in the majority of OECD countries, there was some increase in inequality in the 1980s. But timing and extent differed greatly and it was far from being a universal phenomenon. See also Ayala, Martinez, and Ruiz-Huerta (2001).

[27] Many formerly socialist countries experienced even sharper increases in inequality during the period of transition which was also accompanied by negative income growth. In Kyrgyzstan and Ukraine this resulted in dramatic welfare losses up to 75 per cent for the period 1988-1995 according to Atkinson ($\varepsilon = 2$) and Dagum measures. For a detailed discussion, see Grün and Klasen (2001).

[28] For a more detailed description of the data source see Klasen (1994).

[29] Also here, one can see the difference between the Gini-based measures and the Atkinson measures. The poorest did particularly badly in the 1980s and the Atkinson measure with $\varepsilon = 2$ shows a deterioration in well-being.

more slowly than in the much-maligned 1960s where high growth was accompanied by falling inequality.

The story for Britain looks much the same (Figure 3.11). The income data is again taken from the World Bank (WDI, 2002) but now combined with inequality series produced by the Institute of Fiscal Studies (IFS) covering the time span 1961-1991.[30] Looking at the total period, changes in well-being become gradually smaller when more and more importance is attached to the existing inequality. But again, the development within sub periods was highly diverse. In the first two decades, moderate income growth was accompanied by falling inequality thus leading to sharper increases in well-being. In the 1980s, moderate income growth translated into stagnation of well-being once the sharply rising inequality is accounted for (see also Atkinson, 1997).

3.2.4 Global Well-Being and Inequality

As is well-known, global inequality is more a result of inequality between nations than inequality within nations (e.g. Anand, 1993; Berry, Bourguignon, and Morrison, 1991; Milanovic, 2002). The richest 20 per cent of the world consume some 70-80 per cent of world income (depending on the calculation and the countries included), leaving some 2-3 per cent to the poorest 20 per cent, which is far larger than the discrepancy between the rich and poor in any one country (UNDP, 1999; Milanovic, 2002). As a result, one would expect that consideration of this inequality between nations should have a considerable impact on measures of well-being. Figure 3.12, based on a sample which captures some 81 per cent of the world population in 1998 but leaves out quite a few of the poorest countries as well as many transition countries, shows that it does indeed. Using the Atkinson measures, world well-being is less than half if applying $\varepsilon = 1$ and only about a quarter if $\varepsilon = 2$ is assumed for all the years considered. This is to say that 'the world' would be as well off as it is currently if it only had half or a quarter its income but that distributed evenly. Including the missing poor and transition countries, even more dramatic reductions in well-being would occur. Global inequality is not just a political, economic, and social problem, it is a welfare problem as it reduces aggregate global well-being considerably.

Figures 3.12 and 3.13 furthermore suggest that global inequality in the underlying sample does not seem to have increased a great deal over the last 30 years. While it was relatively stable between 1970 and 1980, it somewhat decreased since then. The growth of the Atkinson measures far surpasses the growth in mean global income, particularly in the 1980s. This is mostly due to high and fairly evenly spread per capita growth in

[30]Gini coefficients and income shares by decile group (based on before housing costs) are kindly provided by Jayne Taylor.

China and India, as well as high growth in other dynamic Asian economies which push up income growth of the poorest three quintiles of the world income distribution, as Figure 3.13 shows (see also Schultz, 1998).

Income growth and changing distribution could also result in a considerable degree of income mobility. Table 3.12 illustrates how many country quintiles fall into the particular global quintiles and what changes took place between 1970 and 1998. According to the admittedly rather crude measure, there seems to be a great deal of stability, since 203 out of the 360 country quintiles belong to the same world quintile in both years.[31] Furthermore, this stability is very much concentrated at the lower and upper tail of the world income distribution (see also Quah, 1993). In case of the richest global quintile this finding can be attributed to many OECD economies, which, except for their poorest country quintiles, already succeeded in 1970 to belong entirely to this income group. Turning to the bottom end, most African countries considered in this analysis could not drop out of the lowest spots in the global income distribution.[32] Among the population that managed to move upwards and reach the highest income category in 1998 are the second to fourth quintiles of Korea as well as the poorest three quintiles of Singapore. Similar upward mobility can be observed for Indonesia, China, Sri Lanka, Malaysia, and Thailand, while many African countries like Tanzania, Ethiopia, Uganda, Nigeria, Kenya as well as Bangladesh, Colombia, and Guatemala exhibit downward mobility. In 1998, their country quintiles are found among poorer global quintiles than in 1970.

Looking at the results obtained from the expanded sample which considers 15 transition countries in addition, it becomes clear, that the assessment of global inequality and well-being is to some extent driven by sample size, the period considered, and the choice of income data. Figure 3.14 illustrates the well-being changes between 1988 and 1998 for this second global analysis. The qualitative findings are largely the same, but from a quantitative perspective, results do differ from those shown in Figure 3.13. Income growth per global quintile happened at a much smaller scale and the richest 20 per cent even realised a loss in income. The overall mean income remains nearly unchanged. Global inequality seems to have declined as the Atkinson measures indicate positive growth rates.

Exploring the reasons for the striking differences, it turns out that mainly two facts contribute to them. Firstly, for the expanded sample PPP adjusted income data provided by the World Bank (WDI, 2002) had to be used since in the PWT only few data on transition economies are available. As became evident from the comparisons of welfare measures, the World Bank's calculation assumes that incomes in many of the poorer countries are somewhat lower than in the Penn World Tables (see Tables 3.4 to 3.6).[33]

[31] In fact, income mobility is much higher, since there is a lot variability within each world quintile.

[32] The increasing number of country quintiles falling into the poorest world quintile is mainly due to the fact that the second poorest quintile of China could climb into the next income category.

[33] Global inequality automatically appears to be greater when relying on these data.

But not only levels, also growth rates differ considerably between the two data sources. Calculating the average change in income of those countries included in both analyses between 1988 and 1998, income growth amounted to 18.4 per cent according to the PWT, but account for only 5.1 per cent when using the World Bank data. The differences in quintile growth between the two analyses can certainly be attributed to these discrepancies. Secondly, compositional changes of quintiles may especially add to the negative income growth of the richest global quintile. In 1988, the majority of country quintiles of the transition countries belonged to the fourth and fifth global quintiles. By 1998, the transition economies considered here have experienced an average income loss of 37 per cent and many country quintiles fell back to the third global quintile. The drop makes room for other countries to fill the gap, but obviously these losses cannot be balanced out. On the other hand, as the spread of incomes has become smaller, both Atkinson measures reward these developments and point to considerably increases in global welfare.

Thus, in line with some other work (e.g. Schultz, 1998) but in contrast to findings from studies by UNDP (1999) and Milanovic (2002), there has not been a uniform rise in global inequality, nor has there been no mobility of countries up and down the world income distribution.[34] Including even more of the poorest countries would, however, somewhat temper this assessment as they are likely to have contributed to increasing global inequality and less mobility.

Clearly, global inequality is associated with major reductions in well-being. In fact, the reductions are larger than similar reductions within countries since inter-country inequality is so much larger than intra-country inequality. At the same time, high growth in China and India, where most of the world's poor live, and considerably mobility suggest that we are not necessarily facing a world of rising and ever more rigid global distribution.

3.3 Concluding Remarks

From a theoretical point of view, the inclusion of income inequality in a measure of well-being is well justified. Empirical studies confirm the hypothesis that individual and thus aggregate welfare is negatively affected if incomes are more widely dispersed. In the past, indicators which explicitly take the existing distribution of income into account when measuring aggregate welfare have been proposed. Here, I tried to demonstrate that

[34]Milanovic (2002) uses micro data to generate estimates for global inequality in 1988 and 1993. He finds sharply rising global inequality. The difference between his and my finding is probably due to the choice of time period, the large representation of transition economies in his data set, and the use of mean income figure that is based on micro data and may bear little resemblance with national accounts data used here. For a discussion of national accounts versus survey data see also Ravallion (2002).

the evaluation of welfare should rely on such indicators as well. The impression of well-being derived from inequality-adjusted measures sometimes drastically differs from the one obtained when looking at the mean income solely.

To summarise the multi-faceted results, considering income inequality clearly affects the absolute level of welfare. Countries like Brazil, Mexico, Chile, but also the US have considerably lower levels of well-being than suggested by per capita income. Ranking the welfare level of countries, these economies perform worse once inequality-adjusted measures are applied. Whereas Indonesia, Bangladesh, Finland, and Belgium are examples of reaching a higher well-being rank than their pure income rank.

As in most countries income distribution has remained fairly stable over the last 40 years, the consideration of income inequality has a comparatively minor impact on intertemporal comparisons of well-being. But in some countries (notably the group of transition economies, but also Britain and the US) the impression of change in well-being differs when level and changes of inequality are allowed for. Thus, it seems worth to explore the linkages between growth, inequality, and well-being further.

Due to the extremely large global income inequality, global well-being is very much lower than it would be if incomes were more equally distributed. On the other hand, for both samples of countries considered (which unfortunately exclude many of the poorest countries) changes in global well-being are larger than suggested by the income growth measure since especially in the 1980s inequality seems to have declined. But the global analysis also illustrated that sample composition and source of data are critical components in any empirical analysis. Finally, comparing the formation of global income quintiles in 1970 and 1998, it became obvious that countries moved upwards and downwards the world income distribution, suggesting that there is scope for economic policy to influence within-country inequality which then also affects global inequality.

Being aware that much of the data applied here were not intended to be used in such examinations, I tried to verify the results. Although data on inequality are still not sufficiently consistent neither across time nor across countries, many of the main findings turned out to be relatively robust. The late 1990s have seen the evolution of the World Income Inequality Database which provides easy access to indexes and distributions as well as quality ratings thereby enabling us to make a careful choice. Despite these already immense improvements, future developments should be directed at generating consistent and internationally comparable time series on inequality.

Table 3.1: **Income and Inequality Data, 1960-1998**

Country	**Code**	**1960**	**1970**	**1980**	**1990**	**1998**
Algeria	DZA	-	-	-	1988 (38.7)	1995 (35.3)
Australia	AUS	-	1969 (32.0)	1981 (40.0)	1989 (37.3)	1994 (31.1)[b]
Bahamas	BHS	-	-	-	-	1993 (45.3)
Bangladesh	BGD	1963 (37.3)	1973 (36.0)	1981 (39.0)	1989 (28.9)	1996 (33.6)
Barbados	BRB	-	-	1979 (48.9)	-	-
Belgium	BEL	-	1979 (28.3)	1985 (26.2)	1988 (26.6)	1997 (25.0)[b]
Benin	BEN	1959 (42.0)	-	-	-	-
Bolivia	BOL	-	1968 (53.0)	-	1990 (42.0)	-
Botswana	BWA	-	-	1986 (54.2)	-	-
Brazil	BRA	1960 (53.0)	1970 (57.6)	1980 (57.8)	1989 (59.6)	1997 (51.7)[a]
Bulgaria	BGR	-	-	-	1990 (24.5)	1997 (27.3)
Burkina Faso	BFA	-	-	-	-	1994 (48.2)
Burundi	BDI	-	-	-	-	1992 (33.3)
Canada	CAN	1965 (31.6)	1971 (32.2)	1981 (31.8)	1990 (27.6)	1998 (30.5)[b]
Central African Republic	CAF	-	-	-	-	1993 (61.3)
Chad	TCD	1958 (35.0)	-	-	-	-
Chile	CHL	1968 (45.6)	1971 (46.0)	-	1990 (56.1)[a]	1994 (54.8)[a]
China	CHN	-	-	1980 (32.0)	1990 (34.6)	1997 (39.8)[a]
Colombia	COL	1964 (62.0)	1970 (52.0)	1978 (54.5)	1991 (51.3)	-
Costa Rica	CRI	1961 (50.0)	1971 (44.4)	1981 (47.5)	1989 (46.1)	-
Cote d'Ivoire	CIV	1959 (43.0)	-	1985 (41.2)	1988 (36.9)	1995 (36.7)
Denmark	DNK	1963 (37.0)	1976 (31.0)	1981 (31.0)	1987 (33.1)	1995 (37.4)
Dominican Republic	DOM	-	-	1984 (43.3)	1989 (50.5)	-
Ecuador	ECU	-	1968 (38.0)	-	1988 (43.9)[a]	1995 (43.7)
Egypt	EGY	-	-	-	1991 (32.0)	1995 (28.9)
El Salvador	SLV	1965 (53.0)	-	1977 (48.4)	-	-
Ethiopia	ETH	-	-	1981 (32.4)[a]	-	1995 (40.0)
Fiji	FJI	-	1968 (46.0)	-	-	-
Finland	FIN	1966 (31.8)	1977 (30.5)	1980 (30.9)	1987 (26.1)	1997 (23.6)
France	FRA	1962 (50.0)	1970 (39.8)	1979 (34.9)	-	-
Gabon	GAB	1960 (64.0)	1975 (59.3)	1977 (63.2)	-	-
The Gambia	GMB	-	-	-	-	1992 (47.8)
Ghana	GHA	-	-	-	1989 (36.7)	1997 (32.7)
Greece	GRC	1957 (38.0)	1974 (35.1)	1981 (33.3)	1988 (35.2)	-

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Table 3.1: *continued*

Country	Code	1960	1970	1980	19890	1998
Guatemala	GTM	-	-	1979 (49.7)	1989 (59.1)	-
Guinea	GIN	-	-	-	1991 (46.8)	1994 (40.3)
Guinea-Bissau	GNB	-	-	-	-	1991 (56.2)
Guyana	GUY	1956 (56.2)	-	-	-	1993 (40.2)
Honduras	HND	-	1968 (61.9)	-	1990 (57.4)[a]	1992 (52.6)
Hungary	HUN	-	1972 (22.8)	1982 (21.0)	1991 (23.3)	1998 (25.3)
India	IND	1960 (32.6)	1970 (30.4)	1983 (31.5)	1990 (29.7)	1997 (37.8)
Indonesia	IDN	-	1976 (34.6)	1980 (35.6)	1990 (33.1)	1995 (34.2)
Ireland	IRL	-	1973 (38.7)	1980 (35.7)	1987 (34.6)	-
Italy	ITA	-	1977 (36.3)	1980 (34.3)	1989 (32.7)	1995 (34.2)[b]
Jamaica	JAM	1958 (54.3)	1975 (44.5)	1988 (43.2)	1990 (41.8)	1996 (36.4)
Japan	JPN	1962 (37.2)	1970 (35.5)	1980 (33.4)	-	-
Jordan	JOR	-	-	1980 (40.8)	1991 (40.7)	1997 (36.4)
Kenya	KEN	-	-	-	1992 (54.4)	1994 (44.5)
Republic of Korea	KOR	1965 (34.3)	1970 (33.3)	1980 (38.6)	1988 (33.6)	1993 (31.6)
Laos	LAO	-	-	-	-	1992 (30.4)
Lesotho	LSO	-	-	-	1987 (56.0)	1993 (57.9)[a]
Luxembourg	LUX	-	-	-	1985 (27.1)	1994 (23.5)[b]
Madagascar	MDG	1960 (53.0)	-	1980 (46.9)[a]	-	1993 (43.4)
Malaysia	MYS	-	1970 (50.0)	1979 (51.0)	1989 (48.4)	-
Mali	MLI	-	-	-	1989 (36.5)[a]	1994 (50.5)
Mauritania	MRT	-	-	-	1988 (42.5)	1995 (38.9)
Mauritius	MUS	-	-	1980 (45.7)	1986 (39.6)	1991 (36.7)
Mexico	MEX	1963 (53.0)	1968 (57.7)	1984 (50.6)	1989 (55.0)	1992 (50.3)
Mongolia	MNG	-	-	-	-	1995 (33.2)
Morocco	MAR	-	-	1984 (39.2)	1991 (39.2)	1999 (39.5)
Mozambique	MOZ	-	-	-	-	1997 (39.6)[a]
Namibia	NAM	-	-	-	-	1993 (74.3)[a]
Nepal	NPL	-	1977 (53.0)	1984 (30.1)	-	1996 (36.7)
Netherlands	NLD	1962 (42.0)	1975 (28.6)	1981 (26.7)	1987 (29.4)	1994 (25.3)[b]
New Zealand	NZL	-	1973 (30.1)	1980 (34.8)	1989 (36.6)	1990 (40.2)
Nicaragua	NIC	-	-	-	-	1993 (50.3)
Niger	NER	1960 (34.0)	-	-	1992 (36.1)	1995 (50.6)
Nigeria	NGA	1959 (51.0)	-	1986 (37.0)	1992 (41.2)	1997 (50.6)

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Table 3.1: *continued*

Country	Code	1960	1970	1980	19890	1998
Norway	NOR	1962 (37.5)	1973 (37.5)	1979 (31.2)	1990 (33.3)	1995 (23.8)[b]
Pakistan	PAK	1969 (30.6)	1970 (29.9)	1979 (32.3)	1988 (31.4)	1997 (31.2)
Panama	PAN	1969 (48.0)	1970 (57.0)	1980 (47.5)	1989 (56.5)	1997 (48.5)
Papua New Guinea	PNG	-	-	-	-	1997 (50.9)
Paraguay	PRY	-	-	-	1991 (39.7)[a]	-
Peru	PER	1961 (61.0)	-	1981 (49.3)	1986 (42.8)	1997 (46.2)[a]
Philippines	PHL	1961 (49.7)	1971 (49.4)	1985 (46.1)	1988 (44.7)	1997 (46.2)
Poland	POL	-	1976 (25.8)	1980 (24.9)	1990 (26.2)	1996 (33.7)
Portugal	PRT	-	1973 (40.6)	1980 (36.8)	1990 (36.8)	1991 (35.6)
Romania	ROM	-	-	-	1989 (23.4)	1994 (28.7)
Rwanda	RWA	-	-	1983 (28.9)	-	-
Senegal	SEN	1960 (56.0)	-	-	1991 (53.8)	1994 (41.3)
Sierra Leone	SLE	-	1968 (60.8)	-	1989 (62.9)	-
Singapore	SGP	-	1978 (37.0)	1980 (40.7)	1988 (41.0)	-
South Africa	ZAF	-	-	-	1993 (62.3)	1994 (59.3)
Spain	ESP	1965 (32.0)	1973 (37.1)	1980 (34.2)	1989 (25.9)	1991 (33.0)
Sri Lanka	LKA	1963 (47.0)	1970 (37.7)	1980 (42.0)	1990 (30.1)	1995 (34.4)
Sweden	SWE	1967 (37.9)	1975 (31.4)	1980 (29.4)	1990 (29.0)	1995 (22.1)[b]
Tanzania	TZA	1964 (54.0)	-	-	1991 (59.0)	1993 (38.1)
Thailand	THA	1962 (41.3)	1969 (42.6)	1981 (43.1)	1990 (48.8)	1998 (41.4)
Trinidad and Tobago	TTO	1958 (46.0)	1971 (51.0)	1981 (41.7)	-	-
Tunisia	TUN	1965 (42.3)	1971 (53.0)	1985 (43.4)[a]	1990 (40.2)	-
Turkey	TUR	1968 (56.0)	1973 (51.0)	-	1987 (44.1)	1994 (41.5)
Uganda	UGA	-	-	-	1989 (33.0)	1993 (39.2)
United Kingdom	GBR	1961 (25.3)	1970 (25.1)	1980 (24.9)	1990 (32.3)	1999 (34.5)[b]
USA	USA	1960 (34.9)	1970 (34.1)	1980 (35.2)	1990 (37.8)	1997 (37.2)[b]
Venezuela	VEN	1962 (42.0)	1971 (47.7)	1981 (42.8)	1989 (44.1)	-
Zambia	ZMB	1959 (48.0)	-	1976 (51.0)	1991 (48.3)[a]	1996 (49.8)
Zimbabwe	ZWE	-	-	-	1990 (56.8)	-

Notes: Gini coefficients are in parentheses. If not otherwise indicated, data are taken from WIID (2000).
[a]: Data taken from the World Bank (World Bank, 2002).
[b]: Data are kindly provided by David Jesuit and Tim Smeeding (LIS).

Table 3.2: **Welfare Measures 1960**

Rank	GNP/cap* (exchange rate)		GNP/cap** (PPP)		Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)		Sen (% of GNP/cap, PPP)		Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)		Dagum (% of GNP/cap, PPP)	
43	TZA	n.a.	TZA	451	TZA	65.5	TZA	46.0	TZA	49.1	TZA	29.9
42	IND	163	PAK	884	NGA	67.0	NGA	49.0	NGA	52.6	NGA	32.5
41	PAK	187	IND	908	PAK	87.8	IND	67.4	MDG	45.8	MDG	30.7
40	NGA	217	NGA	985	IND	86.0	PAK	69.4	IND	75.3	BEN	40.8
39	BGD	222	BGD	1094	BEN	78.6	BEN	58.0	PAK	78.3	IND	50.8
38	LKA	271	BEN	1128	BGD	81.6	MDG	47.0	COL	29.2	PAK	53.1
37	TCD	292	THA	1173	THA	77.4	BGD	62.7	SEN	38.2	THA	41.5
36	BEN	357	TCD	1376	MDG	64.8	THA	58.7	BGD	67.9	BGD	45.7
35	MDG	374	MDG	1437	ZMB	71.8	ZMB	52.0	BEN	66.1	ZMB	35.1
34	NER	413	ZMB	1467	LKA	71.5	LKA	53.0	THA	64.0	LKA	36.1
33	THA	459	CIV	1475	CIV	75.6	CIV	57.0	LKA	52.7	SEN	28.2
32	CIV	601	KOR	1483	SEN	58.3	SEN	44.0	ZMB	57.7	COL	23.5
31	GUY	620	LKA	1496	TCD	84.2	TCD	65.0	CIV	63.6	CIV	39.9
30	ZMB	627	NER	1767	KOR	82.0	COL	38.0	BRA	40.4	GUY	28.1
29	SEN[d]	650	SEN	1929	COL	50.2	KOR	65.7	GAB	27.9	TCD	48.1
28	PHL	715	PHL	2054	PHL	67.2	GUY	43.8	KOR	66.2	PHL	33.6
27	TUN[a]	791	TUN	2155	BRA	61.2	PHL	50.3	PHL	48.4	KOR	48.9
26	COL[b]	1239	GUY	2290	NER	84.3	BRA	47.0	TCD	72.5	BRA	30.7
25	SLV	1328	PAN	2358	TUR	60.2	NER	66.0	TUR	38.9	PER	24.2
24	KOR	1347	BRA	2389	TUN	76.7	JAM	45.7	PER	36.6	GAB	22.0
23	JAM	1395	COL	2461	PAN	70.3	TUR	44.0	GUY	54.6	JAM	29.6
22	TTO	1466	JAM	2578	GAB	48.2	PAN	52.0	PAN	53.6	TUR	28.2
21	PAN	1590	TUR	2717	PER	54.1	PER	39.0	NER	72.3	PAN	35.1
20	MEX	1621	CHL	2755	GUY	74.8	TUN	57.7	TUN	60.7	NER	49.3
19	TUR[d]	1637	PER	3146	JAM	73.9	GAB	36.0	JAM	54.2	TUN	40.5
18	PER	1857	SLV	3400	CHL	71.8	CHL	54.4	CHL	52.9	CHL	37.4
17	BRA	1887	GAB	3473	SLV	64.0	SLV	47.0	SLV	47.9	SLV	30.7
16	GAB	1911	CRI	3593	MEX	62.1	CRI	50.0	MEX	42.0	CRI	33.3
15	CRI	2010	GRC	3837	CRI	69.9	MEX	47.0	TTO	46.8	MEX	30.7
14	CHL	2209	MEX	3963	TTO	69.9	TTO	54.0	CRI	54.1	TTO	37.0
13	GRC	3537	TTO	4143	GRC	80.7	GRC	62.0	FRA	31.6	GRC	44.9
12	VEN[c]	3896	ESP	4330	JPN	79.9	JPN	62.8	GRC	69.5	JPN	45.8

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Table 3.2: *continued*

Rank	**GNP/cap*** **(exchange rate)**		**GNP/cap**** **(PPP)**		**Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)**		**Sen (% of GNP/cap, PPP)**		**Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)**		**Dagum (% of GNP/cap, PPP)**	
11	ESP	4740	JPN	4431	ESP	88.2	ESP	68.0	JPN	63.9	ESP	51.5
10	JPN	8372	VEN	5512	VEN	73.6	VEN	58.0	VEN	53.7	VEN	40.8
9	GBR	9752	FIN	7425	FRA	59.9	FRA	50.0	ESP	76.1	FRA	33.3
8	FIN	10087	FRA	8072	FIN	86.1	FIN	68.2	NLD	52.1	NLD	40.8
7	FRA	10857	NOR	8225	NLD	73.1	NOR	62.5	SWE	50.0	NOR	45.5
6	NOR	11363	NLD	9124	NOR	82.5	NLD	58.0	NOR	64.0	FIN	51.7
5	CAN	11795	GBR	9668	SWE	75.2	SWE	62.1	FIN	74.5	SWE	45.0
4	NLD	12416	SWE	9973	DNK	79.4	DNK	63.0	DNK	60.8	DNK	46.0
3	USA	13579	DNK	10227	GBR	89.4	CAN	68.4	CAN	72.8	CAN	52.0
2	SWE	13600	CAN	10244	CAN	85.7	GBR	74.7	GBR	80.4	GBR	59.6
1	DNK	15458	USA	12911	USA	79.7	USA	65.1	USA	60.6	USA	48.3

Notes: All rankings are based on the absolute values of the well-being indicator.
The last four columns present the ratios of the respective adjusted income to unadjusted GNP per capita, PPP.
*: GNP per capita, constant 1996 US-Dollars (WDI, 1999, 2001).
**: Real GNP per capita, 1996 prices (Summers and Heston, 1991; Heston, Summers, and Aten, 2001).
^{a}: Income data of Tunisia (TUN) from 1961.
^{b}: Income data of Colombia (COL) from 1965.
^{c}: Income data of Venezuela (VEN) from 1967.
^{d}: Income data of Senegal (SEN) and Turkey (TUR) from 1968.
n.a.: Income data not available.

Table 3.3: **Welfare Measures 1970**

Rank	**GNP/cap (exchange rate)**		**GNP/cap (PPP)**		**Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)**		**Sen (% of GNP/cap, PPP)**		**Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)**		**Dagum (% of GNP/cap, PPP)**	
48	POL	n.a.	NPL	864	NPL	66.6	NPL	47.0	SLE	27.6	NPL	30.7
47	NPL	160	IDN	879	IDN	84.5	IDN	65.4	NPL	49.5	SLE	24.4
46	IND	215	IND	1110	SLE	50.5	SLE	39.2	HND	24.8	IDN	48.6
45	BGD	261	BGD	1174	HND	48.9	HND	38.1	IDN	72.9	HND	23.5
44	SLE	281	PAK	1323	BGD	82.1	BGD	64.0	BGD	68.6	BGD	47.1
43	PAK	285	SLE	1522	IND	87.7	IND	69.6	IND	77.9	IND	53.4
42	IDN	306	LKA	1617	PAK	88.2	PAK	70.1	PAK	78.9	PAK	54.0
41	LKA	332	HND	1913	LKA	81.3	LKA	62.3	PAN	27.7	LKA	45.2
40	HND	577	THA	2012	THA	75.0	THA	57.4	LKA	67.6	TUN	30.7
39	THA	776	PHL	2451	TUN	60.8	TUN	47.0	PHL	46.1	BOL	30.7
38	BOL	845	ECU	2490	PHL	67.2	BOL	47.0	BOL	43.5	THA	40.2
37	PHL	846	TUN	2609	BOL	63.0	PHL	50.6	THA	57.8	PHL	33.9
36	ECU	906	BOL	2619	MYS	66.7	MYS	50.0	TUN	44.6	MYS	33.3
35	TUN	980	KOR	2664	ECU	80.1	COL	48.0	MYS	47.2	BRA	26.9
34	MYS	1384	MYS	2711	PAN	52.9	BRA	42.4	BRA	38.9	COL	31.6
33	COL	1415	COL	3138	BRA	59.1	ECU	62.0	FJI	48.6	PAN	27.4
32	FJI	1685	FJI	3192	COL	68.9	PAN	43.0	ECU	64.9	ECU	44.9
31	TUR	1703	CHL	3506	FJI	68.9	FJI	54.0	TUR	44.7	FJI	37.0
30	JAM	1911	JAM	3568	KOR	84.4	KOR	66.7	TTO	28.5	TUR	32.5
29	TTO	2029	BRA	3638	TUR	65.5	TUR	49.0	COL	55.2	CHL	37.0
28	KOR	2214	TUR	3706	CHL	70.7	CHL	54.0	CHL	51.4	KOR	50.0
27	MEX	2309	PAN	3899	JAM	71.3	JAM	55.5	JAM	51.0	JAM	38.4
26	CRI	2417	POL	4056	MEX	55.7	MEX	42.3	MEX	34.7	MEX	26.8
25	PAN	2437	CRI	4365	CRI	74.4	CRI	55.6	KOR	71.9	CRI	38.5
24	BRA	2600	HUN	5431	TTO	55.8	TTO	49.0	CRI	57.7	TTO	32.5
23	CHL	2670	MEX	5493	POL	90.7	POL	74.2	GAB	40.6	GAB	25.6
22	HUN	2703	TTO	5968	GAB	59.2	GAB	40.7	POL	82.4	POL	59.0
21	GAB	3446	PRT	5979	PRT	78.3	PRT	59.4	VEN	47.9	PRT	42.3
20	VEN	4196	SGP	6004	HUN	92.1	SGP	63.0	PRT	62.2	VEN	35.5
19	PRT	5166	IRL	7209	SGP	83.4	VEN	52.4	SGP	70.3	SGP	46.0
18	SGP	5589	VEN	7318	VEN	69.5	HUN	77.2	IRL	59.6	IRL	44.2
17	GRC	6984	GRC	7618	IRL	78.7	IRL	61.3	HUN	84.7	HUN	62.9

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Table 3.3: *continued*

Rank	**GNP/cap (exchange rate)**		**GNP/cap (PPP)**		**Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)**		**Sen (% of GNP/cap, PPP)**		**Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)**		**Dagum (% of GNP/cap, PPP)**	
16	IRL	8483	GAB	7805	GRC	82.6	GRC	64.9	GRC	68.0	GRC	48.0
15	ESP	8677	ESP	8201	ESP	82.4	ESP	62.9	ESP	67.0	ESP	45.9
14	ITA	11064	JPN	11107	JPN	75.5	NOR	62.5	FRA	48.7	NOR	45.5
13	GBR	12151	NOR	11294	NOR	77.2	JPN	64.5	JPN	56.2	JPN	47.6
12	CAN	12522	FIN	11404	FRA	71.2	ITA	63.7	NOR	58.7	ITA	46.7
11	NZL	12648	ITA	11433	ITA	83.7	FRA	60.2	ITA	70.5	FRA	43.1
10	AUS	13698	GBR	12063	FIN	85.3	FIN	69.6	FIN	71.7	FIN	53.3
9	FIN	15389	FRA	12730	GBR	90.0	GBR	74.9	NZL	72.8	CAN	51.2
8	NOR	15840	BEL	12740	BEL	88.3	BEL	71.8	CAN	70.6	NZL	53.8
7	BEL	16714	NZL	13165	NZL	86.2	NZL	70.0	BEL	77.3	BEL	55.9
6	FRA	16774	NLD	13302	CAN	84.7	CAN	67.8	GBR	81.8	GBR	59.9
5	USA	17443	CAN	13816	NLD	88.5	NLD	71.4	SWE	69.0	AUS	51.5
4	NLD	17890	AUS	14273	AUS	85.5	AUS	68.0	AUS	72.6	NLD	55.5
3	SWE	19874	SWE	14491	SWE	84.5	SWE	68.6	NLD	78.4	SWE	52.2
2	JPN	20370	DNK	14574	DNK	85.4	DNK	69.0	DNK	72.2	DNK	52.7
1	DNK	22190	USA	17134	USA	81.5	USA	65.9	USA	64.6	USA	49.2

Notes: For definition of columns, see Table 3.2.

Table 3.4: **Welfare Measures 1980**

Rank	GNP/cap (exchange rate)		GNI/cap* (PPP)		GNP/cap (PPP)		Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)		Sen (% of GNP/cap, PPP)		Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)		Dagum (% of GNP/cap, PPP)	
57	ETH[a]	119	POL	n.a.	ETH	705	ETH	86.5	ETH	67.6	ETH	76.1	ETH	51.0
56	NPL	154	COL	n.a.	NPL	934	NPL	88.0	BGD	61.0	ZMB	45.2	ZMB	32.5
55	CHN	170	ETH[a]	721	BGD	1046	BGD	80.5	NPL	69.9	BGD	66.3	BGD	43.9
54	BGD	227	CHN	809	NGA	1059	NGA	82.7	NGA	63.0	MDG	54.5	MDG	36.2
53	IND	234	NPL	862	RWA	1078	ZMB	65.4	ZMB	49.0	NPL	78.5	NGA	46.0
52	NGA	253	BGD	985	CHN	1095	MDG	72.1	MDG	53.2	NGA	69.6	NPL	53.8
51	PAK	325	NGA	1020	IND	1225	CHN	87.3	CHN	68.0	CHN	75.8	CHN	51.5
50	RWA	328	ZMB	1143	MDG	1292	RWA	88.9	RWA	71.1	RWA	80.3	RWA	55.2
49	MDG	345	IND	1178	ZMB	1369	IND	86.9	IND	68.5	IND	76.6	IND	52.1
48	LKA	439	MDG	1178	PAK	1409	PAK	86.4	PAK	67.7	PAK	76.0	PAK	51.1
47	IDN	493	PAK	1178	IDN	1640	IDN	84.0	IDN	64.4	IDN	71.4	IDN	47.5
46	ZMB	553	RWA	1266	LKA	2059	LKA	89.1	LKA	58.0	BWA	43.1	LKA	40.8
45	CIV	1004	IDN	1460	CIV	2677	THA	71.8	BWA	45.8	THA	52.4	BWA	29.7
44	MAR	1111	LKA	1864	THA	2875	CIV	77.4	CIV	58.8	LKA	78.6	CIV	41.6
43	THA	1135	CIV	2163	JAM	2967	BWA	63.1	THA	56.9	CIV	61.1	THA	39.8
42	PHL	1187	THA	2568	MAR	3076	JAM	75.8	JAM	56.8	JAM	59.0	JAM	39.7
41	DOM	1309	MAR	2867	BWA	3309	PHL	73.0	PHL	53.9	COL	40.7	PHL	36.9
40	JAM	1482	JAM	3078	DOM	3375	MAR	80.4	MAR	60.8	PHL	56.1	COL	29.4
39	BWA	1515	BWA	3113	PHL	3381	DOM	75.7	DOM	56.7	DOM	58.6	DOM	39.6
38	SLV	1589	DOM	3763	SLV	4058	COL	62.2	COL	45.5	MAR	66.3	MAR	43.7
37	TUN	1613	GTM	3957	GTM	4169	SLV	69.9	SLV	51.6	SLV	52.0	GTM	33.6
36	GTM	1620	MYS	4080	COL	4353	GTM	69.6	GTM	50.3	GTM	51.5	SLV	34.8
35	MUS	1802	SLV	4115	KOR	4519	MYS	66.6	MYS	49.0	MYS	46.2	MYS	32.5
34	JOR	1880	MUS	4133	TUN	4611	PER	67.8	PER	50.7	BRA	36.8	PER	33.9
33	COL	1957	TUN	4133	MYS	4757	TUN	75.6	TUN	56.6	CRI	44.9	BRA	26.8
32	MYS	2312	PHL	4326	PER	4844	KOR	77.8	BRA	42.2	PAN	50.0	PAN	35.6
31	PAN	2459	JOR	4537	JOR	4849	PAN	69.7	PAN	52.5	PER	52.4	TUN	39.4
30	PER	2490	PAN	4801	PAN	5051	JOR	74.7	KOR	61.4	KOR	60.0	CRI	35.6
29	POL	2967	PER	5170	CRI	5451	BRA	58.0	CRI	52.5	TUN	59.2	KOR	44.3
28	CRI	3044	KOR	5293	MUS	6116	CRI	67.8	JOR	59.2	JOR	58.8	JOR	42.0
27	MEX	3245	GAB	6454	BRA	6277	GAB	53.6	MUS	54.3	GAB	33.7	GAB	22.6
26	KOR	3760	CRI	6472	POL	6361	MUS	82.9	GAB	36.8	MEX	47.9	MUS	37.3

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Table 3.4: *continued*

Rank	GNP/cap (exchange rate)		GNI/cap* (PPP)		GNP/cap (PPP)		Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)		Sen (% of GNP/cap, PPP)		Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)		Dagum (% of GNP/cap, PPP)	
25	VEN	4075	BRA	6876	MEX	7717	MEX	67.2	MEX	49.4	MUS	68.4	MEX	32.8
24	HUN	4210	VEN	7105	HUN	7904	POL	91.4	VEN	57.2	TTO	48.6	VEN	40.0
23	BRA	4512	TTO	7562	VEN	7943	VEN	75.2	POL	75.1	VEN	57.3	TTO	41.1
22	GAB	5057	MEX	7738	PRT	8721	TTO	72.4	TTO	58.3	BRB	35.8	POL	60.2
21	TTO	5065	HUN	9497	TTO	8858	PRT	80.4	PRT	63.2	POL	83.6	PRT	46.2
20	BRB	6909	SGP	9971	IRL	9327	IRL	77.8	IRL	64.4	IRL	59.1	BRB	34.4
19	PRT	7343	PRT	10024	GAB	9396	HUN	93.9	HUN	79.0	PRT	63.6	IRL	47.4
18	GRC	10122	IRL	10253	ESP	10512	BRB	63.3	BRB	51.1	HUN	88.4	SGP	42.2
17	SGP	10886	ESP	12152	GRC	11040	ESP	83.5	ESP	65.8	ESP	69.4	ESP	49.0
16	IRL	11068	BRB	12539	SGP	11830	GRC	84.1	SGP	59.3	SGP	64.7	HUN	65.3
15	ESP	11174	GRC	14087	BRB	12827	SGP	79.1	GRC	66.7	GRC	70.4	GRC	50.0
14	NZL	13966	NZL	14966	GBR	14324	NZL	82.4	NZL	65.2	AUS	56.5	NZL	48.4
13	GBR	14503	GBR	15757	NZL	14363	AUS	76.2	AUS	60.0	NZL	66.8	AUS	42.9
12	ITA	14990	FIN	16179	FIN	15240	JPN	83.5	ITA	65.7	NOR	58.7	ITA	48.9
11	AUS	16001	ITA	16777	JPN	15360	FIN	84.5	JPN	66.6	JPN	68.7	JPN	49.9
10	CAN	16280	AUS	17111	ITA	15430	GBR	89.9	FIN	69.1	FIN	70.6	FRA	48.3
9	FIN	20710	JPN	17481	NLD	16300	NOR	78.5	GBR	75.1	FRA	69.8	FIN	52.8
8	USA	21593	SWE	17797	FRA	16588	ITA	86.7	FRA	65.1	ITA	75.3	GBR	60.1
7	NLD	21868	FRA	17956	NOR	16611	FRA	83.5	NOR	68.9	GBR	81.9	NOR	52.5
6	FRA	21968	NLD	18184	AUS	16816	DNK	85.4	DNK	69.0	DNK	71.6	DNK	52.7
5	BEL	22243	NOR	18852	SWE	16858	SWE	86.8	SWE	70.6	SWE	73.7	SWE	54.6
4	SWE	23218	BEL	19380	BEL	16954	NLD	90.1	NLD	73.3	CAN	71.6	NLD	57.9
3	NOR	23228	DNK	19767	DNK	17058	BEL	90.0	CAN	68.2	NLD	81.1	CAN	51.7
2	DNK	26249	CAN	20224	CAN	18280	CAN	85.6	BEL	73.8	USA	62.2	BEL	58.5
1	JPN	28217	USA	22897	USA	21330	USA	80.1	USA	64.8	BEL	80.5	USA	47.9

Notes: For definition of columns, see Table 3.2.
*: Real GNI per capita, 1996 prices (WDI, 2002).
^{a}: Income data of Ethiopia (ETH) from 1981.

Table 3.5: **Welfare Measures 1990**

Rank	**GNP/cap (exchange rate)**		**GNI/cap (PPP)**		**GNP/cap (PPP)**		**Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)**		**Sen (% of GNP/cap, PPP)**		**Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)**		**Dagum (% of GNP/cap, PPP)**	
70	TZA	185	COL	n.a.	TZA	527	TZA	55.7	TZA	41.0	TZA	33.3	TZA	25.8
69	NGA	224	TZA	498	MLI	654	SLE	39.9	MLI	63.5	SLE	15.9	SLE	22.8
68	NER	234	MLI	672	UGA	741	MLI	82.3	SLE	37.1	MLI	69.0	MLI	46.5
67	SLE	246	NGA	800	NER	990	UGA	85.7	UGA	67.0	ZMB	44.3	KEN	29.5
66	UGA	251	NER	835	NGA	1030	ZMB	66.6	KEN	45.6	KEN	40.9	UGA	50.4
65	MLI	256	UGA	846	ZMB	1115	KEN	60.6	ZMB	51.7	UGA	75.1	ZMB	34.9
64	BGD	289	ZMB	893	SLE	1215	NGA	78.7	NGA	58.9	SEN	41.1	NGA	41.7
63	IND	327	SLE	893	KEN	1227	NER	83.2	NER	63.9	NGA	64.4	NER	47.0
62	KEN	345	KEN	1078	GHA	1264	SEN	62.8	SEN	46.2	MRT	49.7	SEN	30.0
61	GHA	352	BGD	1159	BGD	1353	MRT	72.9	MRT	57.5	NER	70.8	MRT	40.3
60	CHN	358	SEN	1345	MRT	1372	GHA	82.2	GHA	63.3	HND	37.0	HND	27.1
59	MRT	420	MRT	1426	SEN	1565	BGD	89.0	HND	42.6	GHA	68.7	GHA	46.3
58	PAK	454	CIV	1530	IND	1738	HND	58.6	BGD	71.2	GIN	42.8	BGD	55.2
57	ZMB	514	GHA	1553	CIV	1751	CIV	81.8	CIV	63.1	BGD	80.3	ZWE	27.5
56	GIN	517	PAK	1576	CHN	1779	CHN	83.8	CHN	65.4	GTM	30.7	CIV	46.1
55	SEN	557	IND	1600	PAK	1966	IND	88.3	IND	70.3	CIV	67.9	GIN	36.2
54	LKA	580	CHN	1623	HND	2136	GIN	67.1	ZWE	43.2	ZWE	42.8	CHN	48.6
53	HND	634	GIN	1669	GIN	2352	PAK	87.0	GIN	53.2	CHN	70.5	GTM	25.7
52	ZWE	676	BOL	2017	BOL	2424	ZWE	61.1	PAK	68.6	IND	78.9	IND	54.2
51	CIV	693	LSO	2098	LKA	2610	BOL	76.4	BOL	58.0	PAN	30.8	DOM	32.9
50	LSO	748	IDN	2156	IDN	2730	GTM	54.2	GTM	40.9	BOL	60.0	BOL	40.8
49	IDN	761	HND	2249	ZWE	2841	DOM	67.7	DOM	49.5	DOM	48.7	PAK	52.2
48	BOL	805	LKA	2307	DOM	3001	LKA	88.0	PHL	55.3	PAK	76.8	PHL	38.2
47	EGY	967	ZWE	2620	EGY	3152	IDN	86.6	LKA	69.9	LSO	37.8	LSO	28.2
46	PHL	1113	EGY	2840	PHL	3159	PHL	75.7	IDN	66.9	ECU	54.6	PAN	27.8
45	MAR	1285	ECU	2944	PER	3447	LSO	59.6	LSO	44.0	BRA	31.8	ECU	39.0
44	DOM	1333	GTM	3211	ECU	3464	ECU	74.0	ECU	56.1	PHL	60.5	IDN	50.3
43	GTM	1359	MAR	3222	JAM	3554	PAN	56.1	PER	57.2	LKA	78.4	PER	40.1
42	ECU	1436	JAM	3327	GTM	3578	PER	76.9	PAN	43.5	ZAF	28.6	LKA	53.7
41	JOR	1465	JOR	3628	MAR	3599	EGY	86.6	JAM	58.2	IDN	76.8	JAM	41.1
40	ROM	1570	PER	3651	JOR	3748	JAM	77.3	EGY	68.0	PER	61.9	COL	32.2
39	DZA	1595	DOM	3721	LSO	4288	MAR	80.4	MAR	60.8	COL	46.6	BRA	25.3

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Table 3.5: *continued*

Rank	**GNP/cap (exchange rate)**		**GNI/cap (PPP)**		**GNP/cap (PPP)**		**Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)**		**Sen (% of GNP/cap, PPP)**		**Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)**		**Dagum (% of GNP/cap, PPP)**	
38	BGR	1607	PHL	3837	PAN	4612	JOR	78.8	JOR	59.3	JAM	61.7	MAR	43.7
37	JAM	1624	PAN	4265	COL	4619	COL	67.6	COL	48.7	MAR	66.3	JOR	42.2
36	TUN	1797	TUN	4370	CRI	4886	BRA	52.9	BRA	40.4	EGY	76.4	CHL	28.1
35	PER	1882	THA	4393	DZA	4953	THA	67.8	CHL	43.9	JOR	64.3	EGY	51.5
34	PRY	1900	PRY	4648	THA	4998	CRI	71.0	THA	51.2	THA	48.2	ZAF	23.2
33	THA	2013	DZA	5042	TUN	5016	CHL	61.8	CRI	53.9	CHL	42.1	THA	34.4
32	COL	2119	MYS	5262	PRY	5218	ZAF	51.3	ZAF	37.7	CRI	50.5	CRI	36.9
31	PAN	2432	CHL	5436	ROM	5393	TUN	78.5	TUN	59.8	MEX	40.9	MYS	34.8
30	POL	2611	TUR	5668	CHL	5728	DZA	80.4	DZA	61.3	TUN	62.7	MEX	29.0
29	TUR	2673	VEN	5680	POL	5767	PRY	78.6	PRY	60.3	MYS	51.8	TUN	42.6
28	CRI	2982	CRI	5853	TUR	5988	MYS	70.1	MYS	51.7	PRY	62.9	DZA	44.2
27	MUS	2988	BGR	6190	BRA	6004	TUR	74.8	MEX	45.0	DZA	66.7	PRY	43.1
26	MYS	3109	POL	6213	MYS	6099	MEX	61.9	TUR	55.9	TUR	57.7	TUR	38.8
25	MEX	3143	BRA	6271	VEN	6268	VEN	74.0	VEN	55.9	VEN	55.7	VEN	38.8
24	CHL	3237	MUS	6468	BGR[a]	6747	ROM	92.3	ROM	76.6	ROM	85.0	ROM	62.1
23	VEN	3344	MEX	7152	ZAF	7270	POL	90.6	POL	73.8	POL	82.2	POL	58.4
22	ZAF	4026	ROM	7233	MEX	7336	BGR	92.3	BGR	75.5	BGR	85.5	BGR	60.6
21	BRA	4108	ZAF	9215	HUN	9525	MUS	79.4	MUS	60.4	MUS	63.8	MUS	43.2
20	HUN	4740	KOR	10293	MUS	9769	KOR	84.3	KOR	66.4	IRL	57.9	KOR	49.7
19	KOR	8119	HUN	10467	KOR	10013	HUN	92.6	HUN	76.7	KOR	71.9	PRT	46.2
18	PRT	10082	PRT	12878	IRL	11791	IRL	76.6	PRT	63.2	PRT	64.2	IRL	48.6
17	GRC	11265	IRL	13538	GRC	12059	PRT	80.6	IRL	65.4	GRC	67.1	GRC	47.9
16	IRL	14124	GRC	13643	PRT	12157	GRC	82.3	GRC	64.8	HUN	86.2	HUN	62.2
15	ESP	14317	ESP	14848	ESP	13682	NZL	80.8	NZL	63.4	NZL	64.5	NZL	46.4
14	NZL	14442	SGP	15219	NZL	15039	ESP	89.6	ESP	74.1	ESP	79.7	ESP	58.8
13	AUS	18185	NZL	15485	GBR	18091	AUS	80.8	AUS	62.7	AUS	63.8	AUS	45.6
12	ITA	18236	AUS	19044	AUS	18541	GBR	85.4	SGP	59.0	SGP	64.7	SGP	41.8
11	GBR	18253	GBR	19171	ITA	18801	SGP	79.1	GBR	67.7	DNK	64.1	GBR	51.2
10	SGP	18356	ITA	19902	NLD	19132	ITA	87.8	ITA	67.3	GBR	73.7	ITA	50.7
9	CAN	18807	FIN	20064	FIN	19172	SWE	86.3	NLD	70.6	NOR	67.6	NOR	50.0
8	NLD	25737	NLD	20354	SWE	19631	DNK	82.1	NOR	66.7	ITA	77.4	DNK	50.2
7	BEL	26358	SWE	20412	BEL	20190	NOR	82.8	DNK	66.9	SWE	74.3	NLD	54.6

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Table 3.5: *continued*

Rank	**GNP/cap (exchange rate)**		**GNI/cap (PPP)**		**GNP/cap (PPP)**		**Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)**		**Sen (% of GNP/cap, PPP)**		**Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)**		**Dagum (% of GNP/cap, PPP)**	
6	FIN	26614	DNK	21942	SGP	20459	FIN	89.4	SWE	71.0	FIN	78.4	SWE	55.0
5	USA	26721	NOR	21965	NOR	20649	NLD	91.7	FIN	73.9	USA	57.5	FIN	58.6
4	SWE	26836	BEL	22336	DNK	20757	BEL	89.7	BEL	73.4	NLD	84.3	BEL	57.9
3	NOR	28499	CAN	22486	CAN	21328	CAN	88.4	CAN	72.4	BEL	79.9	USA	45.1
2	DNK	31475	USA	27169	USA	26628	USA	77.0	USA	62.2	CAN	76.6	CAN	56.8
1	LUX	46827	LUX	28861	LUX	38421	LUX	89.5	LUX	72.9	LUX	80.1	LUX	57.3

Notes: For definition of columns, see Tables 3.2 and 3.4.
[a]: Income data of Bulgaria (BGR) from 1991.

Table 3.6: **Welfare Measures 1998**

Rank	GNP/cap (exchange rate)		GNI/cap (PPP)		GNP/cap (PPP)		Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)		Sen (% of GNP/cap, PPP)		Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)		Dagum (% of GNP/cap, PPP)	
72	ETH	109	TZA	466	TZA	460	TZA	81.0	TZA	61.9	GNB	32.1	GNB	28.0
71	BDI	148	BDI	563	ETH	637	GNB	57.4	GNB	43.8	CAF	28.5	TZA	44.8
70	GNB	164	ETH	573	BDI	684	ETH	80.2	MLI	49.5	TZA	67.3	MLI	32.9
69	MOZ	181	GNB	593	GNB	706	MLI	68.3	ETH	60.0	NER	36.8	CAF	24.0
68	TZA	187	MLI	690	MLI	765	CAF	51.2	CAF	38.7	MLI	50.4	ETH	42.9
67	NER	219	ZMB	690	MDG	821	NER	62.5	ZMB	50.2	ZMB	49.3	ZMB	33.5
66	NPL	227	MOZ	709	ZMB	843	ZMB	68.5	NER	49.4	ETH	67.2	NER	32.8
65	NGA	233	NER	738	NER	891	BDI	85.2	BDI	66.7	NGA	49.8	NGA	32.8
64	MDG	237	MDG	738	NGA	964	MDG	76.2	MDG	56.6	MDG	60.5	MDG	39.4
63	BFA	262	NGA	748	UGA	964	NGA	68.4	NGA	49.4	BDI	73.7	BDI	50.0
62	MLI	272	BFA	874	MOZ	991	BFA	71.3	BFA	51.8	BFA	55.3	BFA	35.0
61	UGA	340	KEN	971	BFA	1052	UGA	80.4	UGA	60.8	GMB	52.0	GMB	35.3
60	CAF	342	CAF	1049	CAF	1052	MOZ	79.8	GMB	52.2	UGA	66.2	UGA	43.7
59	KEN	342	UGA	1059	GMB	1142	GMB	70.8	MOZ	60.4	MOZ	65.5	MOZ	43.3
58	GMB	354	NPL	1205	KEN	1236	KEN	74.4	KEN	55.5	KEN	57.0	KEN	38.4
57	BGD	369	SEN	1302	MNG[a]	1263	MNG	84.7	MRT	61.1	NAM	19.1	MRT	43.9
56	ZMB	373	LAO	1321	MRT	1363	MRT	79.8	MNG	66.8	MRT	64.7	NIC	33.0
55	GHA	402	BGD	1379	GHA	1391	NPL	82.7	NPL	63.3	NIC	49.0	MNG	50.2
54	NIC	421	GMB	1428	NPL	1412	GHA	85.8	NIC	49.7	MNG	72.1	NAM	14.7
53	LAO	428	CIV	1477	LAO[a]	1569	SEN	78.5	SEN	58.7	HND	46.6	NPL	46.3
52	IND	436	MRT	1477	SEN	1578	NIC	68.1	GHA	67.3	NPL	70.5	SEN	41.6
51	MNG	453	MNG	1593	BGD	1653	LAO	88.1	HND	47.4	SEN	64.0	HND	31.0
50	MRT	468	PAK	1681	CIV	1735	HND	66.5	LAO	69.6	GHA	75.0	GHA	50.7
49	PAK	513	GHA	1710	NIC	1832	BGD	85.5	BGD	66.4	CIV	69.0	CIV	46.3
48	SEN	578	GIN	1778	HND	2114	CIV	82.2	CIV	63.3	BGD	75.0	BGD	49.7
47	GIN	600	NIC	1826	PAK	2139	NAM	36.7	NAM	25.7	LAO	79.1	LAO	53.4
46	LSO	692	IND	2021	GUY	2321	GUY	79.2	GUY	59.8	LSO	34.2	PNG	32.5
45	HND	703	PNG	2059	IND	2437	PAK	87.6	PAK	68.8	GUY	64.4	GUY	42.6
44	CHN	726	HND	2273	GIN	2716	IND	82.8	PNG	49.1	PNG	49.7	LSO	26.6
43	CIV	745	LSO	2331	PNG	3029	PNG	67.8	IND	62.2	PAK	78.4	IND	45.1
42	GUY	775	IDN	2574	CHN	3205	GIN	79.0	GIN	59.7	IND	71.3	PAK	52.4
41	LKA	794	ECU	2963	JAM	3357	LSO	56.1	LSO	42.1	GIN	64.4	GIN	42.6

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Table 3.6: *continued*

Rank	GNP/cap (exchange rate)		GNI/cap (PPP)		GNP/cap (PPP)		Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)		Sen (% of GNP/cap, PPP)		Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)		Dagum (% of GNP/cap, PPP)	
40	IDN	922	LKA	3002	PHL	3393	PHL	72.9	PHL	53.8	PHL	56.2	PHL	36.8
39	PNG	975	EGY	3177	IDN	3393	CHN	78.6	CHN	60.2	CHN	62.7	CHN	43.1
38	EGY	1183	CHN	3206	ECU	3611	ECU	75.0	ECU	56.3	ECU	58.2	ECU	39.1
37	PHL	1206	JAM	3254	EGY	3782	JAM	82.5	JAM	63.6	JAM	69.3	JAM	46.6
36	ROM	1316	MAR	3283	LKA	3812	IDN	84.9	IDN	65.8	PER	52.5	PER	36.8
35	MAR	1378	GUY	3371	LSO	3920	MAR	79.4	MAR	60.5	ZAF	35.3	IDN	49.1
34	BGR	1395	JOR	3643	MAR	3970	PER	71.7	PER	53.8	IDN	73.9	MAR	43.4
33	DZA	1502	PHL	3779	JOR	4146	LKA	84.4	LKA	65.6	MAR	65.1	ZAF	25.5
32	ECU	1584	PER	4303	DZA	4274	EGY	89.1	JOR	63.6	LKA	72.9	LKA	48.8
31	JOR	1644	DZA	4566	NAM	4383	JOR	82.9	EGY	71.1	PAN	46.1	JOR	46.6
30	JAM	1728	BGR	4711	PER	4486	DZA	83.0	DZA	64.7	JOR	70.6	DZA	47.8
29	NAM	2175	PAN	5158	ROM	4742	ZAF	55.5	ZAF	40.7	DZA	69.6	EGY	55.2
28	PER	2339	THA	5479	BGR	4898	ROM	88.7	PAN	51.5	BRA	44.1	PAN	34.7
27	THA	2602	NAM	5741	THA	5766	PAN	67.7	BRA	48.3	EGY	80.5	BRA	31.8
26	PAN	3087	ROM	5935	PAN	6288	BGR	87.4	THA	58.6	THA	63.0	THA	41.4
25	TUR	3329	BRA	6606	BRA	6868	BRA	65.1	ROM	71.3	ROM	78.9	MEX	33.1
24	MEX	3496	TUR	6615	ZAF	7090	THA	77.8	BGR	72.7	MEX	48.3	ROM	55.4
23	POL	3677	MEX	7577	TUR	7226	MEX	67.6	MEX	49.7	BGR	77.5	CHL	29.2
22	ZAF	3910	POL	7713	MEX	7841	TUR	77.5	CHL	45.2	CHL	43.4	BGR	57.1
21	MUS	4001	CHL	8325	POL	8659	CHL	63.0	TUR	58.5	TUR	61.6	TUR	41.3
20	BRA	4545	ZAF	8374	CHL	9305	POL	85.9	POL	66.3	POL	74.9	POL	49.6
19	HUN	4805	MUS	8461	HUN	10919	HUN	91.7	HUN	74.7	BHS	47.6	MUS	46.3
18	CHL	5401	HUN	10074	MUS	12937	MUS	82.1	MUS	63.3	MUS	68.2	BHS	37.7
17	KOR	11084	KOR	13551	KOR	13140	BHS	70.8	BHS	54.7	NZL	57.0	HUN	59.6
16	BHS	12045	BHS	14261	PRT[b]	14448	KOR	86.1	KOR	68.4	HUN	84.2	NZL	42.6
15	PRT	12062	PRT	14843	NZL[b]	15923	PRT	82.7	PRT	64.4	KOR	74.1	KOR	52.0
14	NZL	15585	NZL	16242	BHS[a]	15974	NZL	76.5	NZL	59.8	PRT	67.5	PRT	47.5
13	ESP	16572	ESP	16553	ESP	16612	ESP	84.6	ESP	67.0	ESP	71.4	ESP	50.4
12	ITA	20078	SWE	20682	ITA	20439	ITA	83.6	ITA	65.8	ITA	69.5	ITA	49.0
11	CAN	20698	FIN	20818	GBR	21089	GBR	83.8	GBR	65.5	DNK	63.6	GBR	48.7
10	GBR	21407	ITA	20876	FIN	21506	DNK	80.2	DNK	62.7	GBR	70.8	DNK	45.6
9	AUS	22592	GBR	20915	SWE	22175	AUS	86.0	AUS	68.9	AUS	73.1	AUS	52.6

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Table 3.6: *continued*

Rank	GNP/cap (exchange rate)		GNI/cap (PPP)		GNP/cap (PPP)		Atkinson ($\epsilon = 1$) (% of GNP/cap, PPP)		Sen (% of GNP/cap, PPP)		Atkinson ($\epsilon = 2$) (% of GNP/cap, PPP)		Dagum (% of GNP/cap, PPP)	
8	SWE	28792	AUS	22314	AUS	22625	FIN	92.8	CAN	69.5	CAN	75.0	CAN	53.3
7	FIN	29121	NLD	22712	BEL	22756	CAN	86.9	FIN	76.4	FIN	86.4	FIN	61.8
6	BEL	29878	CAN	23470	NLD	22976	SWE	93.0	BEL	75.0	NLD	81.4	BEL	60.0
5	NLD	30209	BEL	23975	DNK	23170	BEL	91.1	NLD	74.7	BEL	82.8	NLD	59.6
4	USA	30592	DNK	24218	CAN	23606	NLD	90.5	SWE	77.9	SWE	86.2	SWE	63.8
3	DNK	37004	NOR	26977	NOR	26340	NOR	92.1	USA	62.8	USA	65.3	USA	45.8
2	NOR	37538	USA	29852	USA	31142	USA	80.9	NOR	76.2	NOR	84.6	NOR	61.5
1	LUX	48749	LUX	36992	LUX	53669	LUX	92.4	LUX	76.5	LUX	85.7	LUX	61.9

Notes: For definition of columns, see Tables 3.2 and 3.4.

^{a}: Income data of Mongolia (MNG), Laos (LAO), and Bahamas (BHS) from 1996.

^{b}: Income data of Portugal (PRT) and New Zealand (NZL) from 1997.

Table 3.7: **Test of Sensitivity**

Year	Country	Gini used	Based on	Alternative Gini	Based on	Changes in Ranking[a] Atkinson ($\epsilon = 1$)	Sen	Atkinson ($\epsilon = 2$)	Dagum
1960	Brazil	53.0	I G H	54.0	I G P	+2	-	+5	-2
	Chile	45.6	I G H	44.0	I G P	-	-	+1	+1
	Jamaica	54.3	I G H	56.0	I G P	-8	-1	-13	-2
	Mexico	53.0	I G H	55.5	I G H	-	-1	-2	-1
	Philippines	49.7	I G H	48.0	I G P	-	-	+1	+1
	Sri Lanka	47.0	I G H	44.0	I G P	-	-	-	+2
	Sweden	37.9	I G H	33.4	I N H	-	+1	+2	+1
1970	Mexico	57.7	I G H	52.2	I G H	+3	+1	+2	+1
	Sierra Leone	60.8	I G H	56.0	I G P	-	-	+2	+1
	Sweden	31.4	I G H	27.3	I N H	+1	+1	+3	+1
1980	Australia	40.0	I G H	38.6	I G F[b]	+1	+2	-	-
	Canada	31.8	I G F	36.4	I G F[b]	-4	-3	-6	-6
	France	34.9	I G H	31.7	I N H	-1	-	+3	+2
	Norway	31.2	I N H	26.2	I N H[b]	+6	+4	+8	+4
	Spain	34.2	I G H[c]	26.8	E N H	+2	+2	+2	+2
	Sweden	29.4	I G H	32.4	I N H	-2	-2	-2	-2
1990	Algeria	38.7	E N P	40.1	E - H[d]	-	-1	-2	-3
	Australia	37.3	I G H	32.8	I N H	+1	+2	+1	+3
	Brazil	59.6	I G P	63.4	I G P	-1	-1	-1	-6
	Chile	56.1	I - -[d]	51.9	I G P	-	+3	-	+4
	China	34.6	I G P	33.5	I - H[d]	-	-	-	-
	Denmark	33.1	I G H	39.0	I G F	-3	-2	-2	-4
	Finland	26.1	I N H	20.2	I N Heq[c]	+1	+1	+4	+3
	Ghana	36.7	E N P	33.9	E - Hpc	-	-	-	-
	Ireland	34.6	I N H	38.9	I G H	-	-2	-	-1
	Jordan	40.7	E N P	43.4	E - Hpc[d]	-1	-2	-2	-2
	Kenya	54.4	E N P	57.5	E - Hpc[d]	-	-	-	+1
	Mexico	55.0	I G P	46.9	I G H	+2	+2	+6	+5
	Nigeria	41.2	E N P	45.0	E - Hpc[d]	-2	-1	-2	-1
	Pakistan	31.4	E N H	32.4	I G H	+1	-	-	-
	Philippines	44.7	I G H[c]	45.7	I G P	-1	-	-1	-
	Sweden	29.0	I G H	32.5	I N H	+1	-2	-1	-2

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Table 3.7: *continued*

Year	Country	Gini used	Based on	Alternative Gini	Based on	Changes in Ranking[a] Atkinson ($\epsilon = 1$)	Sen	Atkinson ($\epsilon = 2$)	Dagum
	Uganda	33.0	E N Heq	44.4	E - H[d]	-	-2	-3	-2
	Zambia	48.3	E - H[d]	43.5	E N P	+3	+1	+4	+1
1998	Denmark	37.4	I G F[c]	33.7	I N F[c]	-	-	+1	-
	Madagascar	43.4	E N P	46.0	E - Hpc[d]	-	-1	-1	-1
	Turkey	41.5	E - Hpc[d]	49.0	I N H[c]	-1	-2	-1	-4
	Uganda	39.2	E - Hpc	40.8	E - P	-	-	-	-

[a]: A positive sign corresponds to a higher rank, a negative one indicates a worsening in ranking.
Inequality data applied is predominantly provided by Deininger and Squire (1996). Additional data sources are indicated as follows.
[b]: Data originally provided by Luxembourg Income Study.
[c]: See WIID (2000) for further information on data source.
[d]: Data taken from the World Bank (World Bank, 2002).
Income concept is either income (I) or expenditure (E), and both concepts can be gross (G) or net (N).
Unit of reference can be per person (P), household (H), or household per capita (Hpc). In a few cases an equivalence scale was applied to calculate the data (Heq). If any component is not reported or unknown, - is shown.

Table 3.8: **Determinants of Gini Coefficients**

	(1)		(2)	
Expenditure	-3.89**	(0.38)	-3.59**	(0.38)
Net income	-1.94**	(0.27)	1.38**	(0.47)
Unknown income	1.66	(1.43)	1.81	(1.40)
Household	0.99**	(0.28)	1.09**	(0.27)
Family	0.73	(0.45)	0.85	(0.44)
Unknown reference unit	-1.51	(1.55)	-1.45	(1.52)
Equivalized	-4.72**	(0.30)	-4.46**	(0.29)
Primary source unknown	1.81**	(0.63)	1.93**	(0.61)
No consistent source	-0.31	(0.25)	-0.34	(0.24)
OECD * Net income	-		-4.74**	(0.55)
Intercept	36.03**	(0.26)	35.84**	(0.26)
N	2070		2070	
R^2	0.21		0.24	

Significance levels: $*$: 5% $**$: 1%; Standard errors in parentheses.

Table 3.9: **Change in Rankings Due to Adjusted Gini Coefficients**

	No change	1 Rank	2 Ranks	3 Ranks	4+ Ranks
Sen measure					
1960	35	7	0	0	1
1970	28	18	2	0	0
1980	26	22	6	2	1
1990	42	22	3	3	0
1998	43	21	6	1	1
Dagum measure					
1960	24	12	7	0	0
1970	29	14	1	4	0
1980	26	21	7	3	0
1990	31	21	15	3	0
1998	35	30	6	0	1

Table 3.10: **Average Gini Coefficients over Time**

Year	Average Gini	Average adjusted Gini	Number of observations
1960s	37.9	38.6	197
1970s	34.8	36.2	427
1980s	32.7	34.7	780
1990s	34.3	36.6	666

Adjusted Gini coefficients are based on regression (1) reported in Table 3.8.

Table 3.11: **Temporal Trends in Inequality and Kuznets Curve**

	(1)		(2)		(3)		(4)	
Intercept	34.55**	(0.19)	39.77**	(0.89)	37.22**	(0.82)	40.63**	(1.06)
Dummy 1960s	1.31**	(0.40)	1.36**	(0.40)	-		-	
Dummy 1970s	-0.45	(0.32)	-0.44	(0.32)	-		-	
Dummy 1980s	-1.23**	(0.26)	-1.24**	(0.26)	-		-	
Income per capita	-		-		-0.20**	(0.06)	-0.75**	(0.16)
Income per capita, inverse	-		-		1.03	(1.61)	-	
Income per capita, squared	-		-		-		0.02**	(0.00)
N	2070		2070		1570		1570	
R^2	0.03		0.03		0.01		0.02	

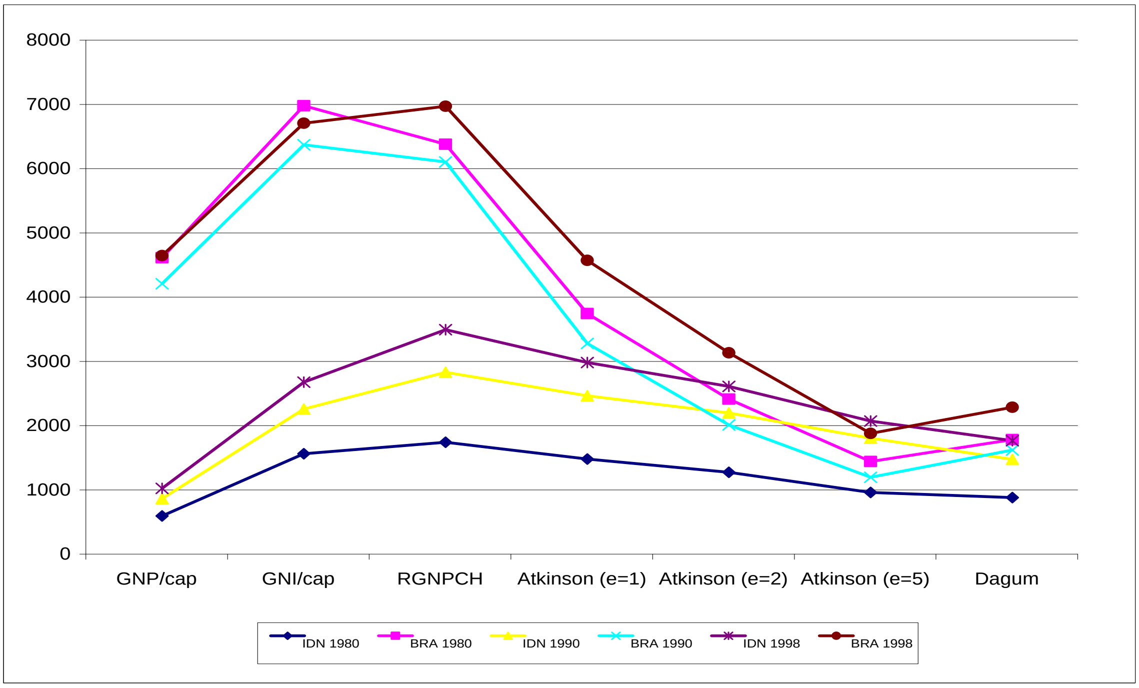
Significance levels: $*$: 5% $**$: 1%; Standard errors in parentheses.
Specification (1) estimates fixed effects, specification (2) random effects. Reference category is the period 1990-1998. Specifications (3) and (4) test for the Kuznets hypothesis using a fixed effects estimation.

Table 3.12: **Income Mobility, 1970-1998**

		1998				
		1st	**2nd**	**3rd**	**4th**	**5th**
1970	**1st**	35	7	0	0	0
	2nd	25	10	4	2	0
	3rd	16	13	13	6	0
	4th	4	14	28	47	28
	5th	0	0	0	10	98

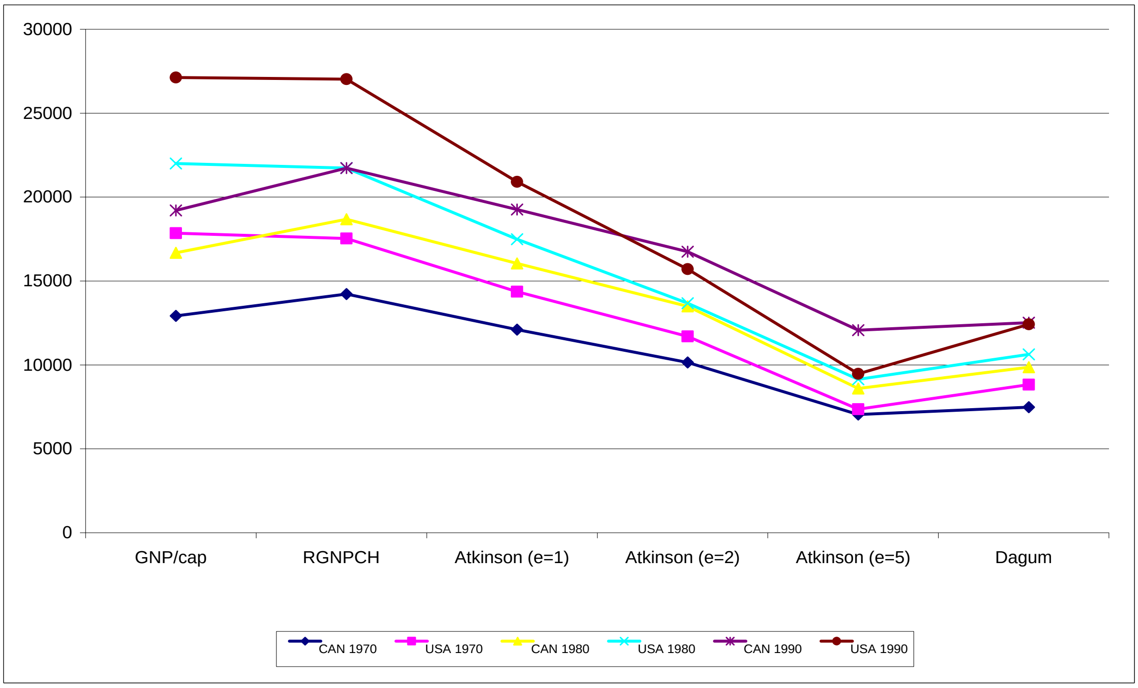
Rows and columns show the number of country quintiles falling into the first to fifth world quintile in 1970 and 1998, respectively.

Figure 3.1: **Welfare Comparison: Brazil versus Indonesia, 1980-1998**



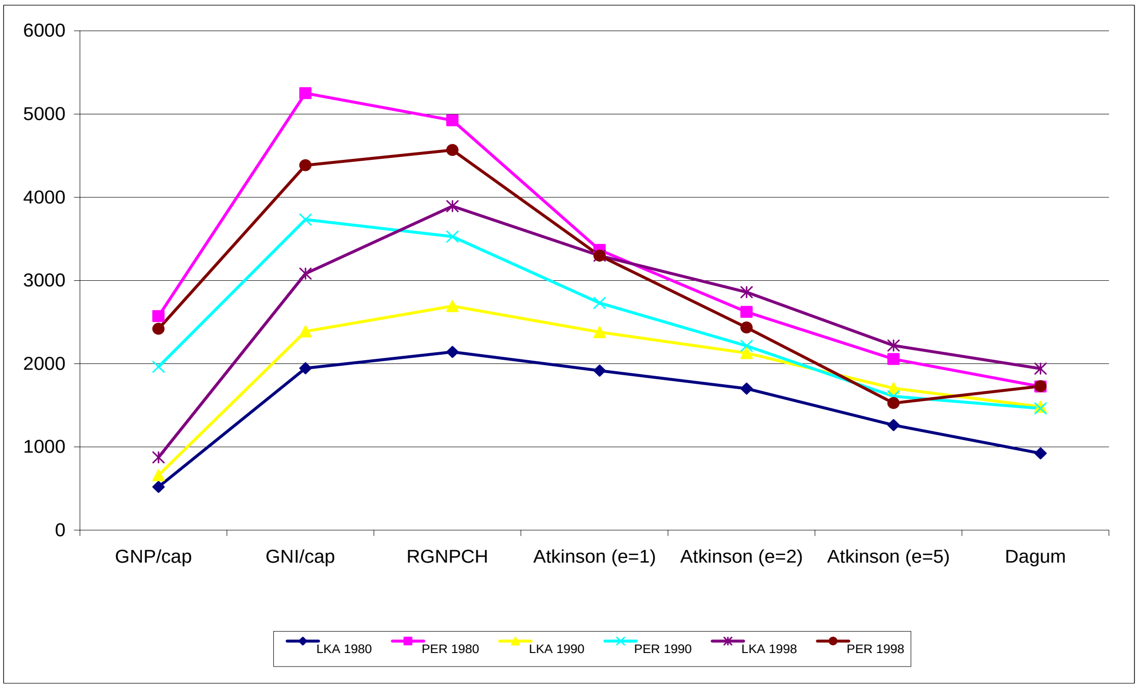
Notes: GNP/cap: GNP per capita, constant 1996 US-Dollars (WDI, 1999, 2001). GNI/cap: Real GNI per capita, 1996 prices (WDI, 2002). RGNPCH: Real GNP per capita, 1996 prices (Summers and Heston, 1991; Heston, Summers, and Aten, 2001).

Figure 3.2: **Welfare Comparison: Canada versus USA, 1970-1990**



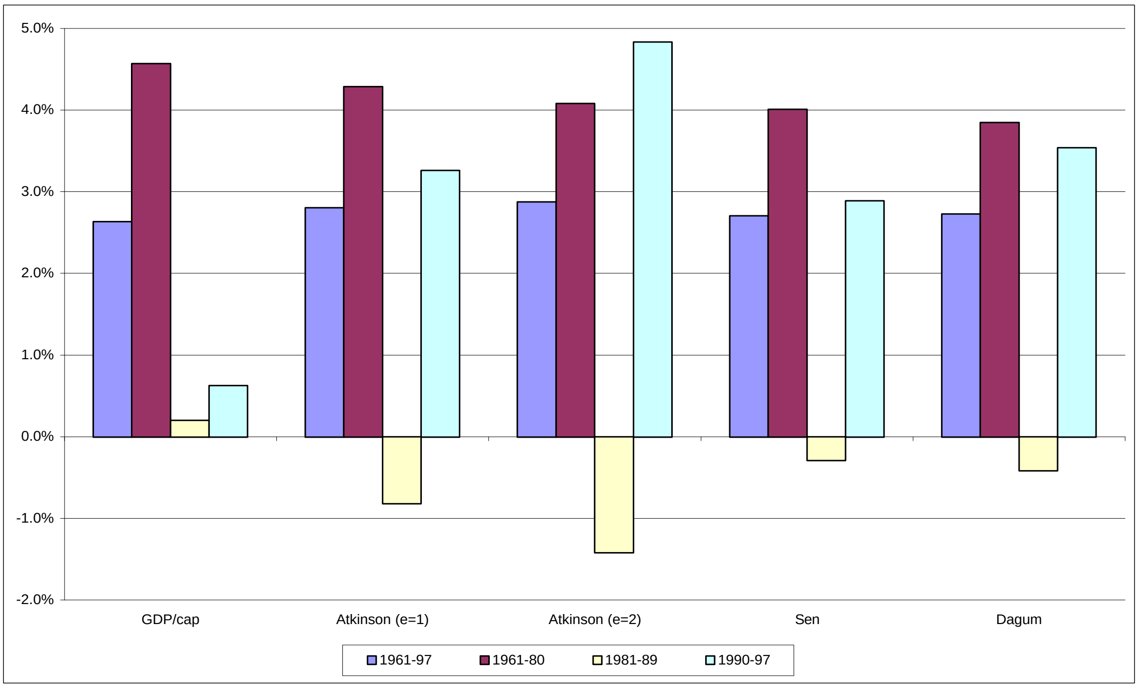
Notes: For definition of incomes, see Figure 3.1.

Figure 3.3: **Welfare Comparison: Sri Lanka versus Peru, 1980-1998**



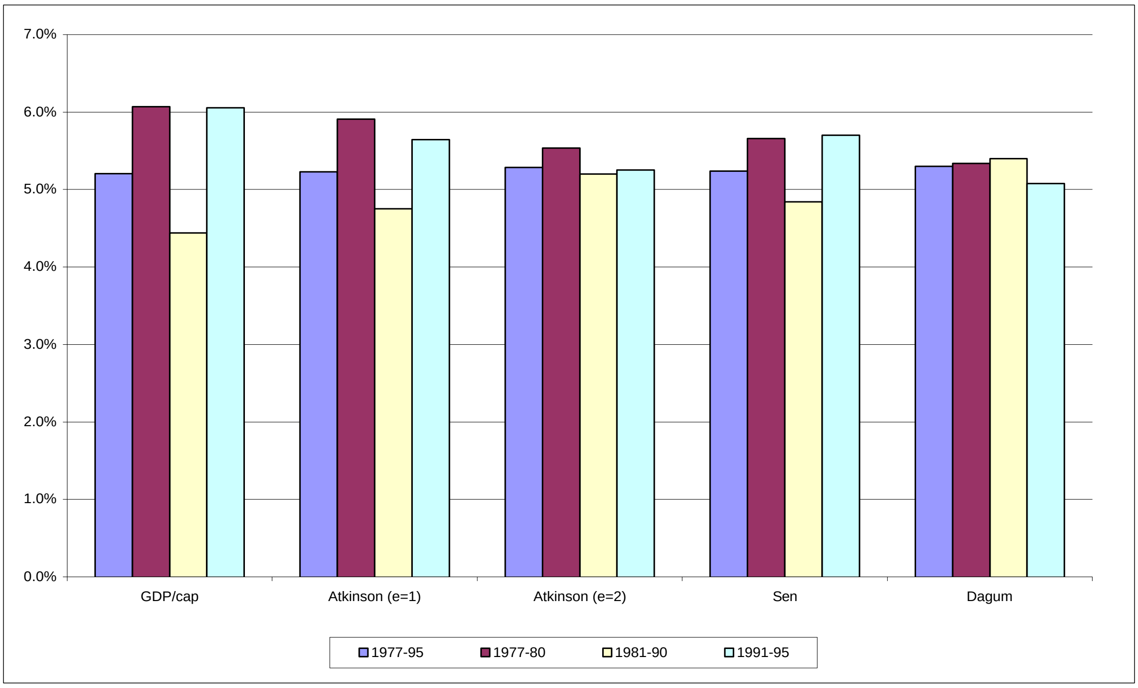
Notes: For definition of incomes, see Figure 3.1.

Figure 3.4: **Average Annual Growth of Well-Being in Brazil**



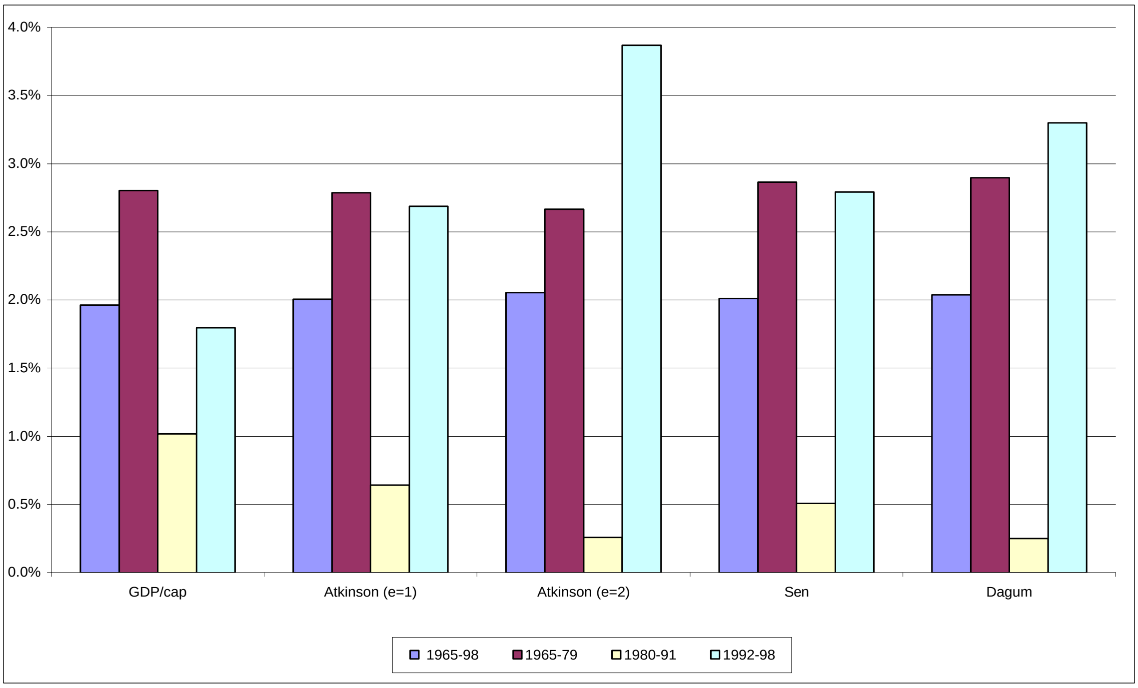
Notes: The income concept used here is GDP per capita at market prices in constant local currency (WDI, 2002).

Figure 3.5: **Average Annual Growth of Well-Being in Indonesia**



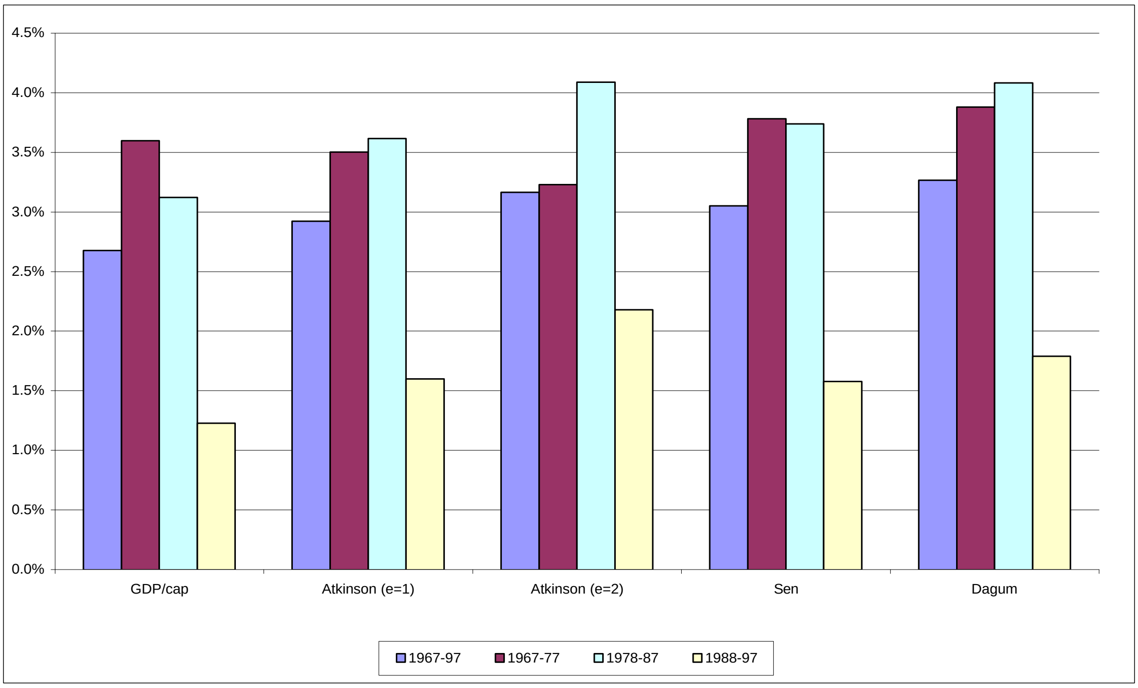
Notes: See notes in Figure 3.4.

Figure 3.6: **Average Annual Growth of Well-Being in Canada**



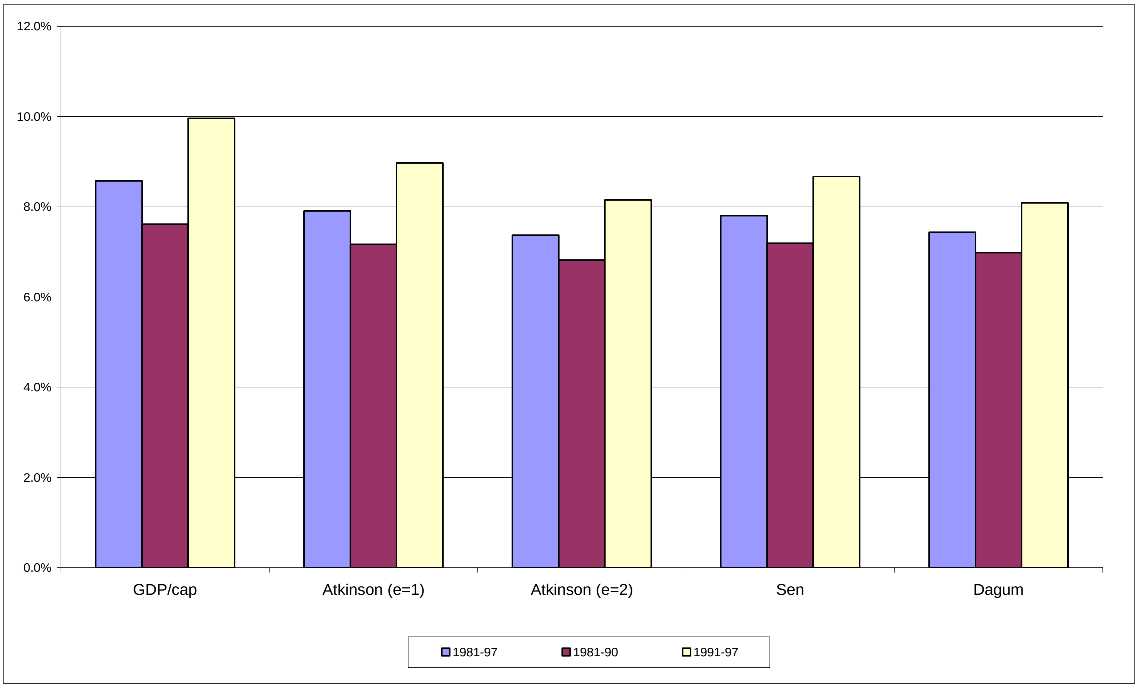
Notes: See notes in Figure 3.4.

Figure 3.7: **Average Annual Growth of Well-Being in Finland**



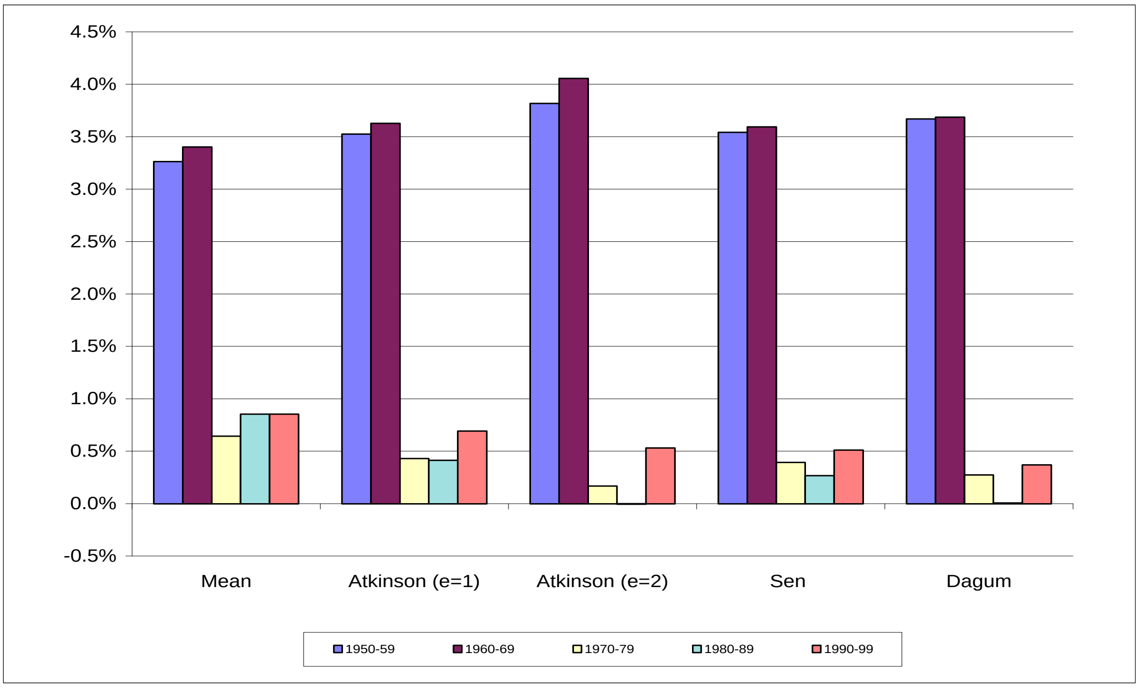
Notes: See notes in Figure 3.4.

Figure 3.8: **Average Annual Growth of Well-Being in China**



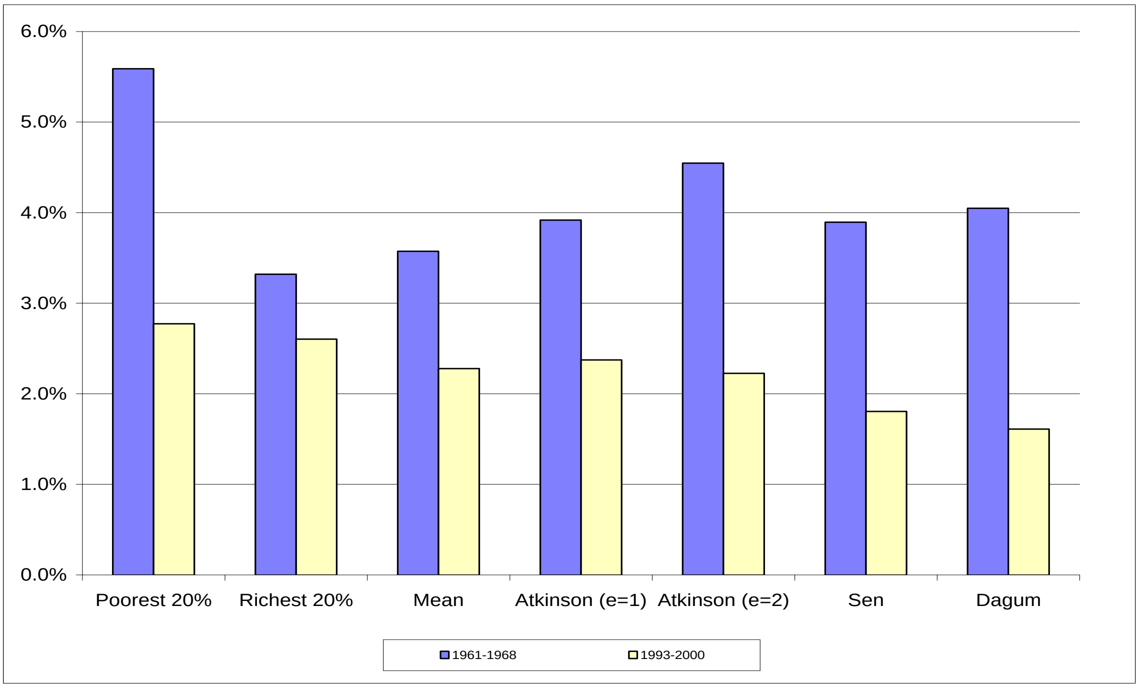
Notes: See notes in Figure 3.4.

Figure 3.9: **Average Annual Growth of Well-Being in the US**



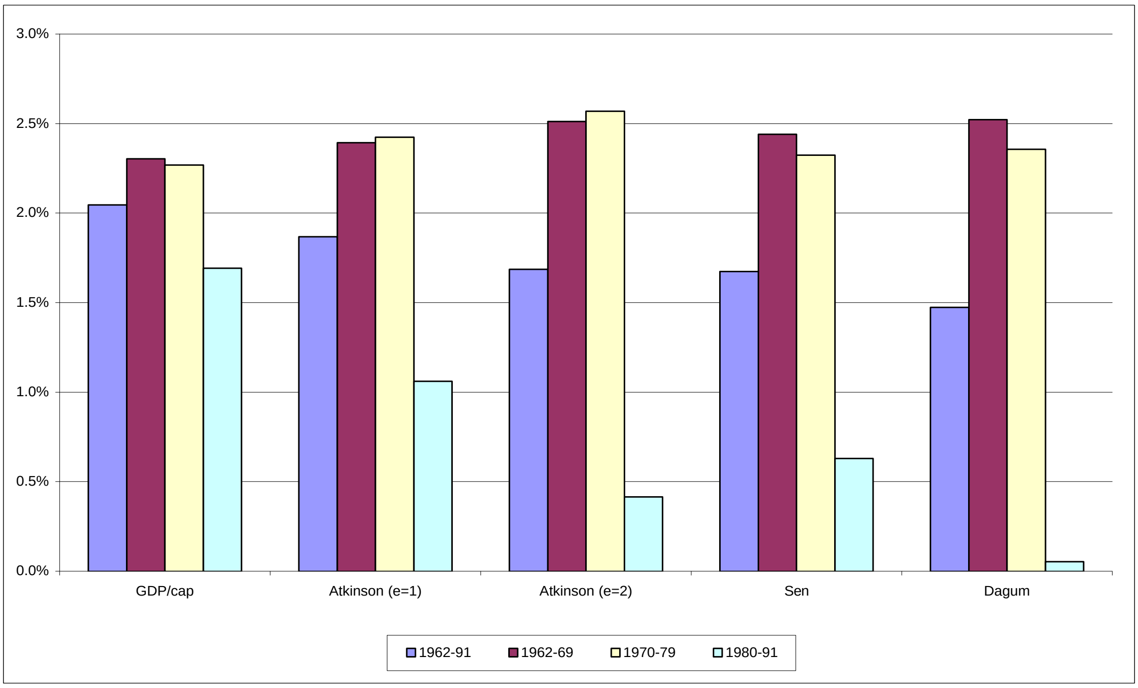
Notes: Calculations are based on U.S. census data (constant 1982 dollars). Mean refers to the mean money income of families.

Figure 3.10: **'Great Society versus New Economy'**



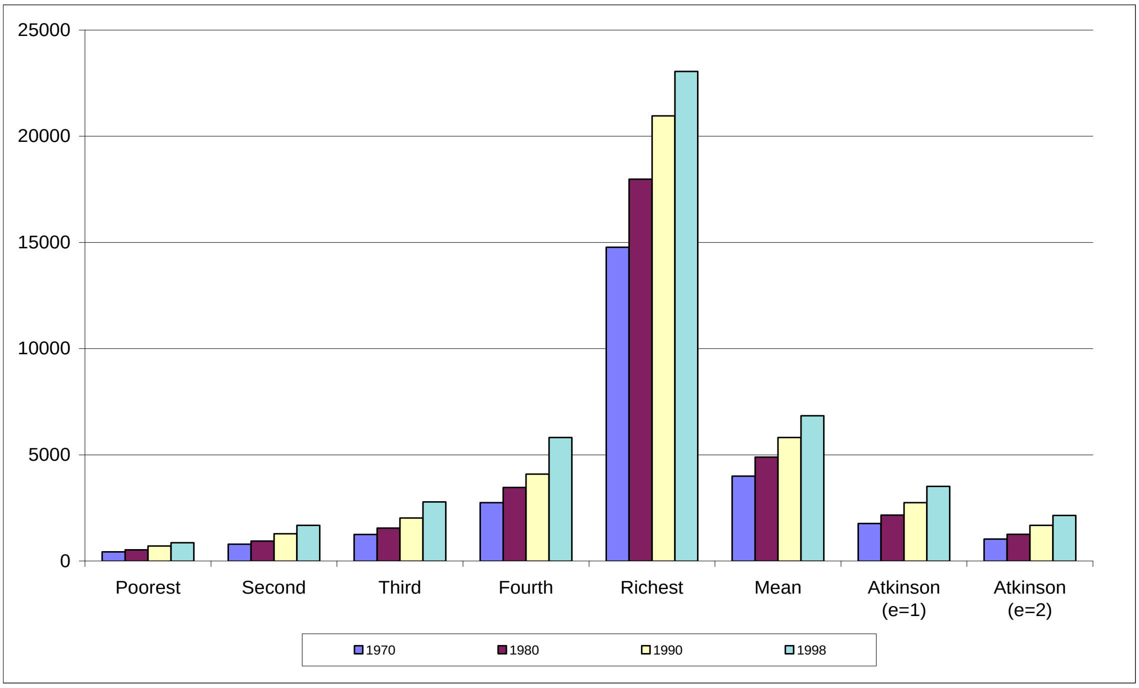
Notes: See notes in Figure 3.9.

Figure 3.11: **Average Annual Growth of Well-Being in Great Britain**



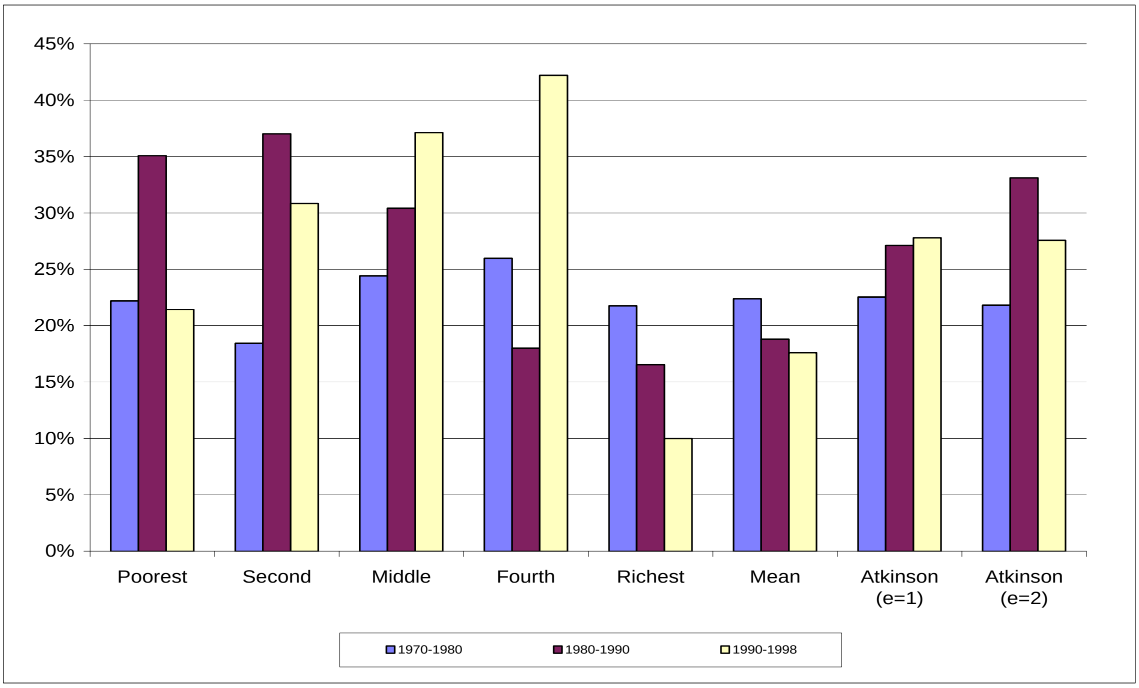
Notes: See notes in Figure 3.4.

Figure 3.12: **World Well-Being, 1970-1998**



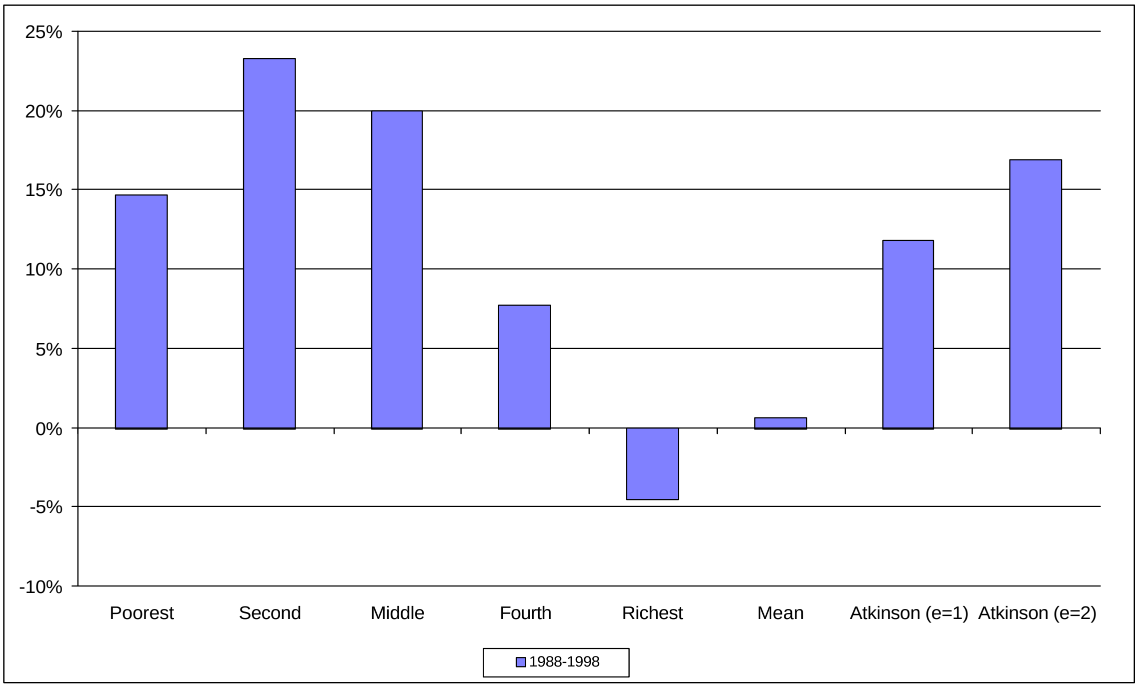
Notes: The first five columns correspond to the five global quintiles. Mean refers to the overall mean income.

Figure 3.13: **Growth in World Well-Being, 1970-1998**



Notes: See notes in Figure 3.12.

Figure 3.14: **Growth in World Well-Being (Including Transition Economies), 1988-1998**



Notes: See notes in Figure 3.12.

Part II

Wage Differentials in South Africa

Chapter 4

Introductory Remarks

4.1 The South African Labour Market

Since a long time, the South African labour market is characterised by peculiarities in many respects. With the official end of the Apartheid in 1994, the new openness also reached labour market issues and a number of profound analyses have been conducted to arrive at a comprehensive picture of the current constitution of the labour market and to derive policy conclusions (e.g. Kingdon and Knight, 2001c,a,d; Klasen and Woolard, 1999; Standing, Sender, and Weeks, 1996). This section presents various aspects of the South African labour market as they provide essential background information for the remaining analysis concerned with wages and wage differentials in the South African labour market.

With an official unemployment rate of 29.4 per cent in 2002, South Africa ranges together with Algeria and Armenia in the group of countries having the highest unemployment rates in the world when the standard definition of the International Labour Organisation is applied (Stats SA, 2002; ILO, 2002). However, as Kingdon and Knight (2001c) show, the expanded definition of unemployment which relaxes the criterion of seeking work constitute a more appropriate measure of unemployment in South Africa as non-searching persons are frequently discouraged workers. According to this indicator, the unemployment rate amounts to 40.9 per cent in 2002 (Stats SA, 2002).[1]

Though these numbers have already reached an alarming magnitude, they still do not tell the total truth. Looking at race specific rates reveals that Africans are much more often affected by unemployment than Whites.[2] Using the broad definition, 47.8 of African

[1] Following the suggestion of Kingdon and Knight (2001c), I will apply the broad definition of labour force participation (and thus unemployment) which includes people who although not actively looking for a job would nevertheless like to work.

[2] The following empirical analysis will only consider these two population groups, whereas *Africans* refer to people regarded as indigenous to Africa and represent 75 per cent of the South African population. Coloured people and Indian descendants are excluded. In total, they account for ca. 11 per cent of the total population. In 2002, official (expanded) unemployment rates amounted to 24.6 (32.4) per cent for Coloureds and 18.7 (24.8) for Indian people (Stats SA, 2002).

labour force participants were unemployed in 2002 whereas the share for Whites lies only by 9.9 per cent (Stats SA, 2002). Within each population groups, unemployment rates also differ across gender, regions, and occupations, with the largest differences occurring among Africans.

People can work either in the formal or informal sector of the economy as employees or being self-employed. Formal wage-employment is normally characterised by regular payments on the basis of a written contract. This is contrary to informal jobs which often come along with casual employment and typically avoid registration as well as tax and social security payments. Such jobs cover a broad set of activities, frequently on a self-employed basis, and are associated with different economic fortune (Devey, Skinner, and Valodia, 2002). In many developing countries, the informal sector acts as a base to search for wage employment and absorbs many unemployed people.[3] In South Africa, only a comparatively small share of 15 to 20 per cent of workers has been engaged in the informal economy in the late 1990s despite high unemployment (Devey, Skinner, and Valodia, 2002). Kingdon and Knight (2001b) explicitly address the question why the unemployed do not enter the informal sector. They decline the hypothesis that people are voluntarily unemployed but argue that there might well exist barriers to enter this sector. Skills, experience, and contacts are required to successfully establish oneself in the informal economy.

The prospects of finding employment are even more dismally as also the formal sector exhibits a certain degree of rigidity. Although not being solely responsible, the slow growth of the South African economy since the mid-1980's contributed to a static or even decreasing number of formal sector jobs (Hofmeyr, 2002; Chandra and Nganou, 2001). In the presence of high and rising unemployment, one would expect to see a decline in real wages. However, over the last decades formal sector wages were found to be rather insensitive to the level of unemployment (Fedderke and Mariotti, 2002; Fallon and Lucas, 1998). Labour market legislation (e.g. minimum wages in much of the formal sector) and powerful trade unions seem to play a major role thereby (Kingdon and Knight, 2001b). Hofmeyr (2002) suggests, that this development has affected new labour market entrants in a particularly negative way and created classes of relatively privileged (unionised) formal sector workers and increasingly marginalised outsiders who are looking for such jobs.[4]

The following empirical analysis of wages and wage differentials will only focus on full-time formal sector employees for basically two reasons. Firstly, as informal sector activities prove to be rather heterogeneous in terms of regularity, continuity, and payments,

[3] For example in the 1990s, urban informal employment in all Africa is estimated to absorb 61 per cent of the urban labour force. Similarly in Asia, where before 1997, between 40 and 50 per cent of the urban labour force was involved in informal sector activities (ILO, 2001).

[4] For further discussion of union wage premia for African and White workers see for example Butcher and Rouse (2001) and Rospabe (2001b).

disregarding them in an analysis assures at least to some extent that only wages earned in a comparable employment status are considered, because all formal sector jobs (have to) meet certain legal standards. Secondly, as income from regular wage-employment on average greatly exceeds the income earned in the informal sector, the former is surely a preferred state (Cichello, Fields, and Leibbrandt, 2002; Kingdon and Knight, 2001b). Working in the informal sector often means to be involved in survivalist activities and provides only a second-best form of employment (Bhorat and Leibbrandt, 1998).

4.2 Assessing the Main Data Source

The data for the empirical analysis in Part II and Part III are taken from the October Household Surveys (OHS). Starting in 1994, the surveys were carried out annually until 1999.[5] The surveys are independent cross sections, i.e. for each of them different samples were drawn. A large but varying number of households across all provinces of South Africa was sampled allowing a detailed snapshot of labour market conditions and outcomes as well as other (development) indicators like health status, access to and use of health services, household structure, or type of dwelling. For the years used in this work, 1995, 1997, and 1999, similar sample designs have been applied. 3000 enumeration areas were sampled and 10 households within each of them have been interviewed, resulting in a sample size of 30000 households. The OHS 1999 differs somewhat as households were selected from a master sample allowing that respondents could be visited again, for example to take part in the twice-yearly Labour Force Survey (LFS) which succeeded the OHS series in 2000 (SADA, 2001).[6]

The basic design of the questionnaire remained relatively unchanged across all survey years. However, some amendments in the way questions could be answered were made. For example, regarding the level of education respondents were given a more detailed list of school grades and degrees in the later years. To arrive at comparable numbers of years of schooling, it was necessary to aggregate the detailed information in 1997 and 1999 to the relatively crude classification in 1995.

There was also a major change in the way incomes could be reported. While in 1995, actual amounts of income were asked, in the later years it was possible to indicate an appropriate income class only. Over the years, an increasing number of workers preferred

[5] In 1993, the South African Labour Development Research Unit (SALDRU) already conducted a household survey in South Africa, in conjunction with the World Bank. With a sample size of 9000 households in 360 clusters it was however a relatively small survey.

[6] The LFS is based on a rotating household panel structure which contrasts with the static nature of the OHS data. It is specifically designed to measure labour market dynamics like changes in employment and unemployment (Stats SA, 2001a).

to report their earnings just by specifying the income category they fall into. From an econometric point of view, working with grouped data has serious consequences as the variance of the data is artificially reduced (see also chapter 7.2). In the surveys used here, respondents could choose among 14 income categories. i.e. a relatively detailed description of the income distribution is possible. Finally, as for a proportion of workers both point and interval data on income are available, the former can be used to approximate actual values for those workers only reporting categories.[7]

To summarise, the series of OHS provides detailed information on working and living conditions in South Africa since the end of Apartheid. The rich data have already been used in a number of studies on labour market issues.[8] The empirical analysis of wages and wage differentials by race and gender that will follow is based on three years of the October Household Survey. In Part II, the surveys are treated as independent cross sections providing information on labour market outcomes at a particular point in time. As several years are studied it is possible to assess changes affecting different groups of workers, like the change in average wages of particular population groups. The analysis in Part III tries to overcome the static nature of cross sectional data. With the help of cohort techniques it is possible to link the survey years in a way that enables us to follow particular age groups over time and to study their particular development.

[7]The discussion in chapter 6.2 will go into detail how the variables used for estimations have been derived.

[8]For example, the extent of racial and gender discrimination was examined by Allanson, Atkins, and Hinks (2000b), Allanson and Atkins (2001), Erichsen and Wakeford (2001), and Rospabe (2001a). The nature of unemployment was subject to studies by Kingdon and Knight (2001a,d,c), and Klasen and Woolard (1999).

Chapter 5

Reviewing the Literature

5.1 Theoretical Models of Discrimination

Different labour market outcomes emerging between people may in principle be ascribed to two effects: Either the persons have different preferences, i.e. supply-side factors play an important role, or they meet different demands. In the classic economic context, the former reflects voluntary choices as people behave rationally to maximise their welfare and no further investigation is needed. As however became evident from sociological and also economic research, social influences and traditions do shape the consciousness of people thereby influencing individual choices as well. In contrast to demand-side factors which especially correspond to labour market discrimination and whereon the present work will focus, such outcomes have been termed pre-labour market or societal discrimination (Blau, Ferber, and Winkler, 1998).[1]

The following analysis aims at determining the extent of wage discrimination by race and gender in the South African labour market. Before shortly browsing the main theoretical models it is advisable to start with a definition of labour market discrimination.[2]

> *"We define labor market discrimination as a situation in which persons who provide labor market services and who are equally productive [...] are treated unequally in a way that is related to an observable characteristic such as race [...] or gender. By 'unequal' we mean these persons receive different wages or face different demands for their services at a given wage" (Altonji and Blank, 1999, p. 3168).*

[1]For further discussion on socialisation and its consequences for individual choices see for example Altonji and Blank (1999), Anker (1997), Becker (1991) and Epstein (1988).

[2]As my emphasis will be on the empirical analysis, I only review the models in brief and refer to original sources and standard text books on labour economics (e.g. Blau, Ferber, and Winkler, 1998; Ehrenberg and Smith, 2000). In addition, a comprehensive overview of both theoretical literature and empirical analysis is given by Cain (1986) and Altonji and Blank (1999).

It is important to note that in accordance with this definition the extent of e.g. wage discrimination equals the 'unexplained gap', i.e. the discrepancy in wages after personal productivity-related characteristics are controlled for. The fact that differences in observable characteristics (e.g. amount of human capital acquired) could date from pre-labour market discrimination is not taken into account. Similarly, anticipation of discrimination may lead to a change in preferences (e.g. to invest less in human capital) and such feedback effects of labour market discrimination are also not considered. Especially the empirical work on labour market discrimination is almost exclusively concentrated on the determination of the unexplained gap (Blau, Ferber, and Winkler, 1998; Altonji and Blank, 1999).[3]

Becker (1957) started the economic analysis of labour market discrimination. He developed the idea that employers, employees, and customers may have prejudices against members of particular (minority) groups and introduced the term of tastes for discrimination. Given, these discriminatory tastes influence the behaviour of people, they do have an impact on earnings and employment chances of the discriminated group. The discrimination coefficient captures the costs associated with discriminatory tastes. It either corresponds to a kind of discount the discriminated group has to accept (employer and consumer discrimination) or reflects a premium that employees command for working with members of the discriminated group.[4] Regarding the persistence of discrimination, the taste based theories suggest various outcomes. If in a competitive labour market both discriminatory and less or non-discriminatory employers coexist, one would expect discrimination to be eliminated in the long run as discriminatory firms produce at higher costs and will therefore be displaced. This is contrary to employee and consumer discrimination which may, as employers' profit maximisation is not distorted, explain why discrimination continues to exist also in the long run (Becker, 1992; Ehrenberg and Smith, 2000).[5]

Continuing discrimination can also be due to certain beliefs employers have regarding the productivity or commitment of particular groups. The theory of statistical discrimination argues that hiring or promoting decisions may not only be based on information on skills and qualification. Employers, who are not assumed to have a taste for discrimination, may also make use of easily observable characteristics like race or gender or rely

[3] In the 1990s, audit studies have been used to alternatively examine labour market discrimination. Resumes of job candidates who have the same paper qualifications relevant for productivity but differ in gender or ethnicity are sent out to companies. Then, the probabilities of getting an interview are compared (Altonji and Blank, 1999). For a critical assessment of the audit methods see for example Heckman (1998).

[4] Employer discrimination may also take on the form of overpaying preferred workers. This behaviour is known as employer nepotism.

[5] If (non-discriminatory) employers could recruit a segregated work force, there is no need to pay a premium. As a result, wage discrimination would not occur but complete segregation (Blau, Ferber, and Winkler, 1998).

on previous experience to judge individual workers (Arrow, 1972; Phelps, 1972). Such behaviour is clearly discriminatory but has even more serious consequences if discriminated people react in the expected way, i.e. do quit jobs more often and become less productive as e.g. participation in firm-specific training was not granted. Discrimination persists since employers are confirmed in their expectations and see no need to change (Blau, Ferber, and Winkler, 1998; Becker, 1992).

Although rather an empirical observation than a theory, occupational segregation, describing the fact that people belonging to different groups tend to work in different occupations, should also be considered explicitly. Similar to the discussion at the beginning of this chapter, both supply-side and demand-side factors can explain the outcome and only the latter can be attributed to (current) labour market discrimination (Ehrenberg and Smith, 2000). Again, cultural values, social norms and the expectancy of labour market discrimination may influence the occupational choice (Anker, 1997). As mentioned before, occupational segregation may be the result of employee discrimination if employers hire segregated work forces to avoid the wage premium. If this strategy is successful, no discriminatory wage gaps will emerge. The overcrowding model by Bergmann (1974) brings the discussion a step forward by linking occupational segregation and earnings differentials. If members of the discriminated group are crowded in particular occupations, either because of discrimination or voluntarily, in comparison to the demand for such jobs the supply of labour may be relatively large. Wage rates in crowded sectors will be compressed and an unexplained wage gap between workers employed in different occupations appears.

Having briefly reviewed the main theories, the question then arises how they relate to discrimination in South Africa. As for more than 40 years the labour market was heavily regulated in favour of Whites, one would expect to detect especially racial differences in labour market outcomes which cannot fully be explained by different personal productivity-related characteristics. But the total extent of discrimination will be considerably larger since pre-labour market discrimination and feedback effects also play a major role. During Apartheid, access to education was restricted for Non-Whites and the resulting level of human capital and thus productivity does not reflect voluntarily choices. Furthermore, a system of job reservations was implemented by the Job Reservation Act in the 1950s, thereby legally excluding Non-Whites from many jobs and training programs. Occupational segregation and even exclusion occurred as a result of such legal constraints. Since the 1980s, the South African government has been undertaking liberalising steps due to increasing internal as well as external pressure. Already at the end of that decade, most of the overt discriminatory acts have been abolished and a non-racial and liberal legislation came into force. Labour market discrimination, however, could not be eliminated so far but rather seems to take on different forms. According to Azam and

Rospabe (1999), today's wage discrimination in South Africa may be best explained by statistical theories. In the empirical analysis to follow, I will investigate to what extent the appearance of wage discrimination changed since the official end of Apartheid.

5.2 Labour Market Discrimination in South Africa

More than 40 years of racial legislation in South Africa resulted in a socially as well as economically heavily segmented society. According to the Gini coefficient which in 1994 amounted to almost 60 per cent, South Africa belongs to the most unequal societies in the world. The official end of Apartheid in 1994 provides a natural benchmark to assess any progress regarding a more equal treatment of people belonging to different population groups. As the previous discussion illustrated, discrimination happens at various fields and to measure its full extent may turn out to be rather difficult. Although an empirical investigation of the magnitude of the 'unexplained gap' cannot take into account all relevant aspects, it gives valuable information to what extent claims and commitments to reduce racial as well as gender discrimination have already been translated into action.

One of the first studies determining the extent of racial wage discrimination in post-Apartheid labour market was conducted by Allanson, Atkins, and Hinks (2000b).[6] Analysing mean hourly wages of male workers of all races in 1994, they at first document the existing racial wage hierarchy. African and Coloured workers are found at the lower end of the distribution of wages, with earnings of about one third of the mean wage for Whites. Asian and White males have considerably higher earnings, but the mean wage of Asian workers was still one third below that of White men. About one third of the wage differential between African and White workers could not be explained by different personal characteristics. Regarding the wage differential between White workers and Coloured and Asian workers, respectively, virtually all of the observed difference is explained by observable characteristics. In a follow-up study the authors focus on the years 1995 and 1997 to see whether the end of Apartheid had immediate economic consequences regarding labour market outcomes (Allanson, Atkins, and Hinks, 2000a). The results were rather disillusioning as racial gross wage differentials were still substantial. Africans were found in an even worse situation as they are the only group of workers that on average could not realise an increase in wages.[7] Regarding the extent of wage discrimination, there is

[6] Income inequality and the extent of wage discrimination during Apartheid have been analysed by Knight and McGrath (1987), Treiman, McKeever, and Fodor (1996), Moll (1998), and Allanson, Atkins, and Hinks (2000a). They all point to a slight declining tendency of both racial wage hierarchy and labour market discrimination between 1980 and the early 1990s.

[7] This result is somewhat controversial, in particular as the authors study nominal wages. The present work also comes to a different conclusion regarding the development of African wages. However, the findings are not directly comparable since the samples of workers differ to some degree.

limited evidence that it was somewhat reduced.

Erichsen and Wakeford (2001) examine wage differentials shortly before and after the formal end of Apartheid. They determine the extent of racial wage discrimination in 1993 and 1995 and expand the scope of analysis by considering wage gaps among women as well. In both years, racial wage gaps among females are smaller than those for males, but mean wages follow the same hierarchy. Earnings of Africans and Coloured workers are considerably lower than earnings of Asian and White workers. Furthermore, they find similar patterns of discrimination for male and female workers. Differences in personal traits explain most of the observed wage differentials emerging between Whites and Coloureds and Asians, respectively, and still a considerable portion of the gap between Whites and Africans.

Rospabe (2002) undertakes one of the most comprehensive studies on labour market outcomes in South Africa. For the years 1993 and 1999, she analyses the extent of racial employment, occupational, and earnings discrimination among African and White men. She concludes that five years after the end of Apartheid racial gaps in all three dimensions are still substantial, but were declining during the period considered. In 1999, the extent of discrimination still accounts for between 30 and 40 per cent depending on the kind of labour market outcome. A second paper of her is devoted to gender discrimination in several labour market outcomes in 1999 (Rospabe, 2001a). Substantial gender inequalities were found which could only partly be explained by gender differences in productivity-related characteristics. Especially occupational attainment is characterised by an utmost unequal distribution which has to be predominantly attributed to discrimination.

So far, studies on discrimination in the South African labour market were either focused solely on earnings or examined several labour market outcomes separately. The extent of discrimination is always derived by decomposing group differences into an explainable term and an unexplained term (Blinder, 1973; Oaxaca, 1973; Gomulka and Stern, 1990).[8] The following analysis proceeds differently. When estimating the wage differential I will take into account that labour force participants may have different probabilities of finding employment. Applying decomposition techniques suggested by Mavromaras (2003) and Neuman and Oaxaca (1998), it is furthermore possible to use the information on the different probabilities to detect effects that already arise at the selection into employment stage and influence the wage rate in an indirect way. Regarding the time scope, three years after the end of Apartheid will enter the analysis which will focus on both racial and gender discrimination.

[8]The next chapter provides a detailed description of the standard method used in many decomposition analyses. Allanson, Atkins, and Hinks (2000b) enhanced the standard technique allowing not only binary but several (multilateral) comparisons of groups' wage levels against a non-discriminatory norm.

Chapter 6

The Empirical Approach

6.1 Determining the Extent of Direct and Indirect Discrimination

Over the last 30 years, the approach to explain wage differentials, introduced into the literature of economics[1] by Blinder (1973) and Oaxaca (1973), has not only been intensively used but was also further developed and prompted to the evolution of alternative techniques, respectively.[2] Despite this, it became standard in decomposition analysis and will be the starting point here.

Consider a standard wage equation:

$$Y_i = X_i'\beta + u_i, \tag{6.1}$$

where Y_i is the log of gross hourly wage of individual i, X_i' is a vector of variables which determine the market wage, β is a vector of parameters to be estimated and u_i presents the identically independently distributed error term. Given, within a population there are different groups (by gender, race, religion etc.) one can calculate the average wage differential between two groups by estimating separate wage equations and taking the difference:

$$\bar{Y_1} - \bar{Y_2} = \bar{X_1'}\hat{\beta}_1 - \bar{X_2'}\hat{\beta}_2. \tag{6.2}$$

Expanding this expression by the *assumed* non-discriminatory wage structure β^*, which is used to reward productivity-determining characteristics of both groups, leads to:

$$\bar{Y_1} - \bar{Y_2} = \bar{X_1'}\hat{\beta}_1 - \bar{X_2'}\hat{\beta}_2 + \bar{X_1'}\beta^* - \bar{X_1'}\beta^* + \bar{X_2'}\beta^* - \bar{X_2'}\beta^*. \tag{6.3}$$

[1] Decomposition methods have been popular also in other branches of study for a long time. Examples in the field of sociology are given by Althauser and Wigler (1972) and Duncan (1968).

[2] Some of the studies suggesting slight modifications of the original model will be referred to later. Contributions to extend the model were also made by e.g. Nielsen (2000) and Leslie, Clark, and Drinkwater (1997). A completely different approach to decompose wage differentials is suggested by Gupta, Oaxaca, and Smith (2001) and Jenkins (1994). See also chapter 7.1.

Valuing group differences of personal characteristics according to β^* yields an estimate of what the wage gap should be in the absence of labour market discrimination. Finally, the right-hand side of equation (6.3) can be reformulated to display the well-known decomposition components:

$$\bar{Y_1} - \bar{Y_2} = \beta^*(\bar{X_1} - \bar{X_2})' + \bar{X_1}'(\hat{\beta}_1 - \beta^*) + \bar{X_2}'(\beta^* - \hat{\beta}_2). \tag{6.4}$$

The first term presents that part of the wage differential which is due to different group means of the productivity determining characteristics considered in X_i' and is therefore called *endowment* or *productivity component*. Presuming $\bar{Y_1} > \bar{Y_2}$, the second term measures overpayment of group 1, the third term underpayment of group 2, always in relation to the assumed non-discriminatory wage structure β^*. The sum of the last two terms equals that portion of the observed wage gap that cannot be explained by different personal traits, i.e. the unexplained gap. This residual is then usually interpreted as *discrimination* or *market component*.[3] This interpretation assumes that all variables which determine productivity differences are observable and accounted for in the wage equation as well as that the functional form of the wage regression is correctly specified. Otherwise, the extent of discrimination might be over- or underestimated due to unobservable variables, measurement errors, or incorrect specification of the model.

There are several possibilities what the non-discriminatory wage structure could be. In the early studies of wage decomposition one of the estimated mean wage structures was often assumed to reflect an environment without discrimination, for example $\beta^* = \beta_1$. Applying this strategy cancels out the second term of equation (6.4). In this context, labour market discrimination corresponds to underpayment of the disadvantaged group only. This approach was first suggested in the fundamental papers by Blinder (1973) and Oaxaca (1973) and was then used in numerous decomposition analyses that followed. Cotton (1988) formalised the idea that discrimination not only means a financial disadvantage for people against who discrimination takes place, but can also show up in a monetary benefit for the favoured group. According to this, the wage paid in the absence of discrimination lies between the observed groups' mean wages.[4] This non-discriminatory wage structure cannot be observed, but has to be derived. Cotton (1988) suggests an average of the observed wage structures, weighted by the groups' labour force shares.[5] This idea was further developed by Oaxaca and Ransom (1994) who proposed a weighting scheme

[3]In the following this decomposition method which results in these two major components will be called *standard approach*.

[4]In fact, even earlier studies already realised that employers' preference for one group and their distaste for another will distort both groups' wages and that the non-discriminatory wage structure would therefore lie "somewhere between them" (Reimers, 1983, p. 573), but failed to provide some kind of theoretical framework.

[5]Reimers (1983) weighted both estimated wage structures by 0.5.

obtained from the estimation of a combined or pooled sample instead of constructing it from a linear combination of separately estimated groups' wage structures. Since this approach yields the smallest estimated standard errors for estimated differentials it became standard in the field of decomposition analysis.

Incorporating consolidated findings from the literature on labour supply is also common in decomposition analysis. It is thoroughly documented that if the workers' sub-sample is no random sample of the population in terms of both observable and unobservable factors, one faces the problem of sample selection. This arises "when some of the determinants of the work decision are also influencing the wage" (Vella, 1998, p. 129). As long as one is interested in making inferences on workers solely, systematic censoring is not a problem. However, conclusions drawn from a non-random sub-sample are not applicable to a larger sample of the same population. If only observable factors cause the differences between the two samples, they could easily be accounted for by using appropriate control variables in the wage equation. If the relationship between employment and wage is characterised by a correlation between unobservable factors affecting work decision and unobservables determining the wage, matters become complicated. Not including an estimate of the unobservable characteristics influencing the employment process in the wage equation will lead to biased coefficients (Vella, 1998).

Heckman (1976, 1979) proposed an estimator which basically treats the selection problem as an omitted variable problem. Sample selection is expected to lead to a correlation of the error terms of employment and wage equation. By estimating a probit model on employment propensity it is possible to determine the conditional expectation of the error term, which is called the inverse Mills ratio (IMR). The IMR is then added to the set of explanatory variables used in the wage equation.[6] To see, in what respect this additional regressor influences the wage differential, it is helpful to start with the employment equation.

$$Y_i^* = Z_i'\gamma + \epsilon_i \tag{6.5}$$

Y_i^* represents the employment probability, a latent variable that can only be observed if individual i is employed. Z_i' is a vector of variables determining employment, γ a vector of parameters and ϵ_i is the i.i.d. error term with a normalised variance of 1. The probability of being employed can be expressed by:

$$Prob(Y_i^* > 0) = Prob(\epsilon_i > -Z_i'\gamma) = \Phi(Z_i'\gamma), \tag{6.6}$$

where $\Phi(Z_i'\gamma)$ is the standard normal cumulative distribution function. The expected wage

[6] This so-called Heckman correction has been criticised mainly for its restrictive assumptions by Puhani (2000), but is still widely used since it provides a convenient and easily implemented method to correct for sample bias.

conditioned on being employed equals:

$$E(Y_i|Y_i^* > 0) = X_i'\beta + E(u_i|\epsilon_i > -Z_i'\gamma) + v_i = X_i'\beta + \theta\lambda_i + v_i, \tag{6.7}$$

whereby $\theta = \rho\sigma_u$. It is an estimate of the product of the correlation between the error terms of employment equation and the wage equation ρ and the standard deviation of the wage error term σ_u. The inverse Mills ratio is represented by $\lambda_i = \phi(Z_i'\gamma)/\Phi(Z_i'\gamma)$, with $\phi(Z_i'\gamma)$ being the standard normal density function. After having incorporated the IMR into both groups' wage equations the wage differential equals:

$$\bar{Y_1} - \bar{Y_2} = \bar{X}_1'\hat{\beta}_1 - \bar{X}_2'\hat{\beta}_2 + \hat{\theta}_1\hat{\lambda}_1 - \hat{\theta}_2\hat{\lambda}_2. \tag{6.8}$$

Compared with equation (6.2), the wage differential is now enhanced by the difference in the average selectivity bias between the two groups. This difference is called *selection term*. Applying the pooled sample approach as the non-discriminatory norm to the first two terms of equation (6.8) yields:

$$\bar{Y_1} - \bar{Y_2} = \beta^*(\bar{X}_1 - \bar{X}_2)' + \bar{X}_1'(\hat{\beta}_1 - \beta^*) + \bar{X}_2'(\beta^* - \hat{\beta}_2) + (\hat{\theta}_1\hat{\lambda}_1 - \hat{\theta}_2\hat{\lambda}_2).^7 \tag{6.9}$$

Various studies performing decomposition analysis estimated selectivity corrected wage equations. However, when starting the decomposition of the wage differential, the last term of equation (6.9) was mostly neglected. Ashraf and Ashraf (1993), for example, estimate selectivity corrected wage regressions to decompose the gender wage gap in Pakistan, but did not consider this term at all. Similarly, a World Bank study analyses womens' employment and pay in Latin America (Psacharopoulos and Tzannatos, 1992). Ordinary least squares as well as selectivity corrected wage regressions have been estimated, but only productivity-related and unexplained components of both estimation procedures were interpreted. Duncan and Leigh (1980) and Reimers (1983) proceed differently. They also estimate corrected wage regressions but put the selection term on the left hand side. Thereby, they netted out the selection term from the overall wage differential, resulting in "a decomposition of the selectivity corrected wage differential" rather than a decomposition of the observed wage differential (Neuman and Oaxaca, 1998, p. 5).

To the best of my knowledge, only the studies by Neuman and Oaxaca (1998) and Mavromaras (2003) developed techniques how to decompose the selection term as well. This additional decomposition will result in a second set of endowment and discrimination effects associated with the selection into employment. The difference between the two approaches lies in the supposed non-discriminatory norm. Whereas Neuman and Oaxaca

[7] The decomposition procedure, which results in these three major components, will be called *selectivity corrected approach*.

(1998) derive their results by assuming that one of the estimated wage structures is representing a scenario without discrimination, Mavromaras (2003) applies the pooled sample approach. Following the latter, one can expand and rearrange the selection term analogously to the standard decomposition procedure:

$$\hat{\theta}_1\hat{\lambda}_1 - \hat{\theta}_2\hat{\lambda}_2 = \theta^*(\hat{\lambda}_1 - \hat{\lambda}_2) + \hat{\lambda}_1(\hat{\theta}_1 - \theta^*) + \hat{\lambda}_2(\theta^* - \hat{\theta}_2).^{8} \tag{6.10}$$

The first term of the right-hand side compares the mean IMR of the two groups and represents the portion explained by different group means. The last two terms describe to which extent individuals with equal λs are treated differently according to their groups' affiliation. Again, if the non-discriminatory structure is assumed to be represented by one of the estimated group's structure, either of the last two terms would drop out.

Regarding the first term of equation (6.10) (i.e. the endowment component of the selection term), a further decomposition is suggested.[9] According to Mavromaras (2003), interpreting this term as a pure endowment effect is equal to treating the λs as real data. However, the IMR are estimates themselves and "the variables used for the estimation could be a source of indirect discrimination" (Mavromaras, 2003, p. 61). To decompose this endowment component, a counterfactual has to be constructed, representing the mean values of the IMR if group 2 would pass through the same selection (into employment) process as group 1:

$$\hat{\lambda}_2^0 = \frac{\phi(\bar{Z}_2'\hat{\gamma}_1)}{\Phi(\bar{Z}_2'\hat{\gamma}_1)}. \tag{6.11}$$

Thus, $\hat{\lambda}_2^0$ is a combination of data used in group's 2 employment equation and coefficients estimated in the employment equation of group 1. Expanding the endowment term by the counterfactual evaluated by the non-discriminatory norm θ^* leads to:

$$\theta^*(\hat{\lambda}_1 - \hat{\lambda}_2) = \theta^*(\hat{\lambda}_1 - \hat{\lambda}_2^0) + \theta^*(\hat{\lambda}_2^0 - \hat{\lambda}_2). \tag{6.12}$$

The first term of the right-hand side compares different characteristics in the same environment, so clearly this is the part that can be explained by the data. The second term compares a hypothetical situation, namely how would group 2 have been treated in a group 1 environment, with the actual treatment of group 2. This part therefore can be attributed to discriminatory behaviour. Since these effects already arise at the selection (into employment) stage, but also affect the wage, they are labelled *indirect effects* (Mavromaras and Rudolph, 1997).

Hence, when estimating selectivity corrected wage equations and applying the pooled

[8]Parameters estimated from a pooled sample are denoted by an asterisk.

[9]Both Neuman and Oaxaca (1998) and Mavromaras (2003) make use of results obtained by Gomulka and Stern (1990), who introduced the decomposition of non-linear terms.

sample as the non-discriminatory set, the final decomposition equation equals:

$$\bar{Y_1} - \bar{Y_2} = \beta^*(\bar{X_1} - \bar{X_2})' + \bar{X_1'}(\hat{\beta}_1 - \beta^*) + \bar{X_2'}(\beta^* - \hat{\beta}_2) + \\ \theta^*(\hat{\lambda}_1 - \hat{\lambda}_2^0) + \theta^*(\hat{\lambda}_2^0 - \hat{\lambda}_2) + \hat{\lambda}_1(\hat{\theta}_1 - \theta^*) + \hat{\lambda}_2(\theta^* - \hat{\theta}_2). \tag{6.13}$$

The first three terms of the right-hand side are familiar from standard decomposition approach. All other terms are related to the employment process. Terms 4 and 5 reveal the extent of indirect endowment and discrimination, resulting from the decomposition of the λs. Following Mavromaras (2003), the sum of the last two terms corresponds to the degree to which individuals with identical λs may be remunerated differently upon employment by group affiliation. Different treatment of identical traits is a clear sign of discrimination. As shown in Table 6.1, which summarises all individual terms with their particular interpretation, these effects will be subsumed in the overpayment and underpayment component.

Neuman and Oaxaca (1998) suggest an identical decomposition of the selection term, except for the non-discriminatory norm. They assumed $\beta^* = \beta_1$ and consequently $\theta^* = \theta_1$, which leads to the fact that terms 2 and 6 of equation (6.13) are equal to zero. But also their interpretation of the remaining terms differs slightly. Terms 4 and 5 are also interpreted as endowment and discrimination effects, but not labelled as *indirectly*. If the selection term is decomposed, both terms are included in the overall endowment and market components of the observed wage gap. The focus, however, is on the allocation of the last term which now equals $\hat{\lambda}_2(\hat{\theta}_1 - \hat{\theta}_2)$ and in the authors' view captures "the effects of [...] [group] differences in the wage response to the probability of [...] employment" (Neuman and Oaxaca, 1998, p. 6). The paper then discusses, under what assumptions this term can either be assigned to the estimated endowment or discrimination effect, or is to be presented as a separate *selectivity* contribution. As a fourth strategy, the selection term is not decomposed at all, but presented as a individual component of the wage gap, as done in equation (6.9).

How will the various decomposition and allocation strategies affect our impression of labour market discrimination in South Africa? To answer this question, the observed wage gaps will be decomposed according to both the standard OLS-based approach and the selectivity corrected approach. In either setup, estimations from pooled samples are assumed to reflect an environment without discrimination. Regarding the selection term, it will be presented as a separated term as in equation (6.9) (Variant 1). Secondly, a detailed decomposition of the overall wage gap similar to equation (6.13) will be shown. A third variant follows the idea of having a single selectivity contribution.

6.2 The South African Labour Force, 1995 - 1999

Before presenting the results of the various estimations and decompositions, it is necessary to have a closer look at the data used in the analysis. Tables 6.2 to 6.5 present summary statistics of the population groups. The total sample of labour force participants comprises individuals who are aged between 15 and 65 and either reported to be employed or were categorised as unemployed using the expanded definition.[10] To belong to the sample of workers, people had to be employed full-time at a formal sector job.[11] Finally, outliers at both lower and upper end of the wage distribution were excluded from the overall analysis.[12]

The information provided by the summary statistics are rather manifold. I will therefore only comment on particular findings which point out important differences between race and gender on the one hand and labour force participants and workers on the other hand. To start with the educational level, the proxy for human capital, the average number of years of schooling completed slightly increases for all population groups over the total period considered. The racial difference in education is significant in both workers and total sample and relatively constant over time.[13] Gender differences within each population group are almost negligible, except for African workers. In all years, African female workers have considerably more education than African male workers. This result is remarkable, and was also found in other studies (Erichsen and Wakeford, 2001). It suggests, that only very well educated African women are able to find full-time employment in the formal sector.

There are also major differences regarding household composition. Racial comparisons show that in all years the number of children living within the household is somewhat higher for Africans. Again, there is virtually no gender difference within the White population, but not so for the African population. In both samples (labour force and workers), more children live with African women. With respect to household head, men take predominantly this position. However, the proportion of African female workers acting as household head is considerably higher in all years as the corresponding numbers for White females – a fact that also stresses the particular role of African women in the South African labour market.

[10]In 1995, the upper limit with respect to age is 64 due to the limited availability of unemployment variables.

[11]To get classified as working full-time it was not sufficient to affirm the corresponding question but the reported number of hours worked per week had to lie between 35 and 70 as well.

[12]The number of unreasonable high and low wages increased somewhat over the years. In 1999, altogether 84 observations were dropped from the analysis, 73 of them concerning Africans.

[13]Another aspect regarding educational attainment is *quality* of schooling. During Apartheid, separate educational systems existed for the four population groups. They differed in enrollment rates, pupil-teacher ratios and financial resources. If quality of schooling is controlled for, racial gaps in labour market outcomes can be 'explained' much better (Case and Deaton, 1999; Kingdon and Knight, 2002).

With respect to the marital status of economically active population, the percentage of married people is higher among Whites at any point in time, but the share is declining for all groups. Moving from labour market participants to workers, the portion of married people increases for all population groups, with the least change for Whites and the most significant increase for African men. It seems that *if* African men are married, they have to find employment to be able to support their families.

There are also important geographical differences. The share of people living in rural areas is considerably higher among Africans, which is one of the legacies of Apartheid. Regarding the distribution across provinces, 25 per cent of African and up to 45 per cent of White labour market participants live in Gauteng, the smallest, but in terms of finding employment a province with good prospects. Together with Western Cape it has one of the lowest regional unemployment rates and highest average earnings in South Africa (Klasen and Woolard, 1999; Stats SA, 2000).

Turning to the distribution across different occupations and industries, racial as well as gender segmentation is obvious but there also seems to be some mobility. For example, the share of Africans employed as skilled workers increased for women and even more for men in the period. Among the latter, the share of unskilled workers also dropped considerably, whereas for female workers this percentage is unchanged. In 1999, more than one third of African females were still employed as unskilled. Such jobs are mostly provided by the service sector, the industry where almost 50 per cent of African females are employed. On the other hand, the share of Africans working in responsible and well paid jobs like managers and professionals is still small, but increased slightly.[14] Already in 1995, the majority of Whites was employed in more 'prestigious' jobs, but the portion of White women working as managers and professionals amounted to 11 per cent only. In 1999, the gender gap among Whites regarding such positions was still considerable, but the female share has come to 27 per cent.

On an industrial level, mobility is also visible, although not that dynamic. The share of African men employed in agriculture seems to have dropped quite dramatically from 20 per cent in 1995 to only 12 per cent in 1999.[15] The share of Africans working in the financial sector increased somewhat. Most African females are working in the service sector. Regarding White workers, more and more were employed in the financial sector. At the same time, about one third of White women and one fifth of White men also earned their money in the service sector.

[14] Looking at African women, it seems that the data for 1997 are partly flawed by showing a relatively big increase of female professionals when compared to 1995 and 1999. The share of women working as technicians in 1997 seems to be too low when compared to adjacent years.

[15] Again, the 1997 data might be problematic. Comparing 1995 and 1997, the drop of African male workers employed in agriculture is even more pronounced, compensated by an alleged rise in 1999. The portion of African men working in the manufacturing sector records an increase in 1997, and falls back in 1999 to the same level as already quoted four years ago.

The dependent variable in all regressions is log of gross hourly wage. This variable had to be calculated from the reported amount of income and the number of hours worked per week. People could either report total pay before tax or deductions (including overtime, allowances, and bonuses) or indicate an income category, i.e. the variable takes the form of both point and interval data. The appropriate econometric approach would be to estimate interval regressions. As the estimation of selectivity corrected interval regression has not been documented so far, I had to proceed differently. If only an income category was given, I calculated gender and race specific mean values for each income category from observations that specified the exact amount. Tables 6.4 and 6.5 show that the proportion of workers reporting income categories is increasing. In 1997, almost 60 per cent of White full-time workers employed in the formal sector did not report their actual amount of income and their share increases to more than 70 per cent in 1999. For African workers there is also a rising tendency for indicating income category only, but with 31 per cent in 1997 and 39 per cent in 1999 the share remains substantially smaller. Assuming that the preference to report only an income class is not randomly distributed, the replacement approach is not beyond question. By including a dummy variable in the wage regressions I hope to have accounted for this problem.

The average gross wage earned per hour and the corresponding log values increased for all groups for the period considered. Racial differences are slightly decreasing, but are still considerable for all years. On average, log hourly wages earned by Whites are more than one and a half times higher than Africans. Among White workers men earn considerably more than women. In case of African workers the gender gap is narrower. Probably the most surprising result, however, is that according to the data, in 1995 African women who were full-time employed in the formal sector had on average higher wages than their male colleagues. Due to a jump of men's wages from Rand 8.6 (1995) to Rand 9.9 (1997), for the last two years the gender gap among African workers is as expected: men have on average higher earnings than women. Erichsen and Wakeford (2001) also report male and female wages disaggregated by population group in 1995. They find the same pattern. This finding, however, is rather unrealistic and probably due to incorrect numbers regarding wages for African men in 1995.

Finally, a few words on how the variables are used. Age, educational level, current job tenure, union membership, living in a rural or urban area and a set of dummy variables controlling for different occupations, industries, and regions enter the wage regressions. However, variables like age, education, and living in a rural area are also supposed to determine employment. To solve the identification problem, the employment equation must also include variables which are supposed to influence only the probability of being employed. Household variables are often said to fulfill this exclusion restriction. I will use the marital status, number of children living in the household, annual gross income earned by spouse or partner, and whether individual i is head of household.

6.3 Results

6.3.1 Wage Regressions

Ordinary Least Squares Wage Regressions

Tables 6.6 and 6.7 present regression results obtained by estimating OLS wage regressions. The coefficients are mainly in accordance with the literature on wage determination and are similar to the ones obtained from previous studies on the South African labour market (e.g. Rospabe, 2002; Allanson, Atkins, and Hinks, 2000a). With respect to age, one would expect that as a worker gets older she is more experienced which will result in a higher wage.[16] However, due to depreciation this relationship is rather concave than linear, leading to a turning point in the wage-experience profile. This pattern can be observed for nearly all population groups in all years, whereas the importance of this relationship seems to be stronger for men.

Estimated coefficients for Africans indicate that more education leads to higher wages. Results are statistically significant for both sexes in all years. Returns to schooling are higher for women. Regarding White men, the coefficients for 1995 and 1997 are also statistically significant and suggest a dramatic decline in returns to education between these two years. Results for 1999 are insignificant as are all coefficients for White female workers.[17]

Tenure in current job is used to measure firm-specific human capital. Here, a similar relationship as with age is expected. The longer a person is working with her current employer, the more firm-specific knowledge she could accumulate, the higher her wage. Again, this relationship is assumed to be nonlinear because of depreciation of that capital. Estimation results for African workers strongly confirm such a relationship for all years. In case of White workers, it only shows up in 1995.

Union membership is supposed to have a positive effect on wage levels, because unions have a more powerful position in the wage bargaining process (e.g. Butcher and Rouse, 2001; Azam and Rospabe, 1999). This result is strongly confirmed for African workers for all years but there is no significant association for White workers. This might be partly due to the somewhat lower rate of unionised workers among Whites.

[16] In the following, *wage* is used as an abbreviation for the dependent variable which is log of gross hourly wage.

[17] There is probably too little variation across the educational level of Whites to arrive at significant results.

If jobs in rural areas are limited and labour supply is relatively large, respectively, one would expect wage levels to be compressed (see also Bergmann, 1974). Since the percentage of White workers living in rural areas is relatively small, African workers should be mostly affected by that. The estimation results confirm exactly this hypothesis. In case of African workers, residing in a rural area is strongly associated with lower wages, but for Whites no statistically significant results could be obtained.

Occupational dummy variables reveal that among Africans unskilled workers earn on average the lowest wages in all three years. For Whites, this statement is true for the year 1995 and for White men in 1997. Regarding this population group in 1999, being employed in more prestigious jobs like managers, professionals, and technicians was still associated with higher wages on average, but with respect to other positions no significant difference to the mean wage earned by unskilled workers is identified. However, this result, as well as the insignificant coefficients obtained for White women in 1997 and 1999 may be due to the relatively small number of observations within each occupational category.

On the industrial level, sectors like agriculture and trade are characterised by the lowest mean wages for almost all population groups for the period considered. With respect to other sectors, differences in mean wages in comparison to the average wage earned in the manufacturing sector are usually either relatively small or statistically not significant.

There is an ongoing debate in the decomposition literature, whether or not occupational and industrial dummy variables should be included in wage regressions (e.g. Blau, Ferber, and Winkler, 1998; Brown, Moon, and Zoloth, 1980). Considering such variables in the estimation increases the share of the observed wage gap that is explained by observable factors. If occupational (and industrial) segregation is due to discriminatory behaviour, however, the extent of discrimination will be underestimated. I still include these control variables to be able to compare my results to other studies on wage discrimination in South Africa.

With respect to provinces, wages earned in Gauteng and Western Cape are frequently found to be considerably higher on average than the mean wage in KwaZulu-Natal, the reference region. African workers living in the Free State are at the bottom end of regional mean wages for all years. In case of White workers, regional differences are mostly not statistically significant.

Between 1997 and 1999, significance as well as magnitude of the coefficients on whether or not income was reported in categories are increasing. This confirms the hypothesis that people do not randomly report income categories instead of actual amounts. Statistically significant coefficients had a positive sign, suggesting the distribution of log wages had been shifted to the right. This bias has been deliberately introduced by the replacement procedure. To assess, whether the overall results are affected by this approach, I estimated also interval regressions, the appropriate estimation method given the particular structure of the data. Results suggest that the influence of the bias on both the magnitude of the predicted wage gaps as well as the resulting decomposition components is only marginal. I therefore proceed with the replacement approach.

Selectivity Corrected Wage Regressions

Tables 6.8 and 6.9 present estimation results obtained by the selectivity corrected wage regressions. The upper panels show results for the wage equations now augmented by the inverse Mills ratios (*Lambda*). Estimated coefficients of the employment equation are shown in the lower panels. The results regarding the IMR support the chosen estimation method as in all regressions statistically significant coefficients have been identified. Conceptually, the IMR is a monotonically decreasing function of the probability of being full-time employed in the formal sector, i.e. for individuals who have a high probability, the IMR will be low. In addition to being highly significant, all coefficients of the IMR have a negative sign, indicating that people with higher employment propensities also have above average wage prospects.

Comparing the coefficients of the selectivity corrected wage equations with those obtained by OLS regressions, there are several things to comment on. Significance and, to a lesser degree, magnitude of the coefficients of variables considered in the wage equation only did not change, as expected. Variables assumed to influence both wage level and propensity of being employed, now seem to play only a minor and sometimes less significant role on the wage determination process. In terms of being employed these variables do not turn out to be significant for all population groups. For instance, age seems to be important for African people but not for Whites. The relationship between age and employment status is similar to the one identified for wages: the elder a person, the higher her propensity of being employed, but at a decreasing rate.

Similar results are obtained with respect to education. Only among Africans, with the exception of men in 1995, a positive effect of more schooling on being employed could be identified. The insignificant coefficients for Whites should probably not be interpreted in the sense that education does not effect employment probabilities, but may in turn be caused by too little variance.

With respect to living in a rural or urban area, there are some important differences between employment and wage equation. While the wage level for Whites is never significantly affected by this variable, men have a lower propensity of finding full-time formal sector employment when living in rural areas in all years. For White women, this result is only found in 1997. Looking at Africans, statistically significant coefficients could only be detected in 1995 and 1997. For women, living in a rural area significantly lowers their propensity of finding employment, as it is the case for African men in 1997. In 1995, the relatively large share of male workers employed in agriculture might have caused the statistically significant positive coefficient for that particular year.

Turning to variables assumed to determine employment only, it is noticeable that they affect different groups in different ways. In 1995, married women had a lower propensity of being employed. This is in line with the literature on labour markets. Married women are supposed to have higher reservation wages as they are more likely specialised in household production, for example to take care of children (e.g. Blau, Ferber, and Winkler, 1998). However, in subsequent years, this effect becomes insignificant for both races. Regarding men, one would expect that being husband will lead to higher employment propensity, because traditionally they are the main earner. In case of African men, the results do confirm this, but for White men, the expected effect can only be shown in 1997.

The results for the number of children living in the household may be partly in contrast to the things just said. Following the above argument, the association with the employment probability of women should be negative and regarding men, a positive coefficient is expected. With the exception of White women in 1995, the anticipation is confirmed by the regressions ran for females. However, the coefficients for men are either insignificant or negative as well. To explore this interesting relationship further, household structure and other income sources should be investigated in more detail.

Finally, two control variables are left, which have rather homogenous effects on employment across all population groups. Regardless of gender, acting as head of household is often supposed to lead to a higher employment propensity. The particular coefficient corresponds in nearly all cases to this expectation, but as Klasen and Woolard (2000) show, the causality can also run the opposite way.[18] With respect to gross income of spouse or partner statistically significant positive coefficients support the positive assortative mating theory, arguing that people who have similar educational levels and therefore similar employment prospects tend to live together (e.g. Becker, 1991).

6.3.2 Decomposition Results

Tables 6.10 to 6.13 present the decomposition results for all comparisons. The non-discriminatory norm is assumed to be reflected by a pooled sample approach, comprising the two groups under consideration. The first panel of each table presents decomposition components resulting from the estimation of OLS wage regressions. Variant 1 adds the

[18]Excluding this control variable does not change overall results.

selection term which is wholly decomposed in the next panel (Variant 2). Finally, by allocating indirect effects to overall endowment and discrimination components and being left with the selectivity component as a separate contribution to the overall wage gap, one of the decomposition strategies suggested by Neuman and Oaxaca (1998) is applied in Variant 3.

It seems helpful to think about changes that could occur when turning from the standard to the selectivity corrected approach. If we assume that all variables which affect the wage are considered in the wage equations, the productivity component is not expected to change. But the unexplained proportion could change in several ways. It could stay unchanged, leaving the selection term close to zero suggesting different selection into employment is not an issue. The discrimination term itself could become zero, meaning that discrimination takes place only at the hiring stage. Finally, any split of the amount unexplained by the standard approach between discrimination and selection term is also possible. Table 6.10 shows the comparison of wages earned by African men and women. According to the standard decomposition approach (Oaxaca), the unexplained component, interpreted as total discrimination, reaches alarming dimensions. The further breakdown into overpayment and underpayment reveals that in 1997 and 1999, almost two thirds of the discrimination component are due to underpayment of women.[19] If women would have been paid like men, they in fact would have earned higher wages than men. This is indicated by the endowment component which corresponds to the predicted wage gap, i.e. the wage differential that should have been observed in the absence of labour market discrimination. The comparison between standard and selectivity corrected approaches reveals that African female workers suffer a lot from discrimination that arise at the selection into employment stage. In other words, it is very hard for them to find full-time employment in the formal sector and they get paid less for their work, compared to African men. Both the selection component in Variant 1 and the selectivity component in Variant 3 are increasing over time suggesting that the women's situation became even worse.

Turning to Table 6.11, the inspection of the second gender comparison shows that the observed wage gap between White men and women was considerably reduced between 1995 and 1997. It remained almost constant after. In 1995, only half of the differential could be explained by different personal productivity-related characteristics according to the standard approach and Variant 1. In the last two specifications, the endowment share is somewhat lower. A common finding across all decompositions is that over time the

[19]As mentioned before, the observed wage differential in 1995 is probably an aberration caused by too low wages for men. During a research stay in South Africa, I also consulted experts on this finding. They basically supported my view. Despite this, I decided to report the numbers as mean wages for men have been frequently used, but I refrain from interpreting the results in detail.

explainable parts of the wage gaps became further reduced. Therefore, the good news of a closing gender wage gap among Whites is diluted by an increasing unexplainable part of it. If selectivity into employment is controlled for, our impression of labour market discrimination is changed. For example in 1995, the selection term (Variant 1) and also the selectivity term (Variant 3) become almost as large as the discrimination component in the Oaxaca decomposition. This suggests that White women suffer predominantly from discrimination at the hiring stage. Looking at subsequent years, however, this kind of discrimination cannot be detected anymore. Results rather suggest that in 1997 selection into employment was in favour of women (negative selection and selectivity term) and in 1999, there was virtually no gender difference regarding the hiring process. Of course, fluctuations of these magnitudes are unlikely and need further investigation.[20]

Table 6.12 presents the results of the female racial comparison. The observed wage differential is steadily increasing. In 1997, White women earned on average more than twice as much as African women. However, due to relatively large differences in productivity-related characteristics predicted wage gaps in all specifications are also large and increasing. Consequently, the extent of discrimination is relatively small. According to the standard approach, in all years it amounts to circa 30 per cent and occurs predominantly in terms of overpayment of White women. Applying the selectivity corrected approach leads to considerable selection terms (Variant 1). In 1997 and 1999, the selection terms exceed the unexplained part of the standard approach by far. This is only possible if the extent of total discrimination becomes negative. This in turn means that the detected amount of discrimination is no longer widening but reducing the wage differential.[21] As many components turn out to be rather volatile, it seems inappropriate to exactly interpret the numbers shown. But two conclusions can be drawn. Firstly, when compared to White women, African women seem to be especially disadvantaged in terms of finding full-time formal sector employment. Secondly, this kind of discrimination is becoming larger over time.

Table 6.13 provides the results for the second racial comparison. Wage differentials between African and White male workers are the largest observed.[22] Compared to the discussion of female wage differentials, a number of similarities are found. The overall wage gap is also widening between 1997 and 1999. Starting with the Oaxaca decomposition, large differences in mean characteristics result in large predicted wage gaps. In all

[20] The variability of particular terms over time has to be attributed rather to changing coefficients of the men's inverse Mills ratio than to the IMR itself. A semiparametric estimation may perform better in this context (see also Newey, Powell, and Walker, 1990).

[21] Again, the rather restrictive estimation approach applied is surely contributing to this finding. For example, the relatively large increase of the selection term when going from 1995 to 1997 is mainly due to changing coefficients of African women's IMR and not to a change in the IMR itself.

[22] Again, the 1995 numbers will not be discussed in detail.

years, the unexplained portion amounts to around 40 per cent and can be largely ascribed to overpayment of White workers. Looking at the results obtained from the selectivity corrected approach reveals that African men experience a different kind of racial discrimination than African women. In 1997 and 1999, selection and selectivity terms have negative signs. This implies that for African men it is relatively easy to find employment in comparison to White men. However, once they are employed, they experience more discrimination than was detected by the standard approach.

To conclude the empirical analysis, I will shortly review both the methods applied and the main findings. Estimation results obtained from selectivity corrected wage regressions strongly confirm that selectivity into employment exists in the South African labour market. Individuals do have different probabilities of finding full-time formal sector employment. As Rospabe (2002, 2001a) shows, racial and gender differences in employment probability can only partly be explained by differences in observable characteristics. It is thus possible to conclude that discriminatory behaviour occurs at the hiring stage. The question then arises whether this kind of discrimination also affects wages and hence wage differentials. Mavromaras (2003) and Neuman and Oaxaca (1998) suggest similar decomposition techniques that help to answer this question.

Decomposing wage differentials estimated by selectivity corrected wage regressions leads at first to one additional term, called selection term, which incorporates the inverse Mills ratio. Analogously to the standard decomposition approach, the selection term can be decomposed into an explained and unexplained component. However, the IMR are estimates themselves and they may reflect discriminatory behaviour at the hiring stage. With the help of a counterfactual it is possible to detect whether or not the 'explained' component arising from the decomposition of the selection term is really fully explained by different personal characteristics. Neither Mavromaras (2003) nor Neuman and Oaxaca (1998) preferred a particular way how to allocate the additional terms but offered several options. I presented three alternatives. Generally spoken, they suggested similarly tendencies. In addition, I also decomposed the wage differentials according to the standard approach to see whether the two approaches arrive at different results.

The extent of labour market discrimination determined by the standard decomposition approach corresponds to results of other studies (e.g. Allanson, Atkins, and Hinks, 2000a; Rospabe, 2002, 2001a). Once differences in employment probability are taken into account, the appearance of discrimination changes. It has been shown that African women suffer particularly from discrimination at the hiring stage when compared to African men. But also when compared to White women, they face this kind of discrimination. African men, on the contrary, were found to have relatively easy access to the labour market but encounter considerable direct wage discrimination in comparison to White men. Regarding the gender gap among Whites, good and bad news can be told. The overall wage gap decreased especially between 1995 and 1997. However, the extent of direct wage discrimination was found to have increased.

6.4 Concluding Remarks

To expect that only few years after the official end of Apartheid disparities in employment, earnings, and occupations could have been substantially reduced is of course unrealistic. But since 1994, a number of fundamental labour market reforms have been introduced which explicitly aim for improving the situation of previously disadvantaged population groups.[23] It therefore seems natural to ask whether labour market outcomes have been sensitive to the change in legislation.

The existence of racial but also gender discrimination in labour market outcomes has been documented in previous studies (e.g. Allanson, Atkins, and Hinks, 2000b; Sherer, 2000; Rospabe, 2001a). To determine the extent of discrimination, the standard decomposition approach (Oaxaca, 1973; Blinder, 1973) or slight modifications of it have been applied. This work proceeded differently. By jointly considering employment propensity and wage determination it is possible to determine indirect effects arising at the hiring stage but also influencing the wage rate (Mavromaras, 2003; Neuman and Oaxaca, 1998). A comparison between the standard approach and the selectivity corrected decomposition approach allows to assess whether the appearance of wage discrimination changed over time.

The need to reduce wage inequality between Africans and Whites has been explicitly addressed by labour market legislation (Preamble of Employment Equity Act 1998). Regarding the sample of workers that I focused on, racial wage gaps between men and women were found to have increased between 1995 and 1999. Large differences in productivity-related characteristics account for a considerable proportion of the wage differentials. Therefore, promoting the accumulation of human capital and developing skills among disadvantaged population groups will help to close the existing gap. On the other hand, for the unexplained amount of the wage gaps, interpreted as discrimination, neither for women nor for men a declining tendency could be detected. Instead, the extent of discrimination either remained relatively constant or was even growing. Results obtained from the selectivity corrected approach furthermore showed that African women increasingly

[23]For example, the Labour Relations Act 1995 regulating trade unions registration and collective bargaining; The Basic Conditions of Employment Act 1997 which establishes standards regarding the conditions of employment; The Employment Equity Act 1998 which prohibits unfair discrimination and commit employers to implement affirmative action measures; The Skills Development Act 1998 which provides an institutional framework to develop and improve the skills of the South African workforce.

suffer from discrimination at the hiring stage. The opposite is found for African men. As indicated by negative selection terms, they enjoy relatively easy access to formal sector employment in comparison to White men. According to the approach correcting for different employment probabilities, the extent of discrimination African men face once they are employed turns out to be larger than the corresponding magnitude determined by the standard approach.

Gender differences in labour market outcomes in South Africa have attracted less attention so far. The results obtained here largely confirm the findings from Rospabe (2001a). Gender wage differentials are considerably smaller for Africans and Whites than racial gaps. However, the extent of discrimination is comparatively large and was growing between 1995 and 1999. Therefore, it is also important to investigate the unexplained gender gap further to suggest appropriate policy measures. Again, the selectivity corrected approach hints at where discrimination predominantly takes places. For African women increasing discrimination when entering employment is found, whereas White women are more affected by direct wage discrimination.

The analysis demonstrated that in the second half of the 1990s labour market discrimination by race and gender was still substantial. As discrimination can arise at different stages, it is necessary to get a detailed understanding of the barriers that exist in the labour market and how they affect particular groups of workers. But not only labour market legislation is in charge, also macroeconomic policy must address the need of the South African labour market by promoting growth which eventually will also stimulate the labour market.

Table 6.1: **Decomposition Terms and Interpretation**

Oaxaca			
Endowment	$\beta^*(\bar{X}_1 - \bar{X}_2)'$		
Total Discrimination			
Overpayment	$\bar{X}_1'(\hat{\beta}_1 - \beta^*)$		
Underpayment	$\bar{X}_2'(\beta^* - \hat{\beta}_2)$		
Variant 1			
Endowment	$\beta^*(\bar{X}_1 - \bar{X}_2)'$		
Total Discrimination			
Overpayment	$\bar{X}_1'(\hat{\beta}_1 - \beta^*)$		
Underpayment	$\bar{X}_2'(\beta^* - \hat{\beta}_2)$		
Selection	$(\hat{\theta}_1\hat{\lambda}_1 - \hat{\theta}_2\hat{\lambda}_2)$		
Variant 2			
Total Endowment			
Direct Endowment	$\beta^*(\bar{X}_1 - \bar{X}_2)'$		
Indirect Endowment	$\theta^*(\hat{\lambda}_1 - \hat{\lambda}_2^0)$		
Total Discrimination			
Overpayment	$\bar{X}_1'(\hat{\beta}_1 - \beta^*)$	+	$\hat{\lambda}_1(\hat{\theta}_1 - \theta^*)$
Underpayment	$\bar{X}_2'(\beta^* - \hat{\beta}_2)$	+	$\hat{\lambda}_2(\theta^* - \hat{\theta}_2)$
Indirect Discrimination	$\theta^*(\hat{\lambda}_2^0 - \hat{\lambda}_2)$		
Variant 3			
Total Endowment			
Direct Endowment	$\beta^*(\bar{X}_1 - \bar{X}_2)'$		
Indirect Endowment	$\theta^*(\hat{\lambda}_1 - \hat{\lambda}_2^0)$		
Total Discrimination			
Overpayment	$\bar{X}_1'(\hat{\beta}_1 - \beta^*)$		
Underpayment	$\bar{X}_2'(\beta^* - \hat{\beta}_2)$		
Indirect Discrimination	$\theta^*(\hat{\lambda}_2^0 - \hat{\lambda}_2)$		
Selectivity	$\hat{\lambda}_1(\hat{\theta}_1 - \theta^*)$	+	$\hat{\lambda}_2(\theta^* - \hat{\theta}_2)$

Table 6.2: **Summary Statistics, African Labour Force Participants**

	1995		**1997**		**1999**	
	Women	**Men**	**Women**	**Men**	**Women**	**Men**
Personal characteristics						
Age	34.7 (0.09)	35.7 (0.10)	34.4 (0.08)	35.4 (0.08)	33.8 (0.10)	34.6 (0.10)
Years of schooling	7.8 (0.04)	7.8 (0.04)	7.9 (0.04)	7.7 (0.04)	8.2 (0.05)	7.9 (0.05)
Income of spouse	3.6 (0.12)	1.6 (0.07)	3.5 (0.10)	1.4 (0.06)	3.5 (0.17)	1.6 (0.11)
Nr of children	2.0 (0.02)	1.5 (0.02)	2.2 (0.02)	1.7 (0.02)	2.0 (0.03)	1.4 (0.03)
Married	0.40	0.48	0.35	0.42	0.33	0.38
Rural	0.43	0.40	0.44	0.42	0.44	0.42
Head of household	0.24	0.56	0.26	0.54	0.30	0.58
Province						
Western Cape	0.04	0.04	0.03	0.04	0.03	0.04
Eastern Cape	0.15	0.12	0.12	0.11	0.14	0.12
Northern Cape	0.01	0.01	0.01	0.01	0.01	0.01
Free State	0.09	0.09	0.08	0.08	0.07	0.08
North West	0.09	0.11	0.10	0.11	0.10	0.11
Gauteng	0.24	0.27	0.24	0.27	0.22	0.26
Mpumalanga	0.07	0.08	0.07	0.08	0.08	0.08
Northern Province	0.11	0.08	0.12	0.10	0.13	0.10
KwaZulu-Natal	0.21	0.19	0.23	0.20	0.22	0.19
Labour market statistics						
Broad participation rate (%)	46.4	62.0	47.7	60.5	54.5	64.5
Broad unemployment rate (%)	45.7	28.6	54.8	39.0	51.9	36.7
N	13,793	14,992	15,850	15,302	14,525	14,616
Population	4,293,002	5,305,447	4,486,091	5,192,015	5,591,100	5,980,393

Income of spouse or partner is measured as annual income in R 1,000.

Participation and unemployment rates for 1995 are taken from Klasen and Woolard (1999).

Participation rates for 1997 and 1999 are calculated by the author. Unemployment rates for these years are taken from Statistics South Africa.

Summary statistics have been estimated using survey weights. Standard errors in parentheses.

Table 6.3: **Summary Statistics, White Labour Force Participants**

	1995		1997		1999	
	Women	**Men**	**Women**	**Men**	**Women**	**Men**
Personal characteristics						
Age	36.0 (0.24)	37.7 (0.22)	36.1 (0.30)	38.3 (0.25)	35.9 (0.31)	37.6 (0.28)
Years of schooling	11.8 (0.04)	11.9 (0.03)	11.9 (0.04)	11.9 (0.04)	12.1 (0.05)	12.2 (0.05)
Income of spouse	23.3 (0.97)	8.1 (0.38)	26.8 (1.30)	10.2 (0.55)	26.4 (1.62)	11.8 (0.83)
Nr of children	0.8 (0.02)	0.9 (0.02)	0.9 (0.03)	0.9 (0.03)	0.7 (0.03)	0.7 (0.03)
Married	0.70	0.76	0.65	0.73	0.63	0.67
Rural	0.06	0.09	0.04	0.06	0.07	0.09
Head of household	0.16	0.83	0.15	0.79	0.17	0.76
Province						
Western Cape	0.19	0.19	0.18	0.17	0.19	0.19
Eastern Cape	0.08	0.08	0.07	0.07	0.07	0.08
Northern Cape	0.02	0.02	0.02	0.03	0.02	0.02
Free State	0.07	0.07	0.07	0.07	0.06	0.07
North West	0.03	0.03	0.03	0.05	0.04	0.04
Gauteng	0.42	0.40	0.41	0.39	0.41	0.40
Mpumalanga	0.04	0.06	0.05	0.06	0.06	0.06
Northern Province	0.02	0.03	0.02	0.02	0.03	0.03
KwaZulu-Natal	0.11	0.12	0.14	0.13	0.11	0.11
Labour market statistics						
Broad participation rate (%)	54.6	78.6	50.5	73.9	60.1	77.4
Broad unemployment rate (%)	7.0	3.0	8.9	4.3	7.3	6.3
N	2,657	3,863	1,496	2,064	1,647	2,136
Population	803,289	1,121,168	765,092	1,062,794	915,333	1,135,738

Notes: See Table 6.2.

Table 6.4: **Summary Statistics, African Workers**

	1995		**1997**		**1999**	
	Women	**Men**	**Women**	**Men**	**Women**	**Men**
Personal characteristics						
Age	36.9 (0.19)	37.8 (0.14)	37.0 (0.17)	37.7 (0.13)	36.7 (0.22)	37.5 (0.16)
Years of schooling	9.2 (0.07)	7.7 (0.06)	9.4 (0.06)	8.0 (0.05)	9.2 (0.11)	8.0 (0.09)
Hourly wage	9.0 (0.16)	8.6 (0.12)	9.2 (0.15)	9.9 (0.12)	11.4 (0.39)	11.5 (0.30)
Log of hourly wage	1.8 (0.02)	1.8 (0.01)	1.8 (0.02)	2.0 (0.01)	1.9 (0.03)	2.0 (0.02)
Income of spouse	7.9 (0.38)	2.9 (0.14)	6.9 (0.31)	2.6 (0.12)	8.4 (0.71)	3.5 (0.27)
Tenure	7.8 (0.14)	8.8 (0.11)	8.0 (0.13)	9.2 (0.11)	7.7 (0.17)	8.9 (0.14)
Nr of children	1.7 (0.04)	1.4 (0.02)	1.9 (0.04)	1.6 (0.02)	1.6 (0.05)	1.1 (0.03)
Married	0.46	0.62	0.41	0.59	0.39	0.58
Union	0.39	0.42	0.47	0.50	0.48	0.54
Rural	0.31	0.39	0.31	0.34	0.37	0.38
Head of household	0.31	0.74	0.32	0.74	0.41	0.83
Income category	-	-	0.31	0.31	0.38	0.39
Occupation						
Manager	0.01	0.02	0.02	0.04	0.01	0.03
Professional	0.04	0.02	0.14	0.05	0.06	0.03
Technician	0.20	0.06	0.12	0.05	0.19	0.07
Clerk	0.15	0.07	0.13	0.05	0.13	0.07
Sales worker	0.17	0.12	0.11	0.12	0.12	0.13
Skilled worker	0.10	0.37	0.15	0.44	0.13	0.47
Unskilled worker	0.32	0.33	0.32	0.24	0.34	0.20
Industry						
Agriculture	0.10	0.20	0.06	0.08	0.10	0.12
Mining	0.01	0.10	0.01	0.11	0.01	0.17
Manufacturing	0.16	0.18	0.17	0.22	0.14	0.18
Utilities	0.00	0.01	0.00	0.02	0.00	0.02
Construction	0.00	0.06	0.01	0.07	0.01	0.05

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Table 6.4: *continued*

	1995		**1997**		**1999**	
	Women	**Men**	**Women**	**Men**	**Women**	**Men**
Trade	0.22	0.12	0.18	0.14	0.18	0.12
Transport	0.01	0.06	0.02	0.07	0.02	0.06
Finance	0.05	0.04	0.05	0.06	0.07	0.07
Services	0.44	0.22	0.50	0.21	0.46	0.20
Province						
Western Cape	0.03	0.05	0.03	0.04	0.04	0.06
Eastern Cape	0.13	0.10	0.10	0.07	0.11	0.06
Northern Cape	0.00	0.01	0.01	0.01	0.01	0.01
Free State	0.07	0.09	0.07	0.10	0.09	0.11
North West	0.09	0.12	0.10	0.12	0.10	0.12
Gauteng	0.34	0.31	0.32	0.33	0.24	0.31
Mpumalanga	0.06	0.09	0.06	0.09	0.08	0.10
Northern Province	0.07	0.06	0.11	0.08	0.11	0.08
KwaZulu-Natal	0.20	0.17	0.20	0.16	0.21	0.14
N	2,971	6,873	3,193	6,023	2,678	4,999
Population	1,051,317	2,356,512	984,052	2,181,363	963,930	1,950,286

Notes: Due to rounding, shares do not always add up to 1.

Summary statistics have been estimated using survey weights. Standard errors in parentheses.

Table 6.5: **Summary Statistics, White Workers**

	1995		**1997**		**1999**	
	Women	**Men**	**Women**	**Men**	**Women**	**Men**
Personal characteristics						
Age	35.3 (0.37)	37.1 (0.32)	36.0 (0.38)	37.7 (0.31)	35.1 (0.43)	36.6 (0.39)
Years of schooling	11.8 (0.05)	11.9 (0.05)	11.9 (0.05)	11.9 (0.05)	12.2 (0.06)	12.2 (0.07)
Hourly wage	17.1 (0.35)	29.7 (0.60)	21.3 (0.50)	30.9 (0.72)	25.4 (0.82)	38.6 (1.26)
Log of hourly wage	2.7 (0.02)	3.2 (0.02)	2.9 (0.03)	3.2 (0.02)	3.0 (0.04)	3.4 (0.03)
Income of spouse	35.8 (1.61)	12.9 (0.65)	30.8 (1.67)	13.5 (0.78)	40.0 (2.84)	19.8 (1.61)
Tenure	6.5 (0.22)	8.7 (0.23)	7.2 (0.25)	9.6 (0.25)	6.8 (0.25)	8.5 (0.31)
Nr of children	0.8 (0.03)	0.9 (0.03)	0.8 (0.04)	0.9 (0.03)	0.6 (0.04)	0.8 (0.04)
Married	0.67	0.77	0.62	0.76	0.64	0.70
Union	0.18	0.30	0.23	0.29	0.31	0.38
Rural	0.05	0.06	0.02	0.04	0.05	0.05
Head of household	0.17	0.84	0.18	0.82	0.18	0.82
Income category	-	-	0.58	0.59	0.71	0.73
Occupation						
Manager	0.04	0.16	0.10	0.22	0.11	0.22
Professional	0.07	0.09	0.17	0.15	0.16	0.13
Technician	0.21	0.19	0.20	0.14	0.22	0.20
Clerk	0.55	0.07	0.38	0.07	0.40	0.09
Sales worker	0.10	0.13	0.08	0.09	0.08	0.09
Skilled worker	0.02	0.35	0.03	0.27	0.02	0.23
Unskilled worker	0.01	0.01	0.03	0.06	0.00	0.04
Industry						
Agriculture	0.01	0.02	0.01	0.02	0.01	0.03
Mining	0.01	0.08	0.02	0.07	0.02	0.08
Manufacturing	0.10	0.22	0.13	0.23	0.09	0.21
Utilities	0.01	0.02	0.01	0.04	0.01	0.01
Construction	0.02	0.05	0.01	0.04	0.02	0.03

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Table 6.5: *continued*

	1995		1997		1999	
	Women	**Men**	**Women**	**Men**	**Women**	**Men**
Trade	0.22	0.16	0.15	0.16	0.17	0.16
Transport	0.07	0.10	0.06	0.10	0.05	0.10
Finance	0.24	0.11	0.23	0.13	0.29	0.19
Services	0.34	0.22	0.38	0.20	0.34	0.19
Province						
Western Cape	0.14	0.14	0.16	0.16	0.19	0.19
Eastern Cape	0.07	0.07	0.07	0.06	0.08	0.08
Northern Cape	0.02	0.02	0.02	0.02	0.02	0.02
Free State	0.06	0.06	0.07	0.07	0.07	0.08
North West	0.04	0.05	0.03	0.05	0.03	0.04
Gauteng	0.51	0.48	0.46	0.43	0.47	0.43
Mpumalanga	0.03	0.04	0.04	0.07	0.05	0.07
Northern Province	0.02	0.02	0.03	0.02	0.03	0.03
KwaZulu-Natal	0.11	0.12	0.11	0.11	0.05	0.06
N	1,119	1,729	834	1,250	751	948
Population	363,160	546,351	417,990	645,301	423,702	517,070

Notes: See Table 6.4.

Table 6.6: **OLS Wage Regressions, African Workers**

	1995				**1997**				**1999**			
	Women		**Men**		**Women**		**Men**		**Women**		**Men**	
Age	0.02*	(0.01)	0.04**	(0.00)	0.00	(0.01)	0.04**	(0.01)	0.02*	(0.01)	0.05**	(0.01)
Age squared	0.00	(0.00)	0.00**	(0.00)	0.00	(0.00)	0.00**	(0.00)	0.00	(0.00)	0.00**	(0.00)
Secondary Education	0.30**	(0.03)	0.24**	(0.02)	0.33**	(0.04)	0.26**	(0.02)	0.32**	(0.04)	0.24**	(0.02)
Tertiary Education	0.72**	(0.05)	0.60**	(0.04)	0.88**	(0.06)	0.79**	(0.04)	0.81**	(0.06)	0.75**	(0.05)
Tenure	0.03**	(0.00)	0.03**	(0.00)	0.03**	(0.00)	0.02**	(0.00)	0.04**	(0.01)	0.03**	(0.00)
Tenure squared	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)
Union	0.16**	(0.02)	0.21**	(0.02)	0.28**	(0.03)	0.17**	(0.02)	0.33**	(0.03)	0.19**	(0.02)
Rural	-0.15**	(0.03)	-0.17**	(0.02)	-0.20**	(0.03)	-0.14**	(0.02)	-0.21**	(0.03)	-0.17**	(0.02)
Income category	-		-		-0.02	(0.03)	0.00	(0.02)	0.08**	(0.03)	0.04*	(0.02)
Occupation												
Manager	0.73**	(0.12)	0.89**	(0.06)	0.37**	(0.09)	0.51**	(0.05)	0.66**	(0.13)	0.66**	(0.06)
Professional	0.91**	(0.07)	0.92**	(0.07)	0.65**	(0.05)	0.54**	(0.05)	0.83**	(0.07)	0.61**	(0.06)
Technician	0.81**	(0.04)	0.72**	(0.04)	0.58**	(0.05)	0.49**	(0.05)	0.72**	(0.05)	0.46**	(0.05)
Clerk	0.53**	(0.04)	0.51**	(0.03)	0.48**	(0.05)	0.27**	(0.04)	0.57**	(0.05)	0.35**	(0.04)
Sales worker	0.20**	(0.04)	0.37**	(0.03)	0.16**	(0.05)	0.23**	(0.03)	0.22**	(0.05)	0.20**	(0.04)
Skilled worker	0.11*	(0.05)	0.29**	(0.02)	0.07	(0.04)	0.17**	(0.02)	0.16**	(0.05)	0.11**	(0.03)
Industry												
Agriculture	-0.67**	(0.05)	-0.87**	(0.03)	-0.47**	(0.06)	-0.85**	(0.04)	-0.43**	(0.06)	-0.79**	(0.04)
Mining	-0.02	(0.11)	-0.03	(0.03)	0.14	(0.14)	0.03	(0.03)	0.14	(0.15)	0.00	(0.03)
Utilities	0.18	(0.18)	0.24**	(0.06)	0.23	(0.22)	0.21**	(0.06)	0.70**	(0.22)	0.24**	(0.07)
Construction	0.14	(0.17)	-0.07	(0.04)	0.12	(0.15)	0.00	(0.04)	-0.08	(0.14)	-0.11*	(0.05)
Trade	-0.13**	(0.05)	-0.20**	(0.03)	-0.06	(0.05)	-0.16**	(0.03)	-0.15*	(0.06)	-0.22**	(0.04)
Transport	0.28**	(0.10)	0.05	(0.04)	0.12	(0.10)	0.01	(0.04)	0.23	(0.12)	0.09*	(0.05)
Finance	0.17*	(0.07)	0.07	(0.05)	0.20**	(0.07)	-0.02	(0.04)	0.23**	(0.07)	-0.01	(0.05)
Service	0.09*	(0.04)	0.07**	(0.03)	0.05	(0.04)	0.09**	(0.03)	0.10	(0.05)	0.11**	(0.04)

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Table 6.6: *continued*

	1995				1997				1999			
	Women		**Men**		**Women**		**Men**		**Women**		**Men**	
Province												
Western Cape	0.08	(0.07)	-0.01	(0.04)	-0.05	(0.08)	-0.08	(0.05)	0.20**	(0.07)	0.15**	(0.05)
Eastern Cape	-0.11**	(0.04)	-0.17**	(0.03)	0.02	(0.05)	-0.12**	(0.04)	-0.23**	(0.06)	-0.27**	(0.05)
Northern Cape	-0.29**	(0.11)	-0.12**	(0.05)	-0.11	(0.11)	-0.09	(0.06)	-0.13	(0.09)	0.02	(0.06)
Free State	-0.52**	(0.04)	-0.56**	(0.02)	-0.22**	(0.05)	-0.28**	(0.04)	-0.43**	(0.05)	-0.25**	(0.04)
North West	-0.04	(0.04)	-0.17**	(0.03)	0.04	(0.05)	-0.14**	(0.03)	0.00	(0.05)	-0.05	(0.04)
Gauteng	0.18**	(0.04)	0.00	(0.03)	0.21**	(0.04)	0.07*	(0.03)	0.15**	(0.05)	0.04	(0.04)
Mpumalanga	-0.06	(0.04)	-0.11**	(0.03)	-0.11*	(0.05)	-0.18**	(0.03)	-0.01	(0.05)	-0.02	(0.04)
Northern Province	0.01	(0.05)	0.02	(0.03)	-0.02	(0.05)	-0.13**	(0.04)	0.01	(0.05)	-0.06	(0.04)
Intercept	0.63**	(0.15)	0.58**	(0.10)	0.97**	(0.18)	0.73**	(0.13)	0.42*	(0.20)	0.56**	(0.14)
N	2,971		6,873		3,193		6,023		2,678		4,999	
R^2	0.65		0.68		0.48		0.43		0.61		0.51	

Notes: Significance levels: $*$: 5% $**$: 1%; Standard errors in parentheses.

Reference categories: Educational level: No and primary education; Occupation: Unskilled worker; Industry: Manufacturing; Province: KwaZulu-Natal.

Table 6.7: **OLS Wage Regressions, White Workers**

	1995				1997				1999			
	Women		**Men**		**Women**		**Men**		**Women**		**Men**	
Age	0.06**	(0.01)	0.10**	(0.01)	0.05**	(0.02)	0.07**	(0.01)	0.04**	(0.02)	0.08**	(0.01)
Age squared	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)
Secondary Education	0.01	(0.32)	2.15**	(0.36)	0.36	(0.30)	0.62*	(0.27)	0.20	(0.44)	-0.49	(0.65)
Tertiary Education	0.19	(0.33)	2.36**	(0.37)	0.58	(0.31)	0.79**	(0.27)	0.34	(0.44)	-0.26	(0.65)
Tenure	0.04**	(0.01)	0.03**	(0.00)	0.03**	(0.01)	0.01	(0.01)	0.03**	(0.01)	0.01	(0.01)
Tenure squared	0.00**	(0.00)	0.00**	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Union	0.03	(0.04)	0.06	(0.03)	-0.05	(0.05)	-0.03	(0.05)	0.02	(0.05)	-0.05	(0.05)
Rural	0.00	(0.05)	-0.02	(0.04)	-0.21	(0.13)	-0.14	(0.10)	-0.16	(0.09)	-0.11	(0.09)
Income category	-		-		0.11*	(0.05)	0.17**	(0.04)	0.18**	(0.05)	0.23**	(0.05)
Occupation												
Manager	0.70**	(0.18)	0.98**	(0.10)	0.51**	(0.16)	0.60**	(0.10)	0.37	(0.29)	0.76**	(0.11)
Professional	0.98**	(0.17)	0.98**	(0.10)	0.61**	(0.16)	0.51**	(0.10)	0.54	(0.29)	0.82**	(0.13
Technician	0.83**	(0.17)	0.86**	(0.10)	0.45**	(0.15)	0.44**	(0.10)	0.20	(0.28)	0.56**	(0.12)
Clerk	0.58**	(0.16)	0.59**	(0.10)	0.35*	(0.15)	0.27*	(0.12)	0.07	(0.28)	0.23	(0.13)
Sales worker	0.39*	(0.17)	0.57**	(0.10)	0.31	(0.16)	0.29**	(0.11)	0.06	(0.29)	0.23	(0.13)
Skilled worker	0.40*	(0.19)	0.57**	(0.09)	0.29	(0.19)	0.20*	(0.09)	-0.25	(0.32)	0.27*	(0.11)
Industry												
Agriculture	-0.10	(0.15)	-0.16*	(0.07)	-0.29	(0.22)	-0.28	(0.16)	-0.16	(0.21)	-0.42**	(0.13)
Mining	0.26*	(0.12)	0.15**	(0.05)	0.04	(0.17)	0.13	(0.09)	0.34*	(0.16)	0.19*	(0.09)
Utilities	0.12	(0.13)	-0.03	(0.08)	0.16	(0.22)	0.00	(0.11)	0.01	(0.29)	0.01	(0.17)
Construction	-0.05	(0.12)	-0.06	(0.06)	0.01	(0.24)	-0.15	(0.11)	-0.12	(0.19)	-0.24	(0.14)
Trade	-0.14*	(0.06)	-0.18**	(0.04)	-0.21*	(0.09)	-0.24**	(0.07)	-0.32**	(0.10)	-0.26**	(0.08)
Transport	-0.09	(0.07)	-0.17**	(0.05)	0.13	(0.11)	0.00	(0.08)	-0.25	(0.13)	-0.10	(0.08)
Finance	0.00	(0.06)	0.05	(0.05)	-0.01	(0.08)	0.04	(0.07)	-0.07	(0.09)	-0.05	(0.07)
Service	-0.08	(0.06)	-0.13**	(0.04)	-0.08	(0.08)	-0.11	(0.06)	-0.20*	(0.09)	-0.13	(0.07)

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Table 6.7: *continued*

	1995				1997				1999			
	Women		**Men**		**Women**		**Men**		**Women**		**Men**	
Province												
Western Cape	0.04	(0.05)	-0.03	(0.05)	-0.12	(0.10)	-0.06	(0.09)	0.41**	(0.12)	0.16	(0.11)
Eastern Cape	-0.06	(0.06)	-0.04	(0.05)	-0.04	(0.13)	0.01	(0.13)	0.23	(0.13)	-0.14	(0.12)
Northern Cape	-0.16*	(0.07)	-0.13	(0.07)	-0.55**	(0.12)	-0.16	(0.12)	0.17	(0.15)	-0.02	(0.14)
Free State	0.01	(0.06)	-0.02	(0.05)	-0.13	(0.12)	-0.25*	(0.11)	0.09	(0.13)	-0.08	(0.12)
North West	-0.05	(0.06)	0.00	(0.05)	-0.48**	(0.14)	-0.47**	(0.12)	0.16	(0.16)	-0.02	(0.14)
Gauteng	0.23**	(0.05)	0.19**	(0.04)	-0.04	(0.09)	-0.02	(0.08)	0.37**	(0.12)	0.02	(0.10)
Mpumalanga	0.02	(0.07)	0.14*	(0.06)	-0.42**	(0.13)	-0.09	(0.10)	0.27	(0.14)	0.04	(0.12)
Northern Province	0.10	(0.09)	0.02	(0.07)	-0.17	(0.20)	-0.30	(0.17)	0.19	(0.15)	-0.30*	(0.14)
Intercept	0.68	(0.39)	-2.01**	(0.40)	0.95*	(0.42)	0.54	(0.38)	1.28*	(0.62)	1.57*	(0.71)
N	1,119		1,729		834		1,250		751		948	
R^2	0.37		0.46		0.23		0.24		0.28		0.37	

Notes: See Table 6.6.

Table 6.8: **Selectivity Corrected Wage Regressions, African Workers**

	1995				1997				1999			
	Women		Men		Women		Men		Women		Men	
Wage equation												
Age	-0.01	(0.01)	0.02**	(0.01)	-0.05**	(0.01)	0.01	(0.01)	-0.04**	(0.01)	0.02**	(0.01)
Age squared	0.00	(0.00)	0.00*	(0.00)	0.00**	(0.00)	0.00	(0.00)	0.00*	(0.00)	0.00*	(0.00)
Secondary education	0.18**	(0.04)	0.23**	(0.02)	0.09	(0.05)	0.23**	(0.02)	0.16**	(0.05)	0.23**	(0.02)
Tertiary education	0.32**	(0.07)	0.58**	(0.04)	0.20	(0.13)	0.70**	(0.05)	0.16	(0.11)	0.69**	(0.05)
Tenure	0.03**	(0.00)	0.02**	(0.00)	0.03**	(0.00)	0.02**	(0.00)	0.04**	(0.01)	0.03**	(0.00)
Tenure squared	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)
Union	0.16**	(0.02)	0.21**	(0.02)	0.28**	(0.03)	0.17**	(0.02)	0.32**	(0.03)	0.19**	(0.02)
Rural	-0.07*	(0.03)	-0.19**	(0.02)	-0.10*	(0.04)	-0.10**	(0.02)	-0.19**	(0.04)	-0.17**	(0.02)
Income category	-		-		-0.02	(0.03)	0.00	(0.02)	0.08**	(0.03)	0.05*	(0.02)
Occupation												
Manager	0.68**	(0.12)	0.85**	(0.06)	0.35**	(0.09)	0.50**	(0.05)	0.63**	(0.13)	0.64**	(0.06)
Professional	0.86**	(0.08)	0.90**	(0.07)	0.64**	(0.05)	0.53**	(0.05)	0.79**	(0.08)	0.59**	(0.06)
Technician	0.79**	(0.04)	0.70**	(0.04)	0.56**	(0.05)	0.48**	(0.05)	0.69**	(0.05)	0.45**	(0.05)
Clerk	0.51**	(0.04)	0.49**	(0.03)	0.46**	(0.05)	0.26**	(0.04)	0.55**	(0.05)	0.35**	(0.04)
Sales worker	0.19**	(0.04)	0.36**	(0.03)	0.16**	(0.05)	0.23**	(0.03)	0.21**	(0.05)	0.20**	(0.04)
Skilled worker	0.11*	(0.05)	0.29**	(0.02)	0.07	(0.04)	0.16**	(0.02)	0.17**	(0.05)	0.11**	(0.03)
Industry												
Agriculture	-0.68**	(0.05)	-0.91**	(0.03)	-0.48**	(0.06)	-0.87**	(0.04)	-0.46**	(0.06)	-0.81**	(0.04)
Mining	-0.08	(0.11)	-0.05	(0.03)	0.11	(0.13)	0.02	(0.03)	0.11	(0.15)	-0.03	(0.03)
Utilities	0.17	(0.17)	0.23**	(0.06)	0.24	(0.22)	0.21**	(0.06)	0.62**	(0.22)	0.24**	(0.07)
Construction	0.13	(0.17)	-0.06	(0.03)	0.15	(0.14)	0.01	(0.04)	-0.11	(0.13)	-0.12*	(0.05)
Trade	-0.13**	(0.04)	-0.20**	(0.03)	-0.05	(0.05)	-0.16**	(0.03)	-0.15**	(0.06)	-0.22**	(0.04)
Transport	0.26**	(0.10)	0.04	(0.04)	0.10	(0.10)	0.01	(0.04)	0.21	(0.12)	0.09	(0.05)
Finance	0.17*	(0.07)	0.07	(0.05)	0.20**	(0.07)	-0.02	(0.04)	0.22**	(0.07)	-0.02	(0.05)
Service	0.06	(0.04)	0.06*	(0.03)	0.05	(0.04)	0.09**	(0.03)	0.11*	(0.05)	0.10**	(0.04)

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Table 6.8: *continued*

	1995				1997				1999			
	Women		**Men**		**Women**		**Men**		**Women**		**Men**	
Province												
Western Cape	0.05	(0.07)	-0.03	(0.04)	-0.10	(0.08)	-0.11*	(0.05)	0.20**	(0.07)	0.13**	(0.05)
Eastern Cape	-0.12**	(0.03)	-0.18**	(0.03)	0.00	(0.05)	-0.13**	(0.04)	-0.22**	(0.05)	-0.27**	(0.05)
Northern Cape	-0.30**	(0.10)	-0.13**	(0.04)	-0.15	(0.11)	-0.10	(0.06)	-0.14	(0.09)	0.02	(0.06)
Free State	-0.53**	(0.04)	-0.59**	(0.02)	-0.25**	(0.05)	-0.31**	(0.04)	-0.41**	(0.05)	-0.27**	(0.04)
North West	-0.06	(0.04)	-0.19**	(0.03)	0.00	(0.05)	-0.17**	(0.03)	-0.01	(0.05)	-0.06	(0.04)
Gauteng	0.15**	(0.04)	-0.03	(0.03)	0.18**	(0.04)	0.04	(0.03)	0.13**	(0.05)	0.02	(0.04)
Mpumalanga	-0.07	(0.04)	-0.11**	(0.02)	-0.13**	(0.05)	-0.20**	(0.03)	0.01	(0.05)	-0.03	(0.04)
Northern Province	-0.03	(0.04)	0.00	(0.03)	-0.04	(0.05)	-0.15**	(0.04)	0.00	(0.05)	-0.08	(0.04)
Intercept	2.06**	(0.23)	1.33**	(0.12)	3.31**	(0.42)	1.49**	(0.18)	3.00**	(0.40)	1.35**	(0.18)
Employment equation												
Age	0.05**	(0.01)	0.05**	(0.01)	0.08**	(0.01)	0.07**	(0.01)	0.09**	(0.01)	0.08**	(0.01)
Age squared	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)	0.00**	(0.00)
Secondary education	0.28**	(0.03)	-0.03	(0.02)	0.41**	(0.03)	0.15**	(0.02)	0.23**	(0.03)	0.04	(0.03)
Tertiary education	0.99**	(0.05)	0.00	(0.05)	1.26**	(0.05)	0.50**	(0.05)	1.08**	(0.05)	0.40**	(0.05)
Rural	-0.12**	(0.03)	0.13**	(0.02)	-0.16**	(0.03)	-0.24**	(0.02)	0.03	(0.03)	0.04	(0.02)
Married	-0.08**	(0.03)	0.19**	(0.03)	-0.04	(0.03)	0.30**	(0.03)	-0.04	(0.03)	0.38**	(0.03)
Income spouse	0.02**	(0.00)	0.02**	(0.00)	0.01**	(0.00)	0.01**	(0.00)	0.01**	(0.00)	0.01**	(0.00)
Nr. children	-0.05**	(0.01)	-0.06**	(0.01)	-0.04**	(0.01)	-0.03**	(0.01)	-0.05**	(0.01)	-0.11**	(0.01)
Head of Household	0.25**	(0.03)	0.76**	(0.03)	0.15**	(0.03)	0.63**	(0.03)	0.23**	(0.03)	0.74**	(0.03)
Intercept	-2.14**	(0.16)	-1.55**	(0.13)	-2.90**	(0.15)	-2.02**	(0.13)	-3.06**	(0.16)	-2.42**	(0.14)
Lambda	-0.52**	(0.06)	-0.30**	(0.03)	-0.72**	(0.12)	-0.25**	(0.04)	-0.78**	(0.10)	-0.24**	(0.03)
N	13,793		14,992		15,850		15,302		14,525		14,616	
χ^2	2,856		14,414		2,021		3,725		2,141		4,522	

Notes: See Table 6.6.

Table 6.9: **Selectivity Corrected Wage Regressions, White Workers**

	1995				1997				1999			
	Women		Men		Women		Men		Women		Men	
Wage equation												
Age	0.05**	(0.01)	0.10**	(0.01)	0.04*	(0.02)	0.05**	(0.02)	0.04*	(0.02)	0.05**	(0.02)
Age squared	0.00**	(0.00)	0.00**	(0.00)	0.00*	(0.00)	0.00*	(0.00)	0.00	(0.00)	0.00*	(0.00)
Secondary education	-0.03	(0.34)	2.04**	(0.36)	0.30	(0.31)	0.49	(0.29)	0.07	(0.44)	-0.71	(0.64)
Tertiary education	0.20	(0.34)	2.26**	(0.36)	0.55	(0.31)	0.71*	(0.29)	0.24	(0.45)	-0.47	(0.64)
Tenure	0.04**	(0.01)	0.02**	(0.00)	0.03**	(0.01)	0.01	(0.01)	0.03**	(0.01)	0.01	(0.01)
Tenure squared	0.00**	(0.00)	0.00**	(0.00)	0.00*	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Union	0.02	(0.03)	0.05	(0.03)	-0.05	(0.05)	-0.03	(0.05)	0.01	(0.05)	-0.06	(0.05)
Rural	0.07	(0.05)	0.02	(0.04)	-0.10	(0.14)	0.12	(0.12)	-0.06	(0.09)	0.04	(0.09)
Income category	-		-		0.10*	(0.05)	0.17**	(0.04)	0.16**	(0.05)	0.23**	(0.05)
Occupation												
Manager	0.63**	(0.17)	0.97**	(0.10)	0.50**	(0.16)	0.57**	(0.09)	0.32	(0.28)	0.74**	(0.11)
Professional	0.90**	(0.16)	0.97**	(0.10)	0.60**	(0.15)	0.47**	(0.10)	0.51	(0.28)	0.79**	(0.12)
Technician	0.77**	(0.16)	0.85**	(0.10)	0.46**	(0.15)	0.42**	(0.10)	0.20	(0.27)	0.54**	(0.11)
Clerk	0.52**	(0.15)	0.58**	(0.10)	0.36*	(0.14)	0.25*	(0.11)	0.09	(0.27)	0.23	(0.12)
Sales worker	0.34*	(0.16)	0.57**	(0.10)	0.32*	(0.16)	0.26*	(0.11)	0.07	(0.28)	0.22	(0.12)
Skilled worker	0.36	(0.18)	0.56**	(0.09)	0.30	(0.19)	0.19*	(0.09)	-0.21	(0.30)	0.26*	(0.11)
Industry												
Agriculture	-0.14	(0.15)	-0.16*	(0.07)	-0.30	(0.21)	-0.34*	(0.15)	-0.15	(0.20)	-0.43**	(0.13)
Mining	0.23	(0.12)	0.16**	(0.05)	0.03	(0.17)	0.11	(0.08)	0.24	(0.16)	0.17*	(0.09)
Utilities	0.11	(0.13)	-0.04	(0.08)	0.13	(0.21)	-0.01	(0.11)	-0.01	(0.28)	0.02	(0.17)
Construction	-0.07	(0.12)	-0.06	(0.06)	0.04	(0.24)	-0.15	(0.11)	-0.14	(0.18)	-0.26	(0.14)
Trade	-0.14*	(0.06)	-0.18**	(0.04)	-0.20*	(0.09)	-0.23**	(0.07)	-0.30**	(0.09)	-0.26**	(0.07)
Transport	-0.08	(0.07)	-0.16**	(0.05)	0.15	(0.11)	-0.02	(0.08)	-0.22	(0.12)	-0.09	(0.08)
Finance	0.01	(0.06)	0.05	(0.05)	-0.01	(0.08)	0.02	(0.07)	-0.08	(0.09)	-0.06	(0.07)
Service	-0.08	(0.06)	-0.14**	(0.04)	-0.08	(0.08)	-0.14*	(0.06)	-0.20*	(0.09)	-0.15*	(0.07)

continued on next page

Table 6.9: *continued*

	1995				1997				1999			
	Women		**Men**		**Women**		**Men**		**Women**		**Men**	
Province												
Western Cape	0.05	(0.05)	-0.02	(0.05)	-0.12	(0.10)	-0.05	(0.09)	0.39**	(0.12)	0.16	(0.11)
Eastern Cape	-0.05	(0.06)	-0.04	(0.05)	-0.04	(0.13)	0.01	(0.12)	0.22	(0.13)	-0.12	(0.11)
Northern Cape	-0.16*	(0.07)	-0.13	(0.07)	-0.55**	(0.12)	-0.15	(0.11)	0.13	(0.15)	-0.02	(0.13)
Free State	0.00	(0.06)	-0.02	(0.05)	-0.13	(0.12)	-0.26*	(0.11)	0.08	(0.13)	-0.06	(0.11)
North West	-0.08	(0.06)	0.00	(0.05)	-0.47**	(0.13)	-0.46**	(0.11)	0.16	(0.15)	0.00	(0.13)
Gauteng	0.20**	(0.04)	0.18**	(0.04)	-0.05	(0.09)	-0.02	(0.08)	0.36**	(0.11)	0.03	(0.10)
Mpumalanga	0.02	(0.07)	0.14*	(0.06)	-0.41**	(0.13)	-0.07	(0.10)	0.25	(0.14)	0.04	(0.12)
Northern Province	0.10	(0.08)	0.02	(0.07)	-0.17	(0.20)	-0.32	(0.17)	0.18	(0.14)	-0.29*	(0.14)
Intercept	1.11**	(0.41)	-1.69**	(0.41)	1.46**	(0.49)	1.47**	(0.46)	1.91**	(0.63)	2.60**	(0.74)
Employment equation												
Age	-0.02	(0.02)	0.02	(0.01)	0.08**	(0.02)	0.01	(0.02)	0.01	(0.02)	0.04*	(0.02)
Age squared	0.00	(0.00)	0.00*	(0.00)	0.00**	(0.00)	0.00	(0.00)	0.00	(0.00)	0.00**	(0.00)
Secondary education	0.54	(0.55)	0.75	(0.41)	0.36	(0.36)	0.18	(0.32)	0.56	(0.49)	0.71	(0.62)
Tertiary education	0.30	(0.55)	0.54	(0.41)	0.18	(0.37)	0.08	(0.32)	0.45	(0.49)	0.61	(0.62)
Rural	-0.14	(0.08)	-0.35**	(0.05)	-0.48**	(0.16)	-0.59**	(0.11)	-0.15	(0.10)	-0.46**	(0.08)
Married	-0.37**	(0.08)	-0.06	(0.07)	-0.20*	(0.10)	0.23*	(0.10)	0.19	(0.09)	-0.15	(0.09)
Income spouse	0.01**	(0.00)	0.02**	(0.00)	0.00**	(0.00)	0.01**	(0.00)	0.01**	(0.00)	0.01**	(0.00)
Nr. children	-0.05	(0.03)	-0.03	(0.02)	-0.17**	(0.04)	-0.06*	(0.03)	-0.22**	(0.04)	-0.02	(0.03)
Head of Household	0.21*	(0.09)	0.10	(0.08)	0.25*	(0.11)	0.17	(0.11)	0.51**	(0.11)	0.48**	(0.09)
Intercept	-0.08	(0.61)	-1.04*	(0.48)	-1.34**	(0.52)	-0.07	(0.48)	-0.71	(0.62)	-1.48*	(0.70)
Lambda	-0.38**	(0.06)	-0.17**	(0.05)	-0.34*	(0.16)	-0.67**	(0.16)	-0.48**	(0.10)	-0.46**	(0.09)
N	2,657		3,863		1,496		2,064		1,647		2,136	
χ^2	665		1,519		263		419		268		553	

Notes: See Table 6.6.

Table 6.10: **Decomposition Analysis: African Men versus African Women**

	1995	**1997**	**1999**
Wage Differential	-0.1799	0.1203	0.1294
Oaxaca			
Endowment	-0.3429	-0.1087	-0.0757
Total Discrimination	0.1630	0.2290	0.2051
Overpayment	0.0492	0.0793	0.0716
Underpayment	0.1138	0.1496	0.1336
Variant 1			
Endowment	-0.2883	-0.0519	-0.0033
Total Discrimination	-0.3586	-0.6323	-0.7709
Overpayment	-0.1211	-0.2161	-0.2615
Underpayment	-0.2376	-0.4161	-0.5093
Selection	0.4670	0.8044	0.9036
Variant 2			
Endowment	-0.2296	-0.0047	0.0747
Direct Endowment	-0.2883	-0.0519	-0.0033
Indirect Endowment	0.0587	0.0472	0.0780
Total Discrimination	0.0496	0.1249	0.0547
Overpayment	-0.0785	-0.0504	-0.0569
Underpayment	0.0071	0.0419	0.0410
Indirect Discrimination	0.1211	0.1335	0.0706
Variant 3			
Endowment	-0.2296	-0.0047	0.0747
Total Discrimination	-0.2376	-0.4988	-0.7002
Overpayment	-0.1211	-0.2161	-0.2615
Underpayment	-0.2376	-0.4161	-0.5093
Indirect Discrimination	0.1211	0.1335	0.0706
Selectivity	0.2872	0.6237	0.7549

Wage differential equals $\log(\bar{Y}_{men}) - \log(\bar{Y}_{women})$.

Table 6.11: **Decomposition Analysis: White Men versus White Women**

	1995	**1997**	**1999**
Wage Differential	0.5137	0.3352	0.3350
Oaxaca			
Endowment	0.2589	0.1334	0.1372
Total Discrimination	0.2549	0.2018	0.1978
Overpayment	0.1001	0.0808	0.0874
Underpayment	0.1547	0.1210	0.1104
Variant 1			
Endowment	0.2595	0.1850	0.1472
Total Discrimination	0.0390	0.3396	0.1840
Overpayment	-0.0815	-0.1283	0.0156
Underpayment	0.1205	0.4680	0.1684
Selection	0.2153	-0.1894	0.0039
Variant 2			
Endowment	0.2171	0.1470	0.1838
Direct Endowment	0.2595	0.1850	0.1472
Indirect Endowment	-0.0424	-0.0381	0.0366
Total Discrimination	0.2966	0.1883	0.1513
Overpayment	0.0837	-0.0001	0.0749
Underpayment	0.1496	0.0849	0.1266
Indirect Discrimination	0.0633	0.1034	-0.0502
Variant 3			
Endowment	0.2171	0.1470	0.1838
Total Discrimination	0.1023	0.4431	0.1337
Overpayment	-0.0815	-0.1283	0.0156
Underpayment	0.1205	0.4680	0.1684
Indirect Discrimination	0.0633	0.1034	-0.0502
Selectivity	0.1944	-0.2548	0.0175

Wage differential equals $\log(\bar{Y}_{men}) - \log(\bar{Y}_{women})$.

Table 6.12: **Decomposition Analysis: White Women versus African Women**

	1995	**1997**	**1999**
Wage Differential	0.9301	1.0414	1.1445
Oaxaca			
Endowment	0.6511	0.6466	0.8240
Total Discrimination	0.2791	0.3949	0.3206
Overpayment	0.2027	0.3131	0.2504
Underpayment	0.0764	0.0818	0.0702
Variant 1			
Endowment	0.7361	0.7237	0.8796
Total Discrimination	-0.1736	-0.5033	-0.4993
Overpayment	-0.4582	-0.8955	-0.4512
Underpayment	0.2846	0.3922	-0.0481
Selection	0.3677	0.8211	0.7642
Variant 2			
Endowment	0.8730	1.0663	1.1796
Direct Endowment	0.7361	0.7237	0.8796
Indirect Endowment	0.1369	0.3426	0.3000
Total Discrimination	0.0572	-0.0248	-0.0351
Overpayment	-0.1608	-0.4443	-0.2215
Underpayment	0.0359	0.0312	0.0265
Indirect Discrimination	0.1821	0.3883	0.1600
Variant 3			
Endowment	0.8730	1.0663	1.1796
Total Discrimination	0.0085	-0.1150	-0.3393
Overpayment	-0.4582	-0.8955	-0.4512
Underpayment	0.2846	-0.3922	-0.0481
Indirect Discrimination	0.1821	0.3883	0.1600
Selectivity	0.0487	0.0902	0.3043

Wage differential equals $\log(\bar{Y}_{white}) - \log(\bar{Y}_{african})$.

Table 6.13: **Decomposition Analysis: White Men versus African Men**

	1995	**1997**	**1999**
Wage Differential	1.6238	1.2564	1.3501
Oaxaca			
Endowment	1.0406	0.7506	0.7959
Total Discrimination	0.5832	0.5058	0.5543
Overpayment	0.4660	0.4188	0.4659
Underpayment	0.1172	0.0869	0.0884
Variant 1			
Endowment	1.0971	0.7863	0.8261
Total Discrimination	0.4107	0.6428	0.6596
Overpayment	0.0503	0.3330	0.3993
Underpayment	0.3604	0.3099	0.2603
Selection	0.1159	-0.1728	-0.1355
Variant 2			
Endowment	1.2907	0.9275	0.9582
Direct Endowment	1.0971	0.7863	0.8261
Indirect Endowment	0.1935	0.1412	0.1320
Total Discrimination	0.3331	0.3289	0.3920
Overpayment	0.4087	0.2072	0.3450
Underpayment	0.1184	0.0764	0.0804
Indirect Discrimination	-0.1940	0.0452	-0.0334
Variant 3			
Endowment	1.2907	0.9275	0.9582
Total Discrimination	0.2168	0.6881	0.6261
Overpayment	0.0503	0.3330	0.3993
Underpayment	0.3604	0.3099	0.2603
Indirect Discrimination	-0.1940	0.0452	-0.0334
Selectivity	0.1164	-0.3592	-0.2341

Wage differential equals $\log(\bar{Y}_{white}) - \log(\bar{Y}_{african})$.

Part III

The Analysis of Cohort Data

Chapter 7

Cross Sections and Synthetic Panel Data

7.1 On the Limitations of Cross Sectional Data

The previous analysis vividly showed that in the South African labour market the probability of finding regular employment as well as formal sector wages differ greatly by race and gender. Differences in measurable personal characteristics could only partly explain the observed gaps. The magnitude of explainable and unexplainable portions of particular wage differentials varies with the chosen specification of the wage regression and the decomposition technique applied. But regarding racial wage gaps between African and White workers, there is consensus that no declining trend of the unexplained part has developed in post-Apartheid South Africa until 1999 (e.g. Rospabe, 2002; Allanson and Atkins, 2001; Erichsen and Wakeford, 2001; Allanson, Atkins, and Hinks, 2000a).

Results like this are derived from a conventional decomposition of mean wage differentials. A linear model of wage determination is specified and the ordinary least squares estimator is used to predict individual wages. But only the average of these predictions is considered further on in most decomposition analyses, thereby disregarding the existing heterogeneity among the individuals.[1]

Studies examining South African labour market outcomes in the second half of the 1990's are often based on the October Household Survey data. As discussed in chapter 4.2, these are cross sectional data and allow a very detailed description of e.g. the earnings situation of individual workers in the particular survey year (e.g. Rospabe, 2001b; Allanson, Atkins, and Hinks, 2000b). The analysis of subsequent years of the OHS data enables us to follow particular groups of people and to study changes of regional, occupational,

[1]An alternative to analyse earnings discrimination is suggested by Jenkins (1994). Following his approach, the discrimination measurement is not based on mean wages, but takes into consideration the complete distribution of predicted and reference wages.

or racial mean wages over time (e.g. Rospabe, 2002; Allanson and Atkins, 2001; Erichsen and Wakeford, 2001; Allanson, Atkins, and Hinks, 2000a). With cross sectional data at hand, it is however not possible to follow individual workers. Only panel or longitudinal data permit to view temporal changes at an individual level, i.e. whether people with relatively low income still belong to this income group in a later period (Baltagi, 1998; Deaton, 1997). To evaluate for example the success of anti-poverty strategies it is exactly such questions that have to be addressed.

The KwaZulu-Natal Income Dynamics Study (KIDS) partly offers an alternative to the OHS data. In the province of KwaZulu-Natal, African and Indian households which took part in the first South African national household survey in 1993, were re-surveyed in 1998.[2] The resulting panel was also subject to studies analysing employment and earnings mobility (e.g. Cichello, Fields, and Leibbrandt, 2002; Klasen and Woolard, 2002; Keswell, 2000).[3] However, as only households residing in that particular province, even though it is the most populous one, and only two population groups did participate in the survey, the sample size is rather small. Hence, and to make the following analysis consistent with the one conducted in Part II, I will not further consider the KIDS data here.

Instead, I will use subsequent years of the OHS to construct cohort data as suggested by Deaton (1985). Individuals who share particular characteristics (e.g. born in the same year) are pooled into cohorts and the means for each group are calculated. Applying this strategy to several survey years allows to follow (birth) cohorts over time and to build up a synthetic panel. That way, the issues of ignoring the heterogeneity among workers as well as the inability of studying the dynamic behaviour of individuals are at least partly tackled. Variables like the mean wage of African women can be split up into several age groups thereby revealing their contributions to the overall average in one particular year. These cohort wages of African women can be compared to the corresponding cohort wages of White women to see how the mean wage differential presented in Part II develop at the cohort level. As cohorts are tracked for various years, it is now also possible to watch their earnings mobility. The comparison of such within cohort changes will show whether or not young and old cohorts develop alongside similar paths. Finally, as different cohorts are observed at the same age, I will attempt to separate life-cycle from generational effects. This decomposition results in an age-earnings profile and allows to ascertain the existence and direction of cohort effects.

[2]For further information on these data, see May, Carter, Haddad, and Maluccio (2000).

[3]Cichello, Fields, and Leibbrandt (2002) found that African workers in KwaZulu-Natal experienced rather volatile earnings. But not only the extent, also the direction of earnings movements was surprising. Low-income earners in 1993 had larger gains on average than those who started with relatively high earnings. Regarding the transition between formal and informal employment it turned out that movements out of regular employment were frequently accompanied by increases in real earnings.

7.2 Constructing a Synthetic Panel

To demonstrate, how synthetic panels can be constructed and what potential problems are associated with this approach, it is helpful to begin at the individual level.[4]

Consider the linear model:

$$Y_{it} = X'_{it}\beta + \alpha_i + u_{it}, \qquad t = 1, ..., T \tag{7.1}$$

where subscript i indicates individuals observed over T periods. X'_{it} is a set of explanatory variables, β the set of parameters to be estimated, and the error terms with the commonly assumed properties are given by u_{it}. The α_i's represent unobserved individual effects which are constant over time, for example inherent ability or motivation. Such individual effects are likely to be correlated with the regressors.[5] As a standard approach the α_i's are treated like group specific constant terms. Since panel data observe the same individuals for more than one point in time, these invariant terms can be eliminated by a within or first difference transformation. The resulting differenced equation is then estimated by ordinary least squares (Greene, 2000).

Deaton (1985) suggests that to any linear individual relationship, as the one shown in equation (7.1), there exists a corresponding *cohort version*. With a series of independent cross sections being available, it is not possible to follow individuals or particular households, but to track cohorts over time.[6] Cohorts are formed among individuals who have one or more characteristics in common. Each individual belongs to one cohort only and this association is constant over time. Aggregating single information to cohort level and substituting individual observations by the cohort average result in the following model:

$$\bar{Y}_{ct} = \bar{X}'_{ct}\beta + \bar{\alpha}_{ct} + \bar{u}_{ct}, \qquad c = 1, ..., C, \qquad t = 1, ..., T \tag{7.2}$$

where, for instance, $\bar{Y}_{ct}$ is the average value of all observed Y_{it}'s in cohort c at time t. Regarding individual fixed effects, the aggregation to cohort level leads theoretically to cohort fixed effects, if a constant (cohort) population is assumed.[7] In practice, however, the average is taken over the surveyed cohort members only. Since for each period different

[4]The theoretical explanation mainly follows Verbeek and Nijman (1992) and Verbeek (1996). For further discussion see also Deaton (1985, 1997) and Baltagi (1995).

[5]If individual effects are assumed to be randomly distributed instead, a random effects approach is applicable, with $\alpha_i + u_{it}$ forming a composite error term.

[6]Early studies of life-cycle models were already based on cohort data but the conducted analysis was sometimes of a rather descriptive nature (e.g. Shorrocks, 1975).

[7]This assumption is necessary as consecutive surveys are used to generate random samples from the same underlying population. In most applications, it is reasonable to suppose an invariant population. The literature frequently discusses two circumstances that may lead to a violation of this assumption. Firstly, if an economy is subject to e.g. substantial migration or death rates, the population structure alters over the years. Secondly, when working with household instead of individual data, cohorts are

individuals are observed, $\bar{\alpha}_{ct}$ is not constant over time, "because it is the average of the fixed effects of different [...] [individuals] in each year" (Deaton, 1997, p. 122). Thus, the $\bar{\alpha}_{ct}$'s cannot be cancelled out by a transformation similar to the ones applicable to genuine panel data.

The time variation of cohort effects is negligible, if the number of observations per cohort is large. In that case, the model changes to:

$$\bar{Y}_{ct} = \bar{X}'_{ct}\beta + \bar{\alpha}_c + \bar{u}_{ct}, \qquad c = 1, ..., C, \qquad t = 1, ..., T. \tag{7.3}$$

The resulting pseudo panel consists of T observations on C cohorts and the parameter vector β could be determined using the standard within estimator $\hat{\beta}_w$.

Deaton (1985) correctly points to an additional measurement error problem. Dependent and independent variables are measured by the observed cohort means $\bar{Y}_{ct}$ and $\bar{X}'_{ct}$ which are error-ridden estimators of the unobservable population cohort means Y^*_{ct} and $X^{*\prime}_{ct}$. The measurement error on the independent variables causes the estimator to be biased toward zero. By applying errors-in-variables techniques it is possible to correct for this. Since the data are available on the individual level, both cohort averages and associated standard errors can be estimated. The estimated standard errors correspond to the variance due to measurement error which then has to be subtracted from the classical estimator to yield a consistent estimator, the later on so-called Deaton's errors-in-variables estimator $\hat{\beta}_D$.[8]

Verbeek (1996) examines the consistency properties of both the within estimator $\hat{\beta}_w$ and Deaton's errors-in-variables estimator $\hat{\beta}_D$ with respect to the total number of observations N, number of cohorts C, number of observations per cohort n_c, and periods T. He concludes that the cohort size n_c is crucial for the consistency of the within estimator. If n_c tends to infinity, $\hat{\beta}_w$ and $\hat{\beta}_D$ become equivalents. This finding supports the approach of many applied papers which argue that if cohort sizes are relatively large, it is possible to ignore the measurement error and use the standard within estimator.[9] But even relatively large cohort sizes may not be sufficient to reduce the bias significantly as shown by

often defined by the age of the household head. However, being head of household is not a constant characteristic but households get reorganised in case of marriage, divorce, or if old people dissolve their own household to live with their children (Deaton, 1997; Moffitt, 1993).

[8]An alternative approach that allows to estimate also dynamic models from a time series of cross-sections was introduced by Moffitt (1993). He disregards the error-in-variables problem and demonstrates that repeated cross sectional data can be used to consistently estimate models with lagged endogenous variables. Since the samples are independently drawn, observed changes in cohort averages are also independently measured. It is therefore possible to use changes from earlier years as instruments (see also Deaton, 1997; Verbeek, 1996). For an application of this instrumental variables procedure see for example Blundell, Browning, and Meghir (1994).

[9]See for example Browning, Deaton, and Irish (1985) with cohort sizes of 190, Deaton and Paxson (1994a) where n_c lies between 150 and 400, Blundell, Meghir, and Neves (1993) who on average have 360 observations per cohort, or Jappelli (1999) grouping up to 700 individual observations.

Verbeek and Nijman (1992):[10]

$$\omega = plim_{C\to\infty}\frac{1}{CT}\sum_{C=1}^{C}\sum_{T=1}^{T}\left(\bar{X}'_{ct} - X^{*\prime}_{ct}\right)^2 = \frac{1}{n_c}\sigma_v^2. \tag{7.4}$$

To minimise the measurement error variance ω in $\bar{X}'_{ct}$, clearly, a large number of observations per cohort is necessary. However, the way individuals are aggregated is also important as it influences σ_v^2, the within cohort variance. Cohorts should be constructed such that within-variation is small and between-variation is large. In other words: "[...] individuals within each cohort should be as 'homogeneous' as possible, while those from different cohorts should be as 'heterogeneous' as possible" (Verbeek, 1996, p. 284). In addition, inspecting the standard errors of the cohort means ensures that regression results are not dominated by the way of sampling (Deaton, 1997).

The number of observations per cohort does not only influence the magnitude of the measurement error, but also determines the size of the pseudo panel and thus the variance of the within estimator. An optimal choice of cohort sizes will therefore take into account consequences for both the bias arising from measurement error and the variance of the estimator. Verbeek and Nijman (1992) examine the magnitude of these two opposite effects. They show analytically that an increase in n_c finally results in an increase in the variance of $\hat{\beta}_w$ and confirm this finding by an empirical test.[11] The effect of a smaller variance if cohort averages are estimated more precisely is more than offset by an increase in the variance if the estimation has to be based on a smaller total number of observations. The existing trade-off between cohort size and the number of cohorts is frequently referred to when discussing the cohort design. In case of the errors-in-variables estimator it is possible to choose an optimal cohort size, but when relying on the standard within estimator, one basically has to weigh up the bias with the variance (Verbeek, 1996).

After having explained how pseudo panels can be constructed, it is reasonable to discuss the usefulness of such strategy. If long series of cross sectional data are available, this method enables us to study the dynamics of particular age groups. Various estimators for static and dynamic models have been developed to yield consistent results when applied to cohort data (see for example Verbeek and Vella, 2000; Collado, 1997; Moffitt, 1993; Verbeek and Nijman, 1993; Deaton, 1985). From a theoretical point of view, synthetic panels may be even preferred to genuine panels. The problem of attrition due to mortality,

[10] For the sake of simplicity, it is assumed that cohort sizes are equal (i.e. $n_c = N/C$). Otherwise, observations have to be weighted by the square root of the cohort size first to obtain a homoscedastic variance (Greene, 1997; Verbeek and Nijman, 1992).

[11] As the derivation of this result is rather complex, I refer to Verbeek and Nijman (1992) for a more detailed discussion. In the empirical part, they analyse food expenditures of Dutch households and come to the conclusion that "fairly large cohort sizes (100, 200 individuals) are needed to validly ignore the cohort nature of the data" (Verbeek and Nijman, 1992, p. 20).

refusal, or mobility let panel data become less representative over the years. Since cross sectional data are based on a newly drawn sample each time, they better fulfill the criterion of representativeness.[12]

From an econometric standpoint, working with grouped data has two major consequences. Parameter estimates are less efficient, since data aggregation leads to a loss of information.[13] The fit of grouped data regressions is considerably higher, sometimes close to one (Greene, 1997). If the number of observations per group differs considerably, heteroscedastic error terms will occur in addition. Weighting the data by the square root of cohort sizes ensures that the error terms are homoscedastic and thus all assumptions of the classical linear regression model are met (Deaton, 1985; Greene, 1997).

In the next chapter individual data of African and White workers will be aggregated to form (birth) cohorts of workers. Compared to the analysis presented in Part II, the resulting data structure allows to examine wages and wage differentials at a disaggregated level. As the cohorts are tracked over time, it is also possible to describe a particular wage path per cohort. Such wage paths might develop differently for young and old cohorts, for example. Lining up cohort wages by age shows a particular pattern which can be split up into several components. That way, it is possible to detect the contribution of age, year of birth, and common shocks to the observed cohort-earnings curve.

[12]Similar problems may of course arise if the sample design is changed over time or if not all population groups have the same probability of being selected into the sample (Deaton, 1997).

[13]On the other hand, in the context of measurement error grouped variables are recognised as an instrument since averaging may reduce or cancel out measurement errors. The loss in efficiency would then be smaller (Kennedy, 1998).

Chapter 8

A Disaggregated Look at Wages and Wage Differentials

8.1 Analysing Cohort Wages for African and White Workers

The independent cross sectional data for the years 1995, 1997, and 1999 of the October Household Survey are used to construct a synthetic panel. The variable of main interest is (the logarithm of) the real hourly wage earned by full-time workers employed in the formal sector.[1] Aggregation could be based on measures of central tendency such as the mean and median or particular percentiles. To ascertain, whether the data used here contain extreme values, cohort averages were calculated applying both the mean and median of real hourly wages. Cohorts are defined by gender, race, and age. The mean wage exceeded the median wage in each cohort, indicating that the within cohort distribution of real hourly wages is skewed to the right. In some cohorts few extreme individual values caused the mean to deviate substantially from the median. These outliers were excluded and the following analysis uses the arithmetic mean of the logarithm of real hourly wages as cohort average.[2]

The definition of cohorts and corresponding cell sizes are reported in Tables 8.1 and 8.2. Aggregating individual data according to race and gender and applying a five-year age band results in six cohorts per population group covering workers aged between 20 and 49 in 1995 (Table 8.1).[3] For example, the first cohort pools all formal sector full-time

[1] See chapter 6.2 for a detailed description of the data preparation. The 1997 and 1999 wages were deflated to the base year 1995 using the consumer price index (Stats SA, 2001b). *Workers* refer to people working full-time in a formal sector job.

[2] The least differences between mean and median wages were found among White female workers, whereas among White men aged 35 to 39 in 1995 seven outliers have been excluded. Regarding African workers, real hourly wages are much more dispersed for both gender. Unreasonably high wages were found in four cohorts and altogether nine observations of African workers were precluded from further analysis.

[3] The number of observations available for White women limits the analysis to these age groups.

workers aged 20 to 24 in 1995. In 1999, workers at the age of 24 to 28 belong to this cohort. For all population groups cohort sizes first increase with age, peak out at the middle cohorts covering workers in their thirties in 1995, and decline thereafter again. The greatest concessions regarding reasonable cell sizes had to be made for White female workers, where the number of observations per cohort is sometimes less than 100. With respect to African workers, cohort sizes are fairly large. To get a more detailed picture for this race, a second set of cohorts has been constructed applying a two-year age band. As shown in Table 8.2, this results in 14 cohorts available for analysis. Descriptive statistics for African workers and the decomposition analysis are based upon these data.

Before turning to the results it should be pointed out explicitly that the following analysis is more of a explorative nature. The synthetic panel is based on only three subsequent cross sections and altogether, cohorts are followed over a time span of five years only. The scope to observe for example different cohorts at the same age is thus rather limited and the obtained results do not represent consolidated findings. Regardless of these limitations, the analysis allows interesting insights and can at least hint to differences that exist between different groups of workers.

8.1.1 Summary Statistics Based on Cohorts

Figure 8.1 gives a first look at the logarithm of real hourly wage by cohort for the different population groups.[4] Each connected line represents the mean wage for one cohort in 1995, 1997, and 1999. Wages earned by African male and female workers are given in the upper panel. Since different cohorts are observed at the same age, lines do overlap. When tracing the wage level across different cohorts it becomes obvious that wages increase with age but at a decreasing rate. Among older cohorts of women mean wages even seem to decline again.[5] Facing the age-group specific averages of one year with the overall mean in that period provides insights into the composition of the latter.[6] For African men, the comparison confirms what the graph had already suggested. In 1995, the mean wages of the first three cohorts, which are incidentally among the lowest observed in the sample, pull down the overall average to 1.73. Overall averages for the subsequent years amount to circa 1.8 as the young cohorts realised considerable increases and older cohorts enjoyed relatively stable earnings for the total time span. Regarding females, the

[4] In the following, *wage* refers to the logarithm of real wage earned per hour.

[5] Such concave age-earnings paths are discussed in relation to the theory of human capital. See chapter 8.2 for further discussion.

[6] I refrained from adding the overall means for the three years to the graphs to keep the pictures clear. As averaging over all workers belonging to the same population group results in mean wages that are very close to those presented in Part II, I refer also to Tables 6.4 and 6.5.

rather heterogeneous picture of cohort wages is striking. To find out whether the various within cohort changes are statistically significant they will be discussed separately. For the moment, it suffices to note that African women had their highest overall mean wage of about 1.83 in 1995 due to the relatively high earnings of the middle cohorts in that year. As these cohorts suffered on average from considerable wage losses in the following years, overall means dropped to 1.71 in 1997 and 1.67 in 1999, respectively.

The lower panel presents cohort wages for White male and female workers. Since for this race the five-year interval has been applied, it is not possible to observe different cohorts at the same age. For both gender the data point to higher wage levels as workers belong to older cohorts. Regarding the total time span, men realised on average somewhat bigger increases. Within cohort trends suggest that White women moved along a relatively smooth path, while males had on average a particularly bad year in 1997. This impression is confirmed when considering the overall averages. In 1997, White men realised the lowest mean of 3.03 and experienced average wages of about 3.15 in the adjacent years. Only White women enjoyed on average constantly increasing wages as the overall mean amounted to 2.73, 2.76, and 2.83 in 1995, 1997, and 1999.

Inspecting related socioeconomic characteristics from a cohort perspective is instructive as well. A detailed look on variables determining wage levels and employment propensity is given in Figures 8.2 and 8.3 for African and White workers, respectively.[7] The first panel in Figure 8.2 shows the number of years of schooling completed by cohort, separated for African men and women. The analysis based on aggregated data demonstrated that the level of education was on average higher among African women employed in a formal sector job than among African men working in this sector.[8] With the exception of the youngest cohort in 1999, this finding turns out to be consistent across all cohorts considered here. Although the differences are rather volatile, the gap becomes somewhat smaller for younger cohorts. Moving from younger to older cohorts, the number of schooling years follows a downward trend for both gender. One would expect older cohorts to be less educated than younger ones, but the level of formal education within cohorts should be relatively constant.[9] Since the distinct decline for middle and older cohorts is also revealed when looking at broader samples like labour force participants and working age population, it cannot be attributed to an education-based selection out of formal sector employment. It would appear that the decline might be due to the changing way of reporting educational levels, as discussed in chapter 4.2. This assumption, however, is not

[7]In the following, the focus will be on particular findings exposed only when examining cohort data. For a general discussion of these variables as well as their relevance for finding employment and wage setting, see chapter 6.

[8]Results presented in Part II are in the following also referred to as derived from the analysis of the *aggregated data*.

[9]It may of course vary in a random way, as every year different individuals are grouped together.

confirmed when turning to White workers (Figure 8.3, first panel). Here, within cohort educational levels do not indicate any particular trend and also across cohorts changes only happen on a small scale.

Following the number of children living in the workers' household across cohorts points to different patterns for Africans and Whites (Figures 8.2 and 8.3, second panel). For the latter the number of children at first increases with age, reaches its maximum around the age of 35-40, and decreases thereafter. Although the observations for African workers are noisier, it becomes clear that there is no such inverted U relationship between age and the number of children living in the household.[10] A maximum number can still be made out for both gender, but a downward trend is discernable for females only. This decline, however, comes to an end as women grow older and finally turns back into an increase.[11] Adapting results of Klasen and Woolard (2000), who examine household formation in the context of unemployment, the re-increasing number of children might be related to a better access to resources when being attached to a worker's household.

The last panel in Figures 8.2 and 8.3 shows for each cohort the proportion of cohort members acting as head of household. Regarding men, this proportion is steadily increasing both within and between cohorts and comes close to 100 per cent for the oldest cohorts. Within single cohorts of African women the share also rises considerably between 1995 and 1999. The proportion of household heads among African female workers aged 44 and above in 1995 lies between 40 and 60 per cent. Among White peers the share is only half as much.

This last example especially points out advantages when working with synthetic panel data. Summary statistics obtained from the cross sections already indicated that the proportion of female headed household among workers is nearly twice as high for Africans than for Whites. Considering various age groups at one particular year would have revealed differences existing *between* younger and older individuals. In the absence of individual panel data, only cohort data constructed from a time series of cross sections facilitate to study also temporal developments *within* particular age groups.

8.1.2 Cohort Specific Wage Differentials

When working with the aggregated data, differences in mean wages between groups of workers (holding either sex or race constant) were already discussed. To summarise briefly,

[10] According to the data, the number of children living in African households peaked in almost every cohort in 1997. It is, however, hard to tell what year(s) might have caused this somewhat peculiar finding.

[11] Admittedly, this course is hardly visible when looking at the graph based on the workers' sample, but shows up a lot clearer when viewing for example labour force participants.

racial gaps were substantially larger than gender gaps in all three years. Individual productivity determining differences could only partly explain the observed differences. Regarding the development of overall wage gaps over time, both narrowing and widening tendencies could be observed, depending on what population groups are considered. The way the data are prepared now allows to break down some of these findings to the level of cohorts.[12]

The upper panel of Figure 8.4 plots cohort wages for White and African men, the lower panel cohort wages for female workers of both races.[13] The racial wage hierarchy observed when examining the aggregated data continues at the disaggregated level: cohort wages for White workers are always above the level of the corresponding African cohorts. Comparing the upper and lower panel of Figure 8.4, the gaps emerging between cohort wages of male workers are always larger than those that exist between female workers. Within cohort wages develop quite differently over time and will be examined separately in the next section. Abstracting from within cohort variation, cohort earnings of White and African men follow similar paths as workers age. As a result, the gap between the wages of younger cohorts is commensurable to the one appearing for older cohorts. Regarding females, the racial gap between cohort wages tend to get larger among older cohorts. But this tendency turns out to be not statistically significant, as the confidence intervals become larger for these group of workers.

Figure 8.5 shows similar graphs for cohort specific wage differentials between male and female workers holding race constant. The gaps shown here are substantially smaller than the racial differences just presented. Focussing African workers depicted in the upper panel, the overall evolution of wages across cohorts is rather similar, except for the oldest cohort. The wage gap between men and women aged 45-49 in 1995 broadens noticeably and becomes finally significant in a statistical sense in 1999. Going back to 1995, the examination of the aggregated data unearthed the peculiar result that wages earned by African females are on average higher than wages of African men. The breakdown into several age groups reveals that especially younger cohorts contribute to this finding. But even if overlapping confidence bands indicate that in nearly all cases the negative wage differential is not statistically significant it remains an unusual outcome.

As regards White workers, the majority of cohort specific gender wage differentials turns out to be statistically significant. Looking at younger cohorts of both gender, they however experience comparable wage levels as well as growth rates resulting in only small

[12]Wage regressions and decompositions comparable to those presented in chapter 6 could not be performed as the number of observations in the synthetic panel is too small. Furthermore, variables used in panel estimations should exhibit a certain degree of random variation over time. However, regressors like the level of formal education and age either do not change over time or vary in a systematic way.

[13]To compare the same birth cohorts of African and White workers, cohorts for the former are now also based on the five-year age band.

and mostly not significant wage differences. Among workers who are in their thirties in 1995 the gender wage gap increases considerably, as female wages now diverge substantially from the men's wage level. Relating this finding to the discussion on the number of children living in the workers' household suggests that on average women at this age cut back their labour market activities to raise children. Moving on to older cohorts the gender gap narrows and becomes statistically insignificant again, as men's wages do on average no longer experience positive growth rates but approach the wage level of women.

To conclude this part of the analysis, it should be emphasised again that wage differentials observed between groups of workers do not automatically point to unequal treatment in the sense of discrimination. As shown in chapter 6, the unexplained portion of wage gaps when averaging over all age groups sometimes assumes alarming proportions and we would expect to see a similar pattern at a disaggregated level. Splitting the workers sample into several age cohorts reveals that cohort specific gaps are relatively constant across cohorts or increase and decrease as workers age. The question then arises, whether similar gaps between age cohorts, as those between White and African men, correspond to similar unexplained components or rather mask changing magnitudes of the explainable and unexplainable portions of the wage gaps. For reasons mentioned before this question must remain open so far.

8.1.3 The Dynamics of Cohort Wages

The structure of the synthetic panel explicitly allows to follow cohorts over time. Although the discussion in previous sections already mentioned wage growth within particular birth cohorts, it will be addressed in detail now to see whether for example young and old cohorts differ in their experienced earnings mobility. As only three points in time covering a total time span of five years are considered, the analysis of within cohort growth will be restricted to a rather short period, but can still point to different tendencies for different cohorts.

Figure 8.4 plots cohort wages for all four groups of workers without intersection. Solid lines in the first graph represent cohort wages for White men, that group of workers who earned on average the highest wage at any given age. When considering the total time span, only the youngest cohort realised a wage increase that also turns out to be statistically significant. Moreover, the gain is in absolute numbers the biggest observed for the total sample. As indicated by the confidence intervals, White male workers aged between 25 and 34 in 1995 experienced relatively stable earnings, in contrast to older cohorts who on average realised losses in real wages between 1995 and 1999.[14]

[14]The 95 per cent confidence bands for the last two cohorts do slightly overlap. But the difference

Only middle and older cohorts among African female workers had to bear similar or even larger declines in earnings in absolute (log) terms (see dashed lines in the lower panel). The already received impression of a very heterogeneous group of workers continues when looking at within cohort changes. Cohort wages jump up and down quite considerably. As regards the youngest cohort this results in no significant trend for the total period. It is thus the only population group of workers aged 20 to 24 in 1995 that cannot realise significant wage increases over the total time span covered here.[15]

Within cohort changes of the two remaining groups of workers follow similar patterns. The first two and three cohorts of African men and White women respectively enjoy significant wage increases between 1995 and 1999. Regarding older cohorts, the first impression gained from the descriptives in Figure 8.1 is confirmed: wages within cohorts remained relatively constant for the period considered. Concerning White women, however, the insignificance of wage differences might partly be due to increasing variance as the number of observations per cohort becomes very small.

Already the limited time frame of five years clearly shows that within cohort wages develop differently for younger and older workers belonging to the same population group. Younger cohorts did realise statistically significant wage increases, except for African women, whereas older cohorts either faced relatively unchanged wage levels or had to cope with real wage losses. Comparing within cohort growth of workers who belong to different groups of the population the analysis suggests that cohorts of young White workers benefitted most from wage increases. Unlike African women, who on average were found to be in an inferior situation, as young cohorts did not realise wage increases but already middle aged workers suffered from declining mean wages.[16] However, to yield consolidated findings on within cohort trends, a greater number of periods T is needed.

8.2 Determining Age, Cohort and Year Effects

8.2.1 General Remarks

Economic theory suggests for a variety of (socio-)economic quantities a particular pattern evolving over an individual's working life or total life time. For example, Modigliani's life cycle hypothesis of saving argues that individuals, while working, will save a certain

between 1995 and 1999 for the two oldest cohorts of White male workers as well as similar marginal cases among other population groups are significant at an interval of 10 per cent.

[15] This rather pessimistic result persists when examining cohorts defined by the two-year age interval. Then, the first three cohorts do not experience significant wage changes between 1995 and 1999.

[16] This does of course not imply that once contemporarily young cohorts are aged they will pass through the same path of wages as the one described for currently old cohorts. See also the next section.

fraction of their income thereby accumulating wealth which is continuously reduced once they are retired. As a result, the relationship between age and wealth will be humped-shaped (Modigliani, 1986). As economies grow, variables like savings, incomes, and wealth are also subject to secular trends. Alongside economic development savings and incomes are growing, whereas for example household sizes tend to decline (Deaton, 1997). In the absence of longitudinal data synthetic panel data have been frequently used to verify various age-related profiles and to disentangle the age effect from the generational or cohort effect.[17]

The relation between age and earnings also follows a distinct pattern. Young workers start with relatively low wages but the average wage level increases as workers grow older. Since the increases diminish over time the overall curve turns out to be concave. A theoretical framework is given by the human capital model (see for example Becker, 1993; Mincer, 1962).[18] The model designs a particular wage path over the working life cycle of individuals. Empirical tests whether concave age-earnings profiles exist are ideally based on longitudinal data. Profiles derived from cross sectional data can appear differently because of secular trends toward higher education and occupational or life-cycle employment changes, for example.[19] Unless such cohort effects can be neglected or do not exist, as in case of a stationary economy, age-earnings profiles obtained from time series and cross sectional data are identical (Becker, 1993).

Table 8.3 brings together real hourly wages (now not in log form) for various groups of workers at two different points in time. To be able to compare the income of a particular age group in 1995 with the appropriate cohort's income in 1999, a four-year age interval has been chosen. The *cross sectional* profiles for all groups of workers are humped-shaped: wages first rise with age, reach a maximum, and decline thereafter. Looking at the data this way also suggests that highly skilled workers realise their maximum earnings later than less skilled workers as the peak in earnings for Africans, who on average work in occupations requiring less skills, happens at an earlier age than for Whites. However, the underlying statistic is not appropriate for such conclusion. Cross sectional data observe workers of

[17]For example, Jappelli (1999) tested the age-wealth profile for Italy, Deaton and Paxson (1994b) examined levels of income, consumption, and saving in Taiwan using cohort data. Pseudo panels have also been used to study the relation between consumption inequality and age in the UK, USA, Taiwan, and Japan (Attanasio, Berloffa, Blundell, and Preston, 2002; Ohtake and Saito, 1998; Deaton and Paxson, 1994a).

[18]According to the theory, differences in earnings (and other labour market outcomes) can be explained by different amounts of human capital. Individuals want to maximise their life time income which is, among other things, subject to the level of human capital acquired. By choosing an optimal amount of both formal education and on-the-job training workers can increase their productivity and maximise their earnings (see also Blau, Ferber, and Winkler, 1998).

[19]For a brief review of analyses either based on cross sectional or longitudinal data conducted in the fields of labour economics and forensic economics see for example Gohmann, McCrickard, and Slesnick (1998) and Rodgers, Brookshire, and Thornton (1996).

different age at one point in time and the resulting age-earnings profile is composed of wages earned by people with different life time earnings. Therefore, the earlier peak for less skilled workers might be a similarly wrong implication as the frequently referred to overstated downturn in earnings for older workers because cohort effects operating towards higher life time incomes for younger workers (regardless the educational or skill level) cannot be taken into account when analysing single cross sections (Deaton, 1997; Becker, 1993).

Turning again to Table 8.3 and comparing the cohorts' income in 1999 with the cross sectional income of the corresponding age group in 1995 makes clear that the two approaches yield different results. But only among older cohorts of White female workers does the cross sectional profile show a more pronounced downturn in earnings. Group specific wages of other workers in 1995 are either similar to or even above the corresponding cohort level in 1999. This somewhat surprising result suggests two things: firstly, as differences between cross sectional and cohort data exist it is important to take generational trends into account and secondly, those trends might be different from the expectation.

A third component that can be identified when decomposing earnings is a time effect which captures macroeconomic shocks affecting all cohorts in the same way. Equation (8.1) illustrates the functional form of such a decomposition.[20]

$$\bar{Y}_{ct} = \alpha + age_{ct} + cohort_c + time_t + u_{ct}, \qquad c = 1, ..., C, \qquad t = 1, ..., T. \tag{8.1}$$

The average of the logarithm of real hourly wages of cohort c at time t, $\bar{Y}_{ct}$, can be separated into an age effect reflecting the typical profile evolving as workers grow older, a cohort effect mirroring secular trends, and a time effect absorbing aggregate shocks as for example business cycle effects (Deaton, 1997). Age control variables are easily specified, cohorts can be conveniently labelled by age at time $t = 1$, and year dummies are often implemented to pick up time effects. Equation (8.1) rules out any interaction between the single components thereby assuming the same age profile for all cohorts.[21] The cohort effect then indicates different positions of that age profile. If variables controlling for age, cohort, and time effects enter equation (8.1) in an unrestricted way, this will lead to an identification problem because of the linear relation between these three effects. For example, as soon as age and year are given, the corresponding cohort (defined by year of birth) is known as well and it is not possible to identify all effects simultaneously.

[20] As it will be applied here, the decomposition is used as an descriptive device only. Regarding work on savings, consumption or wealth the decomposition into age, cohort, and time effects also allows to validate economic models, for example the life cycle hypothesis (e.g. Attanasio, 1997).

[21] In principle, it would be possible to include interaction terms to allow, for example, in the presence of macroeconomic shocks younger cohorts to adjust savings differently than older ones (e.g. Attanasio and Weber, 1994). However, such extensions are not followed up here because, given the small size of the synthetic panel, the number of right-hand side variables should be kept at a minimum.

There are several ways to overcome this problem. If one is willing to assume certainty, which in turn means no unexpected common shocks, there is no need to include any control variables with respect to time.[22] Many applied papers, however, take the existence of macroeconomic influences into account and impose an additional restriction. Following Deaton and Paxson (1994b), all trends observable in the data can be attributed to age and cohort effects, if one assumes that the time effect has a zero mean and is not following any trend.[23] In the context discussed here, it seems reasonable to ascribe wage increases to age and cohort effects and to assume that cyclical fluctuations are zero in the long-run (Deaton, 1997). Studies decomposing earnings (e.g. Johnson and Stafford, 1974), savings (e.g. Kitamura, 2001; Jappelli and Modigliani, 1998), or consumption profiles (e.g. Bardazzi, 2000; Ohtake and Saito, 1998) applied this normalisation strategy or adopted slightly modified versions (e.g. Jappelli, 1999).[24]

8.2.2 Decomposing the Earnings of Africans

In the following, average earnings for the cohorts of African female and male workers shown in Table 8.2 will be subject to a decomposition into age, cohort, and year effects.[25] However, it should be pointed out from the beginning that this empirical investigation will probably encounter difficulties. As only three survey years are used to construct the synthetic panel and furthermore a two-year age interval has been chosen, successive cohorts are observed at the same age for a short period only. Thus, overlapping is extremely limited and it will be hard to distinguish between trends and transitory shocks (Deaton, 1997). Obtained results should therefore be interpreted cautiously.

The upper limit of each age interval specifies the age variable.[26] Cohorts are consecutively numbered so that higher numbers correspond to older cohorts. One year dummy has to be redefined that time effects average to zero and are orthogonal to any trends. All observations have been weighted by the square root of cohort sizes $\sqrt{n_c}$ to accommodate the heteroscedastic nature of the aggregated data. Earnings can be regressed on both polynomials and a set of dummy variables. Table 8.4 shows the estimation results

[22]That way, one would also forgo to capture any non-random influences not correlated with age or cohort, like measurement errors (Jappelli, 1999).

[23]To model orthogonality and zero mean, the standard year dummies $time_t$ have to be redefined to equal the following expression: $time_t^* = time_t - [(t-1)time_2 - (t-2)time_1]$. Finally, only $T-2$ year dummies enter the regression to facilitate identification (Deaton, 1997; Deaton and Paxson, 1994a).

[24]A general discussion on normalisation and associated pitfalls can be found in Heckman and Robb (1985) who conclude "the real problem is finding [...] better explanatory variables and sharper behavioral models" (Heckman and Robb, 1985, p. 148).

[25]Since for Whites different cohorts are never observed at the same age, it is not possible to decompose the earnings of these workers in a similar way.

[26]Again, this labelling has been chosen for the sake of convenience.

separated for African men and women. Columns labelled by (1) show the specification which fitted the data of male and female workers best under the consideration that the number of the remaining degrees of freedom is still acceptable. Regarding men, age and cohort polynomials are included, while for women, a combination of a third-order age polynomial and cohort dummy variables was chosen.[27]

Figures 8.6 and 8.7 provide a graphical illustration of the estimated effects according to specification (1). The top right-hand panels display the time effect that has been calculated from the restricted year dummy. Only for men, the coefficient is significant but compared to the other effects only small in magnitude. Given the short time span covered, it is difficult to interpret the time effect in its theoretical sense of capturing long term, aggregated shocks. But it suggests that in 1995 wages were on average higher even though age and cohort effects were controlled for.[28]

The bottom panels show age and cohort effects. Although the relationship between earnings and age is humped-shaped for both gender, the exact shape differs considerably between the two. Still appropriate for both groups, average wages peak around a relatively early age of thirty.[29] The men's profile increases steeply at first and declines moderately after the maximum. By contrast, the upward trend of the females' age effect is less pronounced among young workers, but as women grow older they face a sizable downturn in earnings. Wages realised by female workers aged forty correspond on average to those observed for the youngest. With advancing age the drop in earnings continues. This substantial downward trend is partly offset by cohort effects that are increasing with cohort age. Contrary to the theory outlined above, 'secular trends' are in favour of older cohorts. As regards men, the estimation result is less controversial since no significant cohort effect could be determined. As mentioned before, the short time span may hamper a correct separation of short term deviations and long term trends. Otherwise, the theoretical argument that generational effects are in support of younger cohorts also hinges on the economy's growth rate (Becker, 1993). For the period 1985-1999, the average annual growth rate of South Africa's GDP per capita amounted to -1.0 per cent (WDI, 2002). Therefore, we no longer would expect to see cohort effects favouring younger workers. In addition, if incumbent workers would not suffer from wage reduction given high and rising levels of unemployment, but young entrants had to agree upon lower initial payments, this could culminate in a positive cohort effect. This hypothesis, however, can be

[27]In all specifications both dummy variables and polynomials of different orders were tested to control for age and cohort. Both approaches yielded similar results and thus statistical parameters were decisive (i.e. R squared, degrees of freedom left, t-statistics, F-Tests).

[28]Specifications using normal year dummies but leaving out either age or cohort controls confirm this interpretation.

[29]Please note that the dependent variable is expressed in logarithms. Running the decomposition on antilog values leads to later peaks for both groups. However, all control variables for age and cohort in the female specification become insignificant.

backed up only partially. Studies analysing the long term trend of African real wages in the formal sector document a certain rigidity of mean wages despite rising unemployment (e.g. Fedderke and Mariotti, 2002; Fallon and Lucas, 1998).[30] But whether young and older cohorts of workers contributed differently to this outcome is hard to answer as entry wages or wage levels by age groups could not be found.

The regression results prove to be relatively insensitive to modifications of the model. In specification (2) a control variable for educational attainment has been added. Figures 8.8 and 8.9 illustrate the results. In accordance with the theory of human capital, higher levels of formal education result in higher wages. For both gender, the age effect follows a compressed but similar path to the one obtained in the previous estimation.[31] The positive correlation between average wages and age in 1995 as a cohort measure still prevails for women and becomes slightly significant for men as well.

The last specification shown here relaxes the assumption of appropriate cohort sizes and considers all workers aged between 15 and 60 in 1995. That way, it is possible to check whether the results are driven by the chosen age span ignoring older workers in particular. But again, the overall picture does not change much (see also Figures 8.10 and 8.11). The age profile for men is concave, for women it is clearly humped-shaped. Almost all dummy variables controlling for different cohorts of women have positive and significant coefficients. For men, the effect becomes insignificant again.[32]

An assessment of the results obtained here turns out to be difficult since studies addressing similar questions about cohort wages in the South African labour market could not be found. There is some literature on earnings and household income mobility of Africans using the KIDS panel data (see for example Cichello, Fields, and Leibbrandt, 2002; Klasen and Woolard, 2002). Both studies conclude that in KwaZulu-Natal mobility between 1993 and 1998 was high and that changes in labour market status as well as movements between the formal and informal sector largely contributed to this. However, given the relatively small sample size and the fact that individuals were interviewed only twice, a cohort analysis with this data could hardly be more instructive.

The number of periods T is crucial in any cohort analysis as it determines for how long cohorts can be followed over time and thus how many cohorts are observed at the same age. The previous analysis tracked cohorts over the short period of five years. It thereby only allows a direct comparison between the average wage of a given cohort with

[30] Fallon and Lucas (1998) conclude that other factors (e.g. African trade unionism) counteracted the exerted downward pressure on wages arising from high unemployment rates.

[31] This also fits in with the human capital theory which predicts steeper and more concave profiles for better educated individuals (Becker, 1993).

[32] Cohort wages were also regressed on either only age or cohort control variables. Depending on the order of the polynomial, concave or humped-shaped cohort effects could be identified but never constantly declining ones. Age effects developed similarly when used as the only regressor.

mean wages for somewhat younger or older workers. In other words, although belonging to different birth cohorts the particular groups of workers might not really have encountered different secular trends that could in turn be detected by any decomposition. To identify such effects it is necessary to follow cohorts over an extended period of time. Only then, the observed paths may non-randomly differ and a decomposition can reveal to what extent age and cohort effects have contributed to this outcome.

8.3 Concluding Remarks

The aim of this work was to go beyond a review of average earnings by population group in South Africa. Following Deaton (1985), I used three successive cross sections to construct a synthetic panel, with cohort means of African and White workers in formal employment replacing individual observations. The average wage per cohort was calculated to examine earnings at a disaggregated level. Preparing the data in that way enables a better utilisation of individual information provided by the October Household Surveys as well as to study changes over time.

The breakdown of overall mean wages into several age groups demonstrated that African women form the most heterogeneous group. Wages varied considerably between workers of different age but also when tracing single cohorts over time. Unlike White women, who on average experienced only small scale wage changes both across and within cohorts. In a similar way, cohort specific wage differentials were looked at. The interest was to see whether or not the gaps emerging between cohorts of different population groups remained relatively constant when moving from younger to older cohorts. Especially the comparisons by gender pointed to changing magnitudes of the differentials. Regarding Africans, cohort wages seem to diverge for older workers whereas in case of Whites the greatest discrepancies between male and female cohort wages were found among middle-aged workers.

As cohorts are followed over time it was also possible to have a closer look at within cohort changes. Although the time period of five years is rather short, different trends for younger and older cohorts could still be detected and were in most cases as expected. Young cohorts realised statistically significant wage increases, except for African women. Older cohorts, instead, either faced relatively unchanged wage levels or encountered on average a wage loss.

The limited number of periods became again crucial to the last analysis. Earnings of Africans were decomposed into age, cohort and year effects to separate life-cycle from generational effects. In the present setup, different cohorts are observed at the same age for a very short period only, causing difficulties as transitory shocks are hard to distinguish from long term trends. Especially the estimated cohort effect of African females is highly controversial as it suggests that older cohorts benefitted from generational trends. Although some features of formal sector employment in South Africa as well as the performance of the overall economy seem to be in line with this (constant or increasing real wages despite rising unemployment, low entrance rates, stagnating economy), an increase in the number of periods is compulsory to arrive at assured results.

With a time series of cross sections available, the construction of cohorts which in turn can be used to synthesise a panel structure provides a good opportunity to address temporal developments also in the absence of genuine panel data. The last decade has seen the development of consistent estimators for static as well as dynamic models. A recent study by Fitzenberger and Wunderlich (2003) tackles one of the remaining short-comings of cohort data, namely that within single cohorts an equal distribution had still to be assumed. Quantile regressions explicitly take into account the movement of the entire distribution which finally allows to use all the variation of the individual data for the estimation.

Table 8.1: **Cohort Definition and Cohort Size: Five-Year Age Band**

No. of Cohorts	Age in 1995	Men 1995	Men 1997	Men 1999	Women 1995	Women 1997	Women 1999
Africans							
1	20-24	462	594	647	222	313	352
2	25-29	1029	989	931	508	570	503
3	30-34	1185	1165	989	551	632	529
4	35-39	1232	1050	799	565	583	472
5	40-44	939	762	588	377	408	286
6	45-49	807	591	392	322	292	206
Whites							
1	20-24	173	156	129	163	142	119
2	25-29	218	172	154	172	131	129
3	30-34	278	203	165	174	118	95
4	35-39	289	183	127	171	120	91
5	40-44	248	144	103	139	109	88
6	45-49	217	157	88	124	89	67

Table 8.2: **Cohort Definition and Cohort Size: Two-Year Age Band**

No. of Cohorts	Age in 1995	Men 1995	Men 1997	Men 1999	Women 1995	Women 1997	Women 1999
Africans							
1	21-22	162	232	233	70	108	145
2	23-24	257	273	325	120	165	140
3	25-26	356	363	389	194	215	223
4	27-28	457	419	349	208	250	198
5	29-30	502	456	388	242	247	177
6	31-32	453	481	399	222	236	219
7	33-34	446	435	395	193	254	215
8	35-36	558	451	359	255	241	204
9	37-38	465	438	309	232	238	197
10	39-40	507	342	236	171	195	134
11	41-42	338	306	257	147	158	137
12	43-44	301	275	226	137	159	86
13	45-46	415	279	193	166	139	115
14	47-48	260	226	134	110	111	64

Table 8.3: **Real Hourly Mean Wage by Cohort, 1995 and 1999**

Age in 1995	Age in 1999	Wage of Cohort in 1995	Wage of Cohort in 1999
African Men			
24-27	28-31	7.32	8.25
28-31	32-35	8.50	8.19
32-35	36-39	9.02	10.66
36-39	40-43	9.23	10.47
40-43	44-47	9.91	9.40
44-47	48-51	9.14	8.93
48-51	52-55	9.53	8.13
52-55	56-59	8.94	7.91
African Women			
24-27	28-31	7.98	8.58
28-31	32-35	9.05	9.52
32-35	36-39	10.14	10.06
36-39	40-43	10.11	11.30
40-43	44-47	9.59	8.60
44-47	48-51	9.28	8.99
48-51	52-55	8.58	7.82
52-55	56-59	7.99	7.54
White Men			
24-27	28-31	20.81	27.02
28-31	32-35	26.23	33.14
32-35	36-39	31.83	34.32
36-39	40-43	32.98	32.39
40-43	44-47	34.32	32.56
44-47	48-51	41.67	33.05
48-51	52-55	35.77	35.24
52-55	56-59	37.35	35.87
White Women			
24-27	28-31	15.39	18.88
28-31	32-35	18.04	24.87
32-35	36-39	16.11	20.54
36-39	40-43	19.99	19.85
40-43	44-47	21.24	22.62
44-47	48-51	20.57	23.50
48-51	52-55	20.06	20.10
52-55	56-59	17.98	23.27

Numbers shown are sample weighted means (1995 prices).

Table 8.4: **Decomposition Analysis for Africans**

	African Men						African Women					
	(1)		**(2)**		**(3)**		**(1)**		**(2)**		**(3)**	
Intercept	7.63**	(1.37)	-8.16	(6.07)	-0.88	(0.57)	10.47**	(1.52)	-12.14	(6.41)	0.50	(0.68)
Education	-		1.95*	(0.74)	-		-		2.48**	(0.69)	-	
Age polynomial												
Age	0.56**	(0.08)	0.42**	(0.09)	0.47**	(0.06)	0.26**	(0.08)	0.17*	(0.07)	0.26**	(0.07)
Age^2	-0.09**	(0.02)	-0.07**	(0.02)	-0.04**	(0.01)	-0.03**	(0.01)	-0.02*	(0.01)	-0.02**	(0.01)
Age^3	0.61**	(0.14)	0.54**	(0.14)	0.14**	(0.03)	0.09	(0.05)	0.06	(0.04)	0.05**	(0.02)
Age^4	-0.02**	(0.00)	-0.01**	(0.00)	0.00**	(0.00)	-		-		-	
Cohort polynomial												
Cohort	0.05	(0.06)	0.14*	(0.06)	-0.02	(0.06)	-		-		-	
$Cohort^2$	-0.04	(0.86)	-0.83	(0.84)	0.14	(0.49)	-		-		-	
$Cohort^3$	-0.01	(0.04)	0.01	(0.04)	0.00	(0.01)	-		-		-	
Cohort dummy variables												
17-18	-		-		-		-		-		0.27	(0.20)
19-20	-		-		-		-		-		0.48*	(0.21)
21-22	-		-		-		-		-		0.63**	(0.23)
23-24	-		-		-		0.20	(0.11)	0.16	(0.09)	0.75**	(0.24)
25-26	-		-		-		0.43**	(0.13)	0.44**	(0.11)	0.89**	(0.26)
27-28	-		-		-		0.46**	(0.15)	0.51**	(0.12)	0.93**	(0.27)
29-30	-		-		-		0.58**	(0.16)	0.63**	(0.13)	1.06**	(0.28)
31-32	-		-		-		0.64**	(0.18)	0.70**	(0.14)	1.11**	(0.29)
33-34	-		-		-		0.81**	(0.19)	0.83**	(0.15)	1.27**	(0.29)
35-36	-		-		-		0.98**	(0.20)	1.00**	(0.16)	1.39**	(0.30)
37-38	-		-		-		1.06**	(0.21)	1.08**	(0.17)	1.45**	(0.30)
39-40	-		-		-		1.21**	(0.22)	1.23**	(0.18)	1.64**	(0.30)
41-42	-		-		-		1.29**	(0.24)	1.27**	(0.19)	1.72**	(0.30)
43-44	-		-		-		1.32**	(0.25)	1.32**	(0.20)	1.76**	(0.31)
45-46	-		-		-		1.54**	(0.27)	1.52**	(0.22)	1.86**	(0.31)
47-48	-		-		-		1.55**	(0.29)	1.52**	(0.23)	2.00**	(0.32)

continued on next page

Table 8.4: *continued*

	African Men						**African Women**					
	(1)		**(2)**		**(3)**		**(1)**		**(2)**		**(3)**	
49-50	-		-		-		-		-		2.15**	(0.33)
51-52	-		-		-		-		-		2.24**	(0.34)
53-54	-		-		-		-		-		2.29**	(0.35)
55-56	-		-		-		-		-		2.33**	(0.38)
57-58	-		-		-		-		-		2.54**	(0.41)
59-60	-		-		-		-		-		2.59**	(0.45)
Year												
1999	-0.02*	(0.01)	-0.01	(0.01)	-0.02**	(0.01)	0.01	(0.01)	0.02	(0.01)	0.02*	(0.01)
N	42		42		69		42		42		69	
R^2	0.97		0.98		0.99		0.95		0.97		0.99	

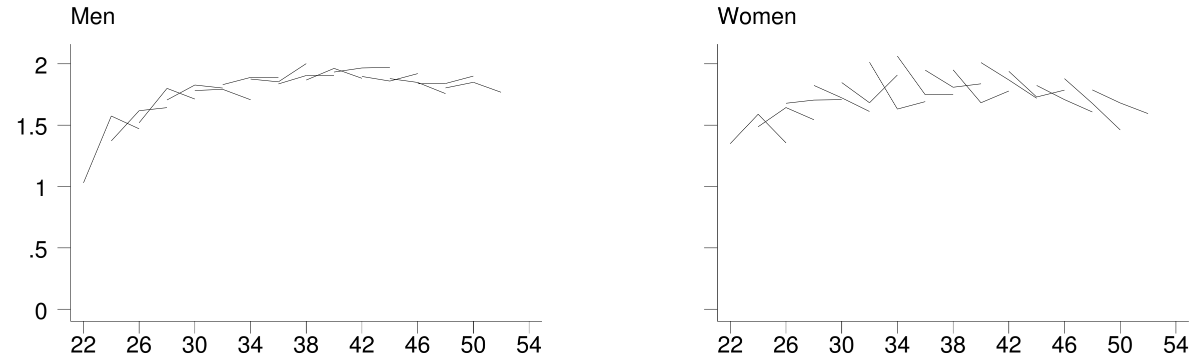
Significance levels: $*$: 5% $**$: 1%. Standard errors in parentheses.

Cohort dummy variables correspond to the age in 1995. Reference categories: Specifications (1), (2): Cohort 20-21, Specification (3): Cohort 15-16.

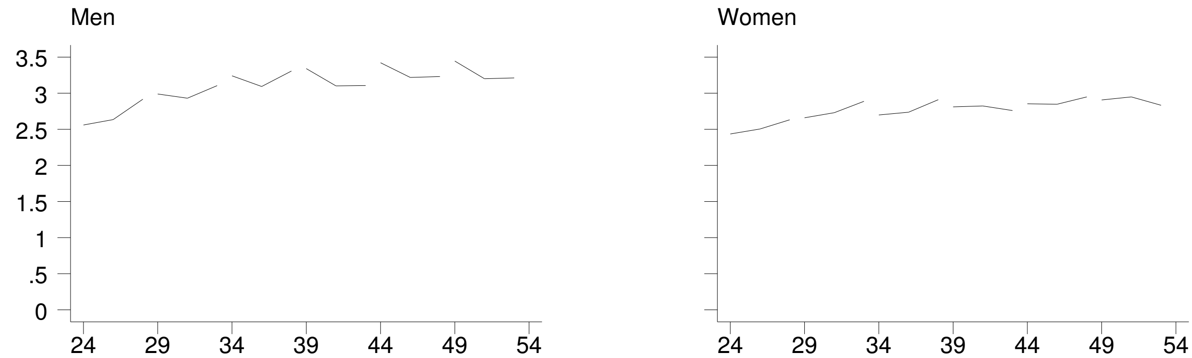
Education is measured in years of schooling completed.

Variables Age^3, Age^4, $Cohort^2$, and $Cohort^3$ have been scaled by 10^{-2}.

Figure 8.1: **Logarithm of Real Hourly Wage (1995 prices) by Cohort**



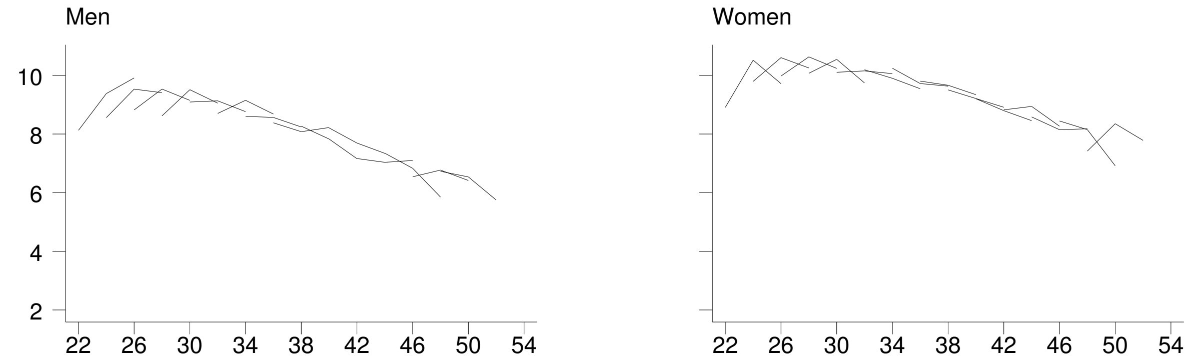
(a) African workers.



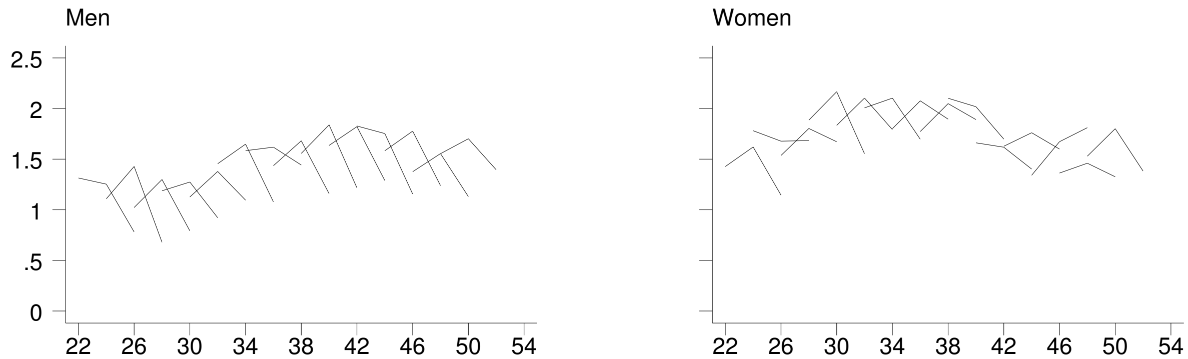
(b) White workers.

Notes: Figures are based on sample weighted cohort means. The x-axis in each graph is labelled according to the upper age limit of the individual cohorts. (This labelling has been chosen for the sake of convenience.)

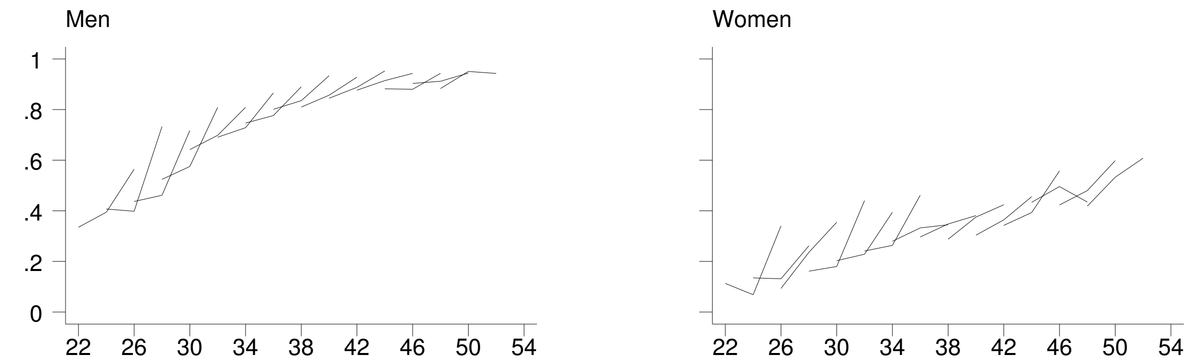
Figure 8.2: **Summary Statistics by Cohort, African Workers**



(a) Number of years of schooling completed.



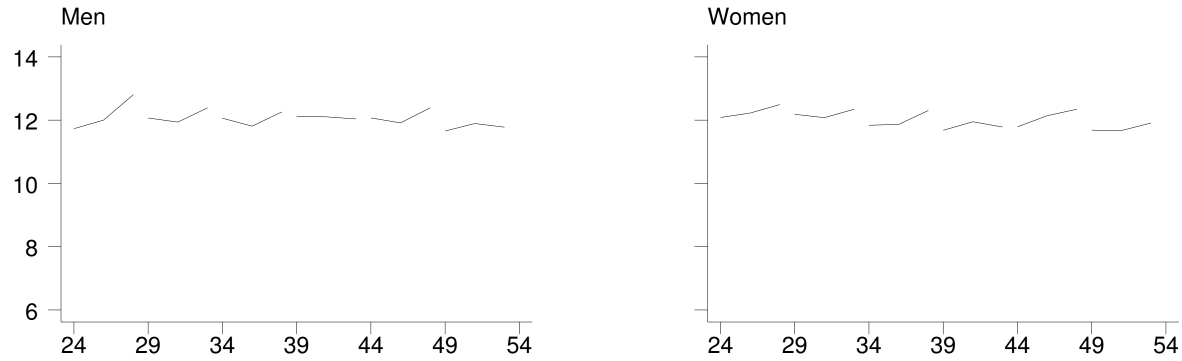
(b) Number of children living in the worker's household.



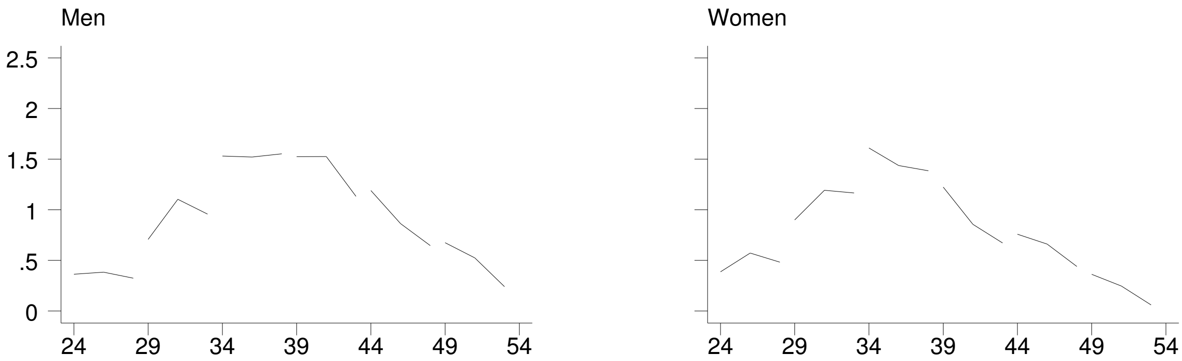
(c) Proportion of workers acting as household head.

Notes: See Figure 8.1.

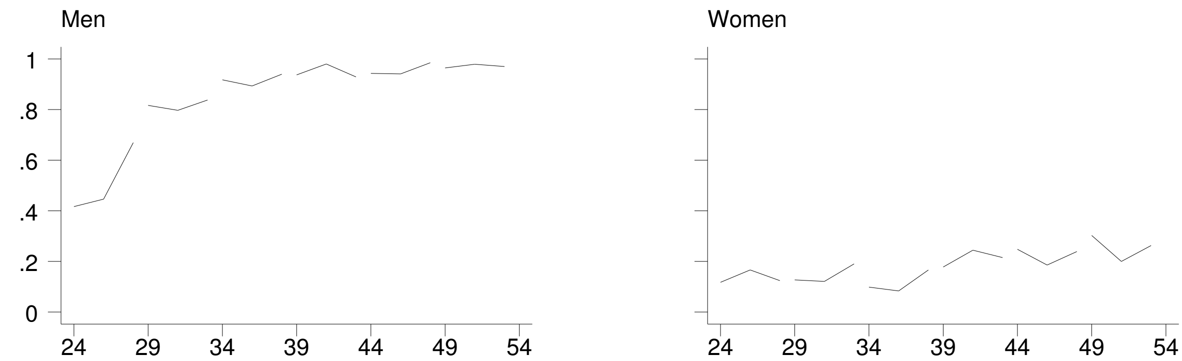
Figure 8.3: **Summary Statistics by Cohort, White Workers**



(a) Number of years of schooling completed.



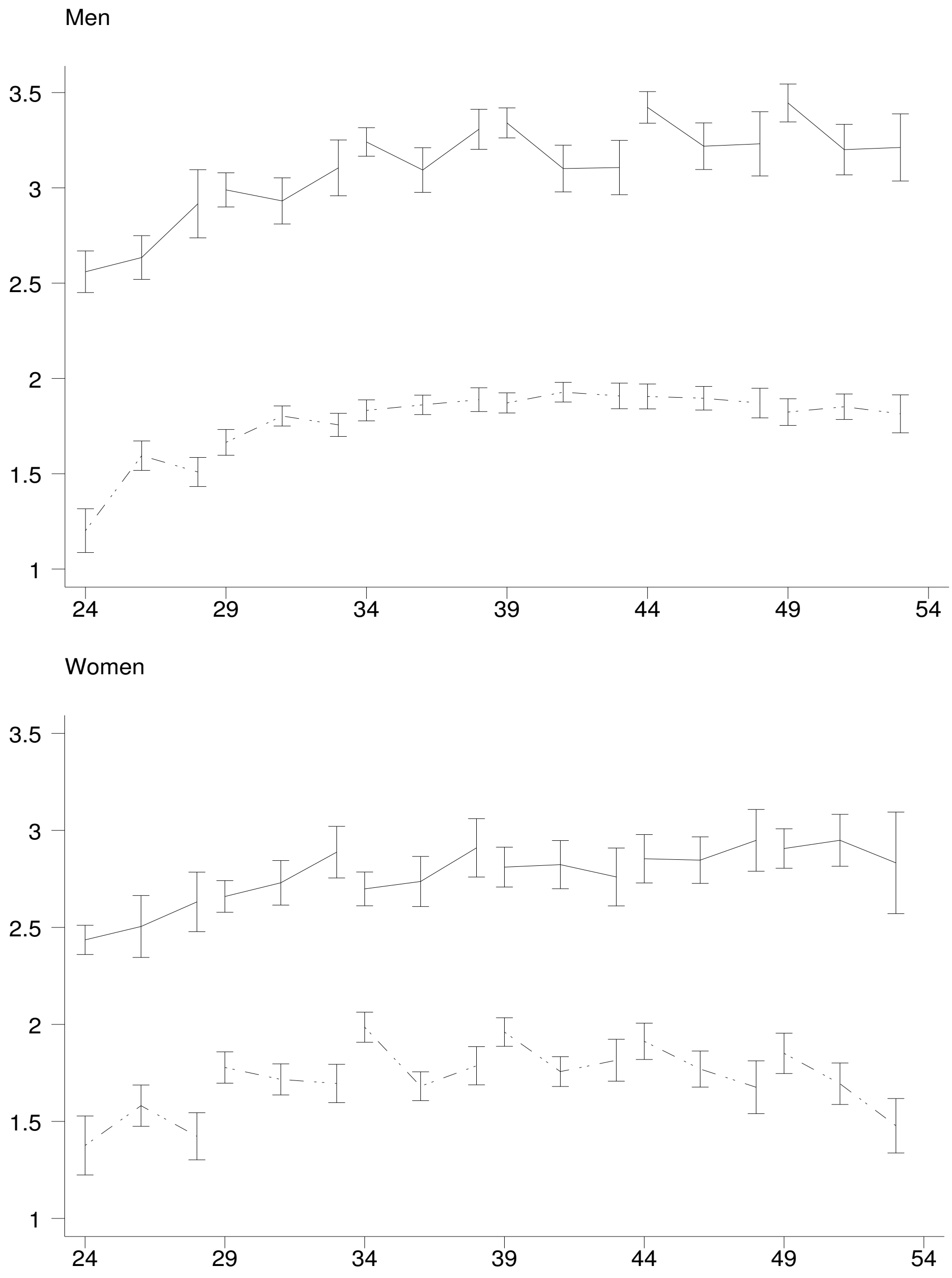
(b) Number of children living in the worker's household.



(c) Proportion of workers acting as household head.

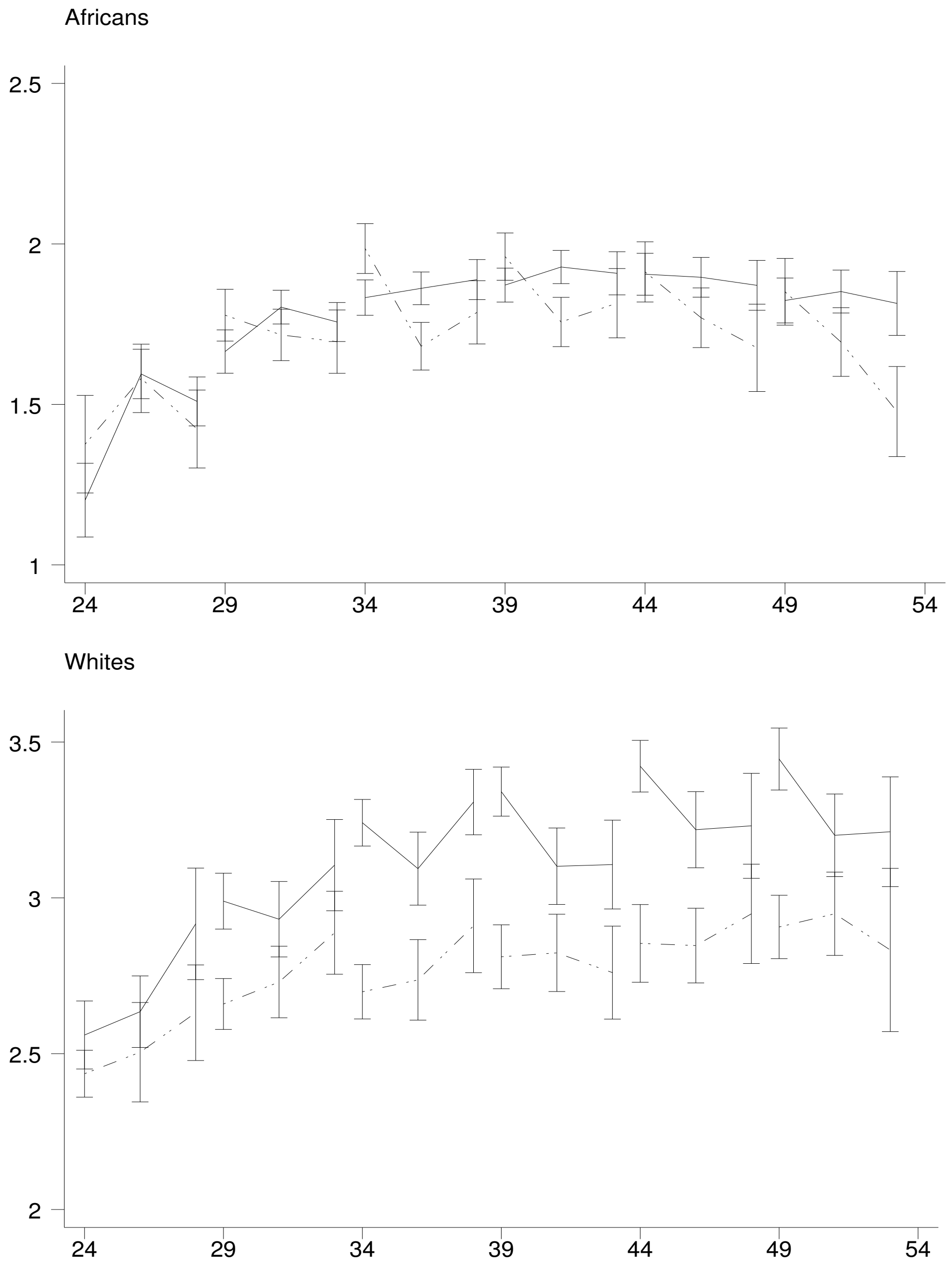
Notes: See Figure 8.1.

Figure 8.4: **Racial Wage Differentials by Cohort**



Notes: See Figure 8.1. Solid lines correspond to cohort wages of White workers, dashed lines to those of African workers. Cohort wages are enclosed by confidence bands of 95 per cent.

Figure 8.5: **Gender Wage Differentials by Cohort**



Notes: See Figure 8.1. Solid lines correspond to cohort wages of male workers, dashed lines to those of female workers. Cohort wages are enclosed by confidence bands of 95 per cent.

Figure 8.6: **Age, Cohort, and Year Effects of Wages Earned by African Men (1)**

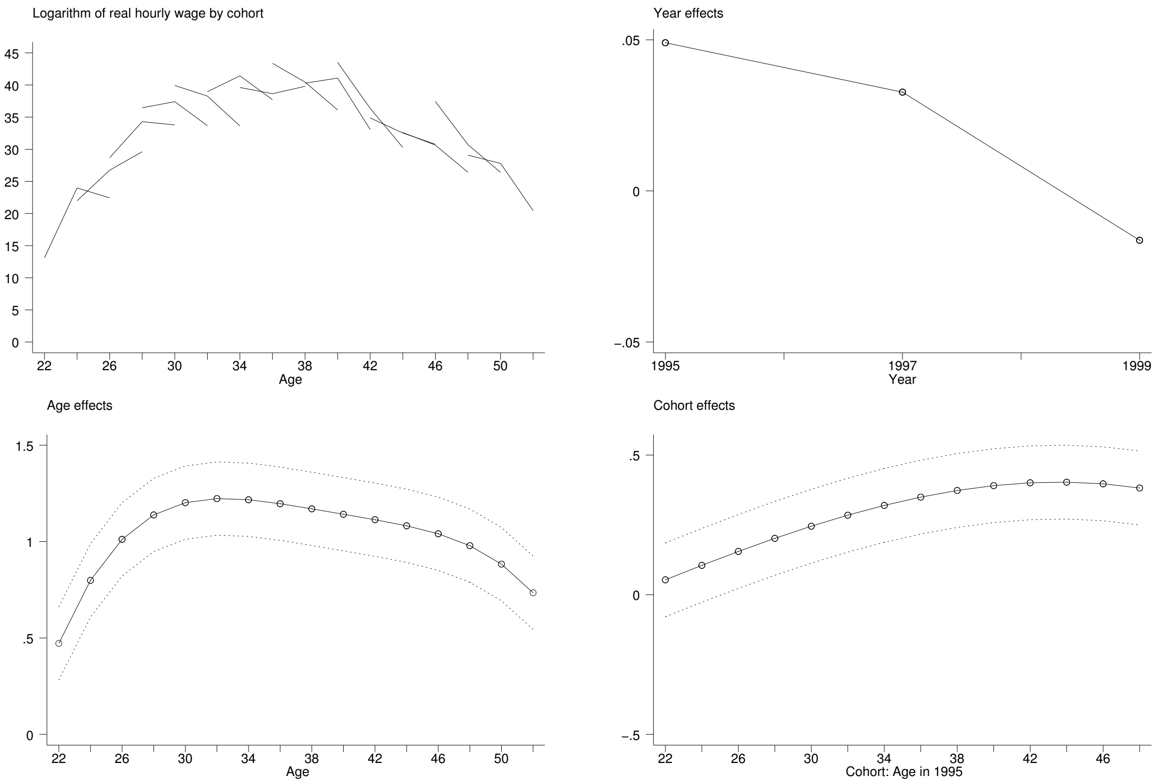


Figure 8.7: **Age, Cohort, and Year Effects of Wages Earned by African Women (1)**

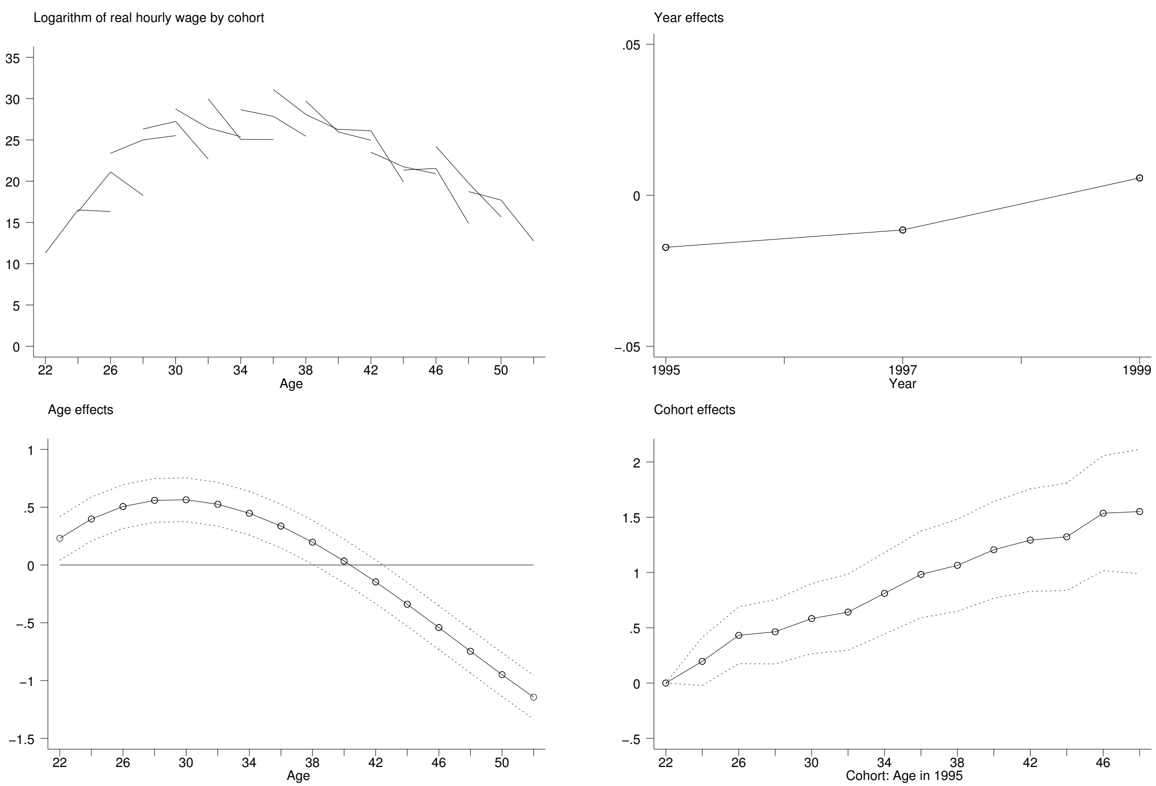


Figure 8.8: **Age, Cohort, and Year Effects of Wages Earned by African Men (2)**

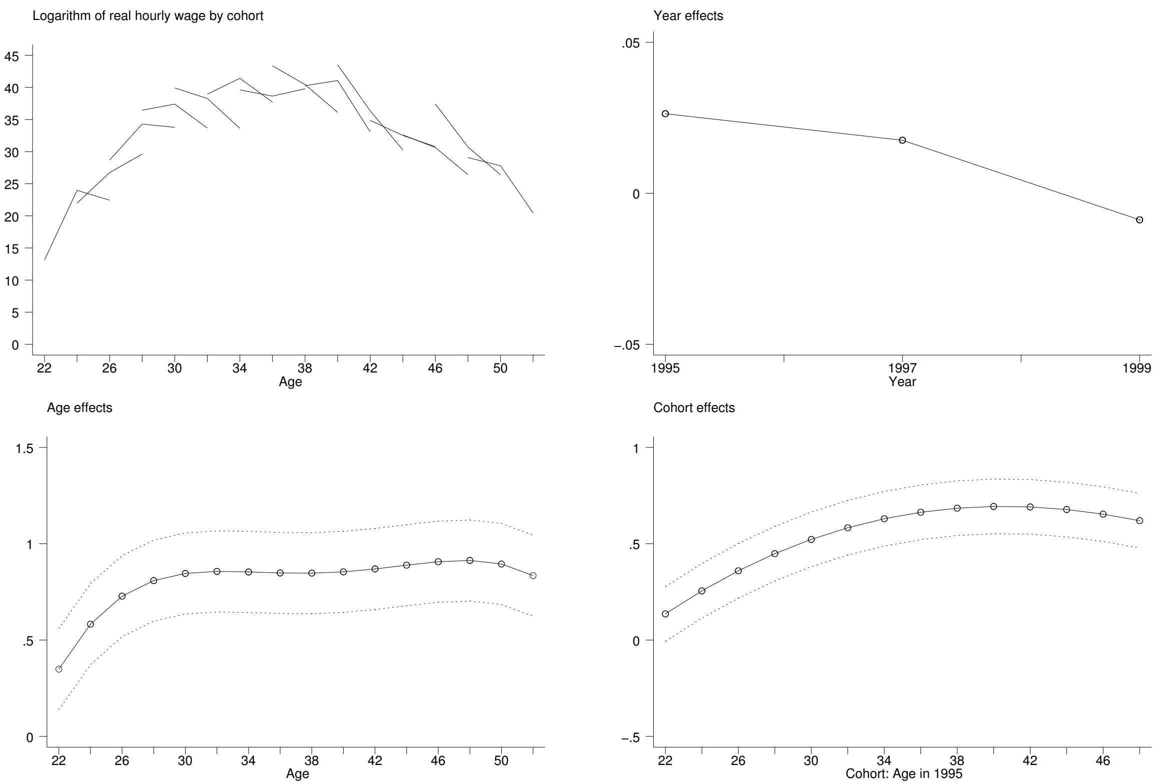


Figure 8.9: **Age, Cohort, and Year Effects of Wages Earned by African Women (2)**

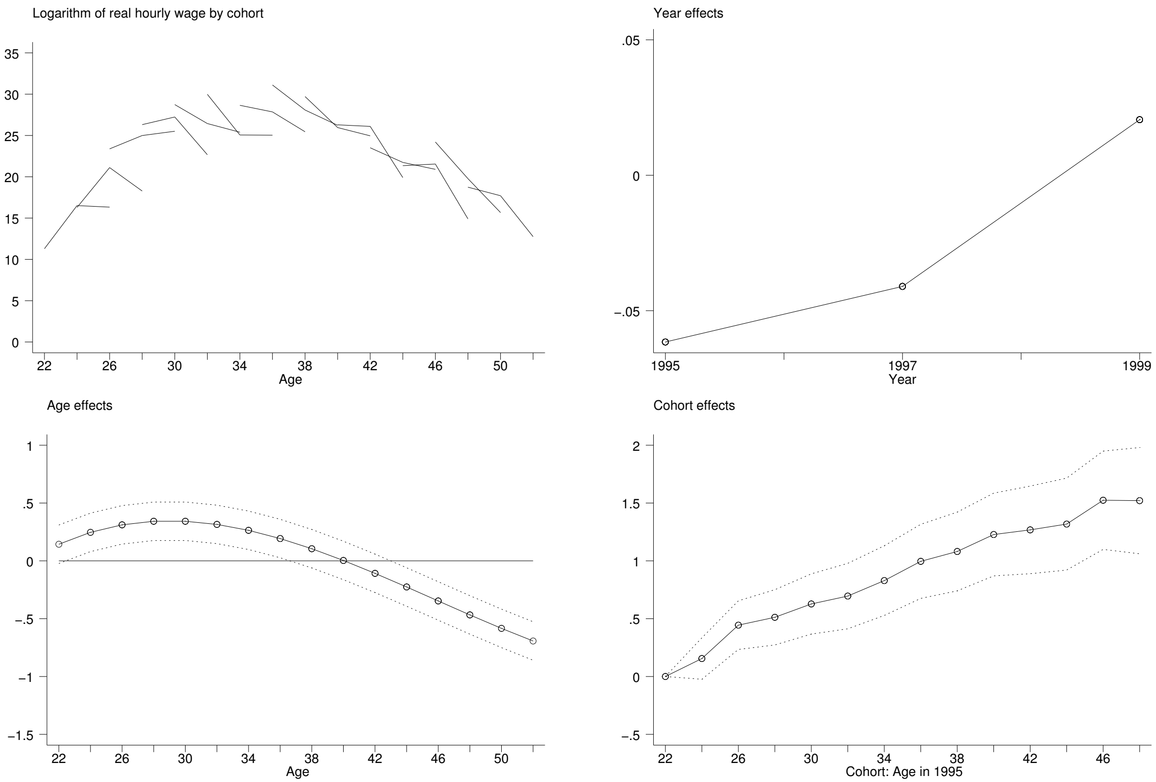


Figure 8.10: **Age, Cohort, and Year Effects of Wages Earned by African Men (3)**

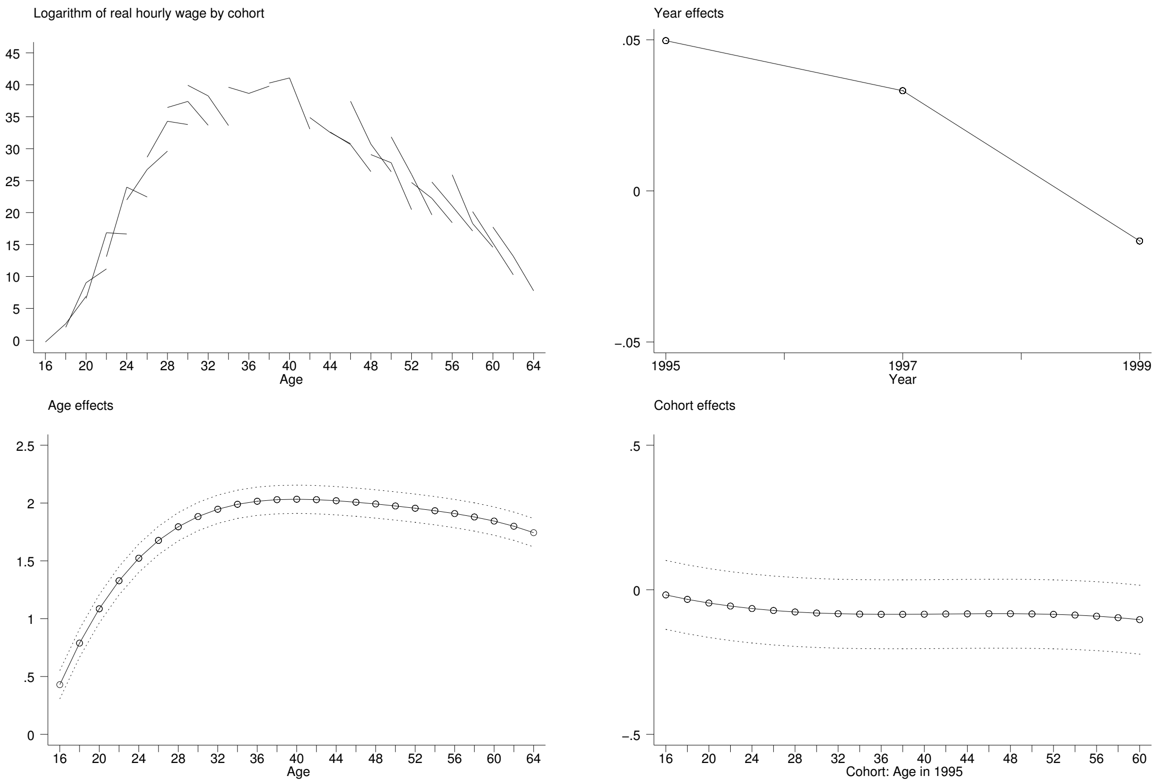
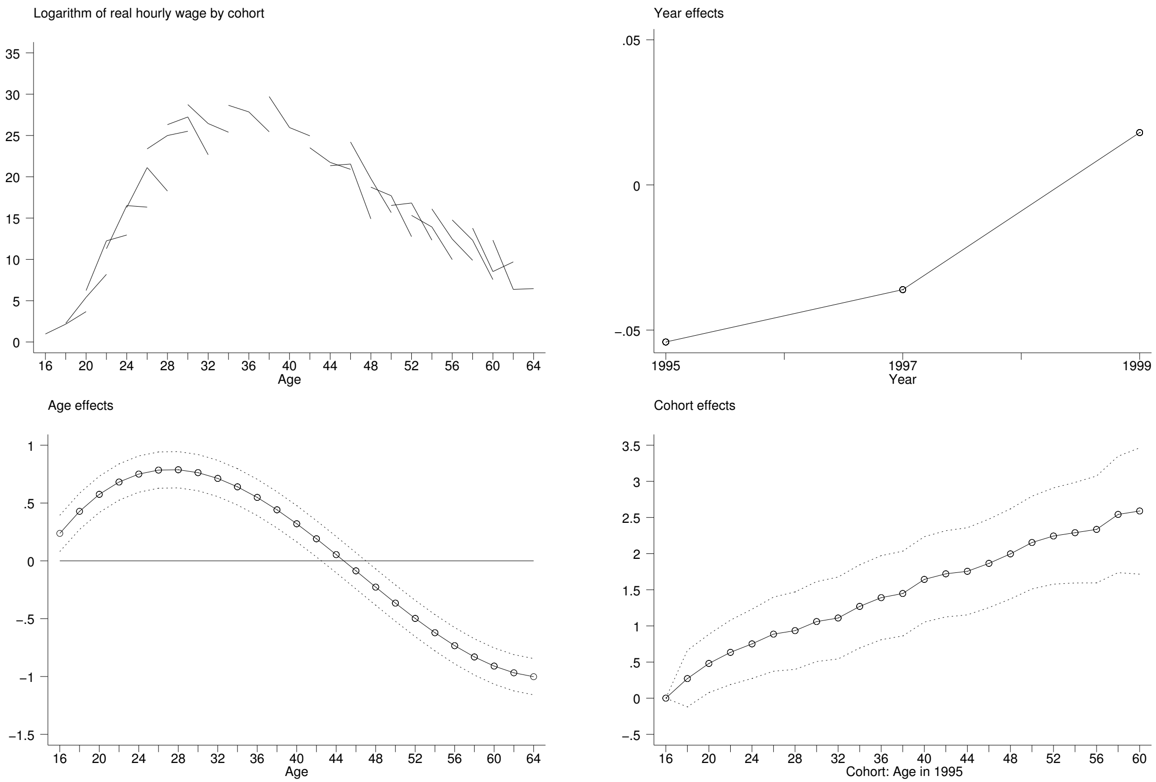


Figure 8.11: **Age, Cohort, and Year Effects of Wages Earned by African Women (3)**



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