Poverty and Inequality Measurement and Determinants: The case of Zambia

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Abstract

This thesis investigates the role of education, employment and household structure in explaining poverty and inequality in Zambia between 1991 and 2004. This period was characterized by macroeconomic and structural adjustment reforms that led to declining public sector employment due to liquidations and retrenchments and changed education distribution due to among many other reasons the introduction of user fees. Therefore, it is important to analyze the impact of these changes on poverty and inequality, especially that existing research has not looked at this area.

After carefully scrutinizing consumption data for quality and consistency to assure comparability across the years, the thesis profiles trends in poverty and Inequality in Zambia from 1991 to 2004. It is found that poverty increased while inequality reduced. The head count poverty increased from 0.628 in 1991 to 0.764 in 2004 an increase of 0.136 points, the poverty gap increased from 0.359 in 1991 to 0.424 in 2004 and the squared poverty gap increased from 0.254 in 1991 to 0.282 in 2004. Restricted poverty dominance tests confirm this. Regarding inequality, from 1991 to 2004, the Gini index decreased from 0.484 to 0.458, the Theil index from 0.40 to 0.31 and the Mean Logarithmic Deviation from 0.509 to 0.375. Inequality dominance could not be established because Lorenz curves intersect.

Having established these changes, the thesis explores some key drivers of these changes. Using a semi-parametric kernel density re-weighting approach, the thesis finds that changes in education endowments and economic returns to education, employment and household attributes explain a substantial part of changes in the distribution of consumption and therefore inequality. Interestingly, the decreasing public sector employment does not explain any of the changes in household welfare distribution.

Further, the thesis investigates the impact of education, employment and household size on poverty using a fitted lognormal consumption distribution. Using maximum likelihood estimation, it is found that households with higher numbers of children might have a higher poverty risk than those with less children, formal sector employment has a poverty reducing effect in almost all household types and that secondary education interacted with self employment has a significant poverty reduction effect. The decomposition of poverty over time, shows that much of the increase in poverty between 1991 and 2004 can be attributed to the conditional poverty function and not changes in the distribution of attributes. These results not only show the direction of change but also the magnitude.

The thesis concludes by pulling these results together and discussing their collective importance for policy.

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Chrispin Mphuka
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Dedication

To Maureen and our children, Grace, Felemeza, Dennis and Juanita.

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Chapter 1

Introduction

1.1 Overview

This thesis investigates how changes in education, employment and household structure have impacted on poverty and the distribution of household wellbeing in Zambia between 1991 and 2004. Within the scope of investigation, the thesis tries to answer two broad questions. The first question is 'what is the trend in inequality and poverty in Zambia since 1991?' And the second is 'to what extent do changes in household characteristics such as education, employment and household structure explain changes in the distribution of wellbeing and poverty?' In most countries where there is active inequality and poverty research, answers to such questions are readily available but that is not the case in Zambia. Existing research on poverty and inequality in Zambia has not come up with a robust ranking. Moreover, the focus has largely been directed towards the investigation of the growth-poverty-inequality relationship. Nothing is known about the relationship between poverty and its covariates or about inequality and factors that drive it. Yet such information is pivotal in Zambia's quest to effectively reduce poverty and attain one of its key Millennium Development goal of halving the number of people living in poverty by 2015. Moreover, Zambia's poverty is still very high. In 2004 official government statistics showed that 68 percent of the 12 million Zambian were living below the official poverty line(GRZ, 2006). This, therefore, explains why the thesis is centred on this topic in the hope that its output will contribute positively to the poverty reduction agenda in Zambia. It tries to make this contribution through a combination of a careful data work. Zambian policy making deserves best-practice empirical work and this is area where this study contributes the most.

1.2 Historical Roots of Poverty and Inequality in Zambia

Zambia experienced one of the highest rates of economic growth in Sub-Saharan Africa during the first seven years after independence in 1964. During that period, government followed market-driven policies and the economy grew by an average annual rate of 4 percent (Kayizzi-Mugerwa, 1991; World Bank, 2007). But, one wonders why the country is so poor today. The answer is largely in the economic events of the 1970s coupled with development, political and social programmes that were pursued at that time.

Beginning in the mid 1970s until the change of government in 1991, the economy declined due to several factors. The price of copper at the international market fell leading to drastic reduction in foreign exchange earnings and declining mining output. Further, the government pursued an import-substitution industrialization strategy through creation of parastatal companies in mining, agriculture, manufacturing and services. Government maintained an overvalued exchange rate and high import tariffs to protect local producers from international competition. Moreover, government maintained a guaranteed national purchase price for maize and provided subsidized inputs to ensure low prices for urban areas. This led to a lack of diversification of agriculture away from maize production. As a result of the these factors, the government started borrowing externally in the hope of copper prices rebounding. By the mid of the 1980s, copper prices had not improved and this led to a huge external debt. So that by 1991, Zambia's external debt swelled to US$7.1 billion(World Bank, 2007; Thurlow and Wobst, 2006).

The economy continued to decline in the 1980s. Real output fell and with it per capita incomes. This period was characterized by failed attempts by the government to restructure the economy guided by the International Monetary Fund (IMF). The movement for multi-party democracy (MMD) was ushered into power in 1991. The new MMD government implemented structural and macroeconomic reforms with vigour. Macroeconomic reforms involved stabilization policies. Structural adjustment programmes (SAP) included the liberalization of agriculture and external trade through harmonization and reduction of tariffs, privatization of state-owned enterprises, public sector downsizing through retrenchments, removal of subsidies including maize and fertilizer subsidies and the introduction of user fees for education and health (McCulloch, Baulch and Cherel-Robson, 2000). These programmes had both costs and benefits. Poverty increased between 1991 and 2004. Companies that could not cope with competition were liquidated or had to downsize (e.g. Zambia Airways and United Bus

Company). Inevitably these reforms led to job losses and structural changes in the economy.

Improved copper prices and a largely private led economy has yielded some benefits over time. After decades of declining standards of living, Zambia's economy started growing and per capita incomes started growing in the late 1990s. According to World Bank (2008), Zambia's recent growth has been accompanied by productivity improvement and presents a break from the past of high growth volatility. World Bank attributes the improvement in economic performance to improved macroeconomic management and increased copper prices, the structural changes that took place in early 1990s and also a broadening of the export base whereby non-traditional exports have increased substantially over the years. Inflation was over 180 percent in the early 1990s but has now returned single digits, government deficits halved as a share of GDP between 2003 and 2006. In the period 1980-2004, the country nearly doubled the number of products exported. Whereas in 1980 the 5 largest exports accounted for 96 percent of total exports, in 2004 they made up of about 80 percent (World Bank, 2008). According to the World Bank (2008), the remaining binding constraints to growth in Zambia include poor access to domestic and international markets, inputs, services and information and high indirect costs mostly attributed to infrastructure related inputs including energy, transport, telecommunication, water insurance and marketing.

1.3 Other Studies on Poverty and Inequality in Zambia

In terms of the implications for poverty and inequality, the above summary would seem to suggest that high poverty and inequality in Zambia is a consequence of poor policies and lack of sustained high economic growth. Sustained growth alone might not translate into poverty and inequality reduction if the right education, employment, taxation and other policies are not in place. Understanding poverty and inequality reduction starts with a clear record of poverty and inequality. This has been the focus of earlier studies on poverty and inequality in Zambia. It is also worth noting that changes in growth that are measured using national income statistics may not be matched by changes in poverty and distribution which are measured with data obtained from household surveys because 'income' from the two data sources is different.

Apart from government survey reports that highlight poverty and income inequality, McCulloch et al. (2000) came up with comparable estimates of poverty and consumption inequality from 1991 to 1998. The poverty and inequality estimates from

government reports are not accurate because of lack of comparability in the consumption measure used. Nonetheless both GRZ (2004) and McCulloch et al. (2000) show that in any given year the head count poverty is higher in rural areas than in urban areas. This is true for the poverty gap and squared poverty gap measures.

The major difference between these studies comes when looking at whether poverty increased or decreased over time. Table 1.1 shows summarizes the gini index and the headcount poverty ratio found in the two studies. GRZ (2004) shows that the head count poverty decreased marginally from 70 percent in 1991 to 69 percent in 1996. And then it increased to 73 percent in 1998 with a marginal decline to 68 percent in 2004. A few points are worth noting regarding this trend. First, there is no effort to ensure that the consumption aggregate remains comparable over time despite some questions changing over time. Second, the 1991 survey did not collect own consumption for the computation of the poverty figure while during the other years, own consumption was collected and included. Third, during the 1991, 1996 and 1998 surveys the same food basket was used to draw the poverty line but this was changed for the 2004 survey.

On the other hand, McCulloch et al. (2000) carefully work out comparable consumption aggregates for 1991, 1996 and 1998. But they do not impute own consumption for 1991. Nonetheless, they find that head count poverty increased from 69.5 percent in 1991 to 81.3 percent in 1996 and reduces marginally to 71.9 percent in 1998. Despite the shortcomings in their methodologies used, both studies show that head count poverty increased slightly between 1991 and 1998.

Government survey reports show that income inequality as measured by the Gini coefficient increased from 0.61 in 1996 to 0.66 in 1998 and decreased to 0.57 in 2004 (GRZ, 2004). On the other hand, McCulloch et al. (2000) shows that consumption inequality decreased from 0.559 in 1991 to 0.518 in 1996 and decreased further to 0.509 in 1998. Given the changes in the income questions over time, it is much more difficult to come up with a comparable income aggregate over time particularly between 1991

Table 1.1: Poverty and Inequality Measures Estimated by Earlier Studies

	1991	**1996**	**1998**	**2004**
Gini Index				
*GRZ Reports***	-	0.61	0.66	0.57
*McCulloch et al. (2000)**	0.559	0.518	0.509	-
Headcount Poverty				
*GRZ Reports***	70%	69%	73%	68%
*McCulloch et al. (2000)**	69.5%	81.3%	71.9%	

***These studies used income as the welfare measure*

** This study used consumption as welfare measure*

and 1998. This renders the income inequality measures by government difficult to give a trend in income inequality. This makes McCulloch et al. (2000) a more realistic study for getting trends in inequality over time though they use consumption. One contribution of this thesis is that it gives trends in inequality and poverty estimates in a way that ensures that the consumption aggregate used is comparable over the period. Even better, this thesis robustly ranks inequality and poverty using ordinal ranking tools.

1.4 Hypotheses and Methods Used

Given the analysis above which has shown that the period between 1991 and 2004 was characterized by both macroeconomic and structural adjustment reforms that led to declining public sector employment and changed education distribution while there is a lack of robust trend of poverty and inequality for the period we come up with the following hypotheses to test in this thesis:

- Poverty increased while inequality reduced between 1991 and 2004. This hypothesis is on account that there has been a lack of robust trends on poverty and inequality to cover the whole period. To test this hypothesis, we carefully derive a comprehensive and comparable household consumption aggregate as a measure of welfare and use it to come up with poverty and inequality trends for the period. We supplement this by looking at ordinal rankings by applying stochastic dominance theory.

- Changes in education explain the reduction in inequality and increase in poverty between 1991 and 2004. We test this hypothesis by employing a semi-parametric kernel density decomposition method to visually see exactly where changes in education impact on the distribution of household welfare. In a complementary way we also derive summary inequality measures which show how changes in education impact on poverty over the period.

- Reduced formal sector employment and education changes led to increased poverty between 1991 and 2004. This hypothesis is tested through the fitting of a log-normal distribution function to consumption and use it to decompose changes in poverty between 1991 to 2004 according to changes in household characteristics (i.e., employment and education) or due to changes in the poverty function conditional on the characteristics. The latter part captures changes in labor markets capturing what happens to the wage. As a supplement we also look at the extent

to which increasing the level of education, the number of household members employed in the formal sector and household size changes the poverty risk.

The thesis has five chapters. After this introduction, Chapter 2 presents a robust account of poverty and inequality in Zambia. It presents trends of poverty and inequality between 1991 and 2004. In addition, it presents stochastic dominance tests to coming up with an ordinal ranking of poverty and inequality over the period. Chapter 3 is focused on inequality analysis using semi-parametric methods. The key finding in the chapter is that changes in education with improvements in the lower quintiles lead to improved welfare at lower levels though this did not offset worsening poverty but it impacted on consumption distribution and inequality in particular. Chapter 4 gives the poverty simulations and decompositions. The key results are that poverty changes are mainly driven by the conditional poverty function and not changes in the distribution of characteristics. This means that returns to factors of production such as labour are important in addressing poverty in Zambia. Chapter 5 summarizes the key findings of the thesis and discusses key policy implications emanating from the findings.

Chapter 2

A Robust Record of Zambia's Poverty and Inequality Trends from 1991-2004

2.1 Introduction

Changes in poverty and inequality in Zambia over the last three decades remain underexplored . Before 1991, this was mainly due to lack of survey data. But from 1991, survey data has been periodically produced by the Central Statistical Office of Zambia (CSO) which has resulted in a few studies being done (e.g. McCulloch et al., 2000; Mulenga and Campenhout, 2008; Thurlow and Wobst, 2006). This chapter aims to estimate poverty and inequality trends in Zambia from 1991 to 2004. In order to come up with robust trends, we undertake a careful data analysis to ensure that the consumption aggregate used is comparable from one year to another and one region to another. We also undertake poverty and inequality sensitivity analyses to ensure that the results are robust. In addition, we undertake poverty and inequality dominance tests to come up with a robust ordinal ranking of both poverty and inequality, especially that poverty or inequality estimates are likely to be sensitive to choice of index used. This was not done in the early studies. However, this is necessary because poverty and inequality comparisons over time or regions are often sensitive to the choice of the indices of inequality and poverty used or poverty lines (Chen and Duclos, 2008). Therefore, a robust poverty ranking is important to guard against the uncertainty and the frequent lack of agreement regarding the choice of precise poverty lines and also helps to come up with a range of poverty lines where a ranking will be the same (Davidson and Duclos, 2000). The same is true for inequality ranking where different inequality indices would rank two income or consumption distributions differently

particularly when Lorenz curves intersect (Foster and Shorrocks, 1988a).

Another key objective of this chapter is to introduce the data used in the analysis not only of this chapter but all subsequent chapters. In that regard, this chapter outlines the major choices made to come up with the living standard measure and also ensuring that it is comparable from one year to another. This area of study is very important. Since 1991, Zambia has gone through economic and structural reforms which led to various changes at both macro and micro levels. It is, therefore, vital to tell how the distribution of welfare has changed as a result. Moreover, Zambia's economic goal in the last decade has centered on achieving economic growth and poverty reduction (GRZ, 2006). From 2000, growth has indeed been recorded, though in modest levels, but the goal of reducing poverty still remains elusive . This challenge emanates partly from lack of credible poverty and inequality trends. This makes poverty and inequality reduction goals difficult to achieve especially that much of the growth is concentrated in urban sectors leaving rural areas where the majority of the people unaffected by growth(GRZ, 2006).

The gap of research in this area is immense. McCulloch et al. (2000) provide a thorough analysis of poverty and inequality but only for the period 1991 to 1998. Moreover, McCulloch et al. (2000) did not fully correct for the omission of own-consumption in the 1991 survey which makes their findings difficult to compare with the other years. This renders questions such as "did poverty increase from 1991 and 1996" difficult to answer.

Another source of trends in poverty and inequality in Zambia is government reports prepared by CSO. However, these have serious analytical weaknesses. The first weakness is that there is little done to ensure that results are comparable in relation to the derivation and choice of welfare aggregates from one year to another. This normally affects the comparability of results. Another weakness relates to poverty measurement. For 1991, 1996 and 1998 survey data, CSO used poverty lines based on a basic needs basket formulated in 1991 and only adjusted for inflation in subsequent years until 1998. After 2000, CSO decided to adjust the basic needs basket which resulted in lower poverty lines. This makes good political appeal because it shows lower poverty levels (GRZ, 2004). But doing this without adjusting earlier data and findings makes poverty comparisons between a year like 2004 and 1998 inconsistent. Furthermore, welfare aggregates have not been the same, especially for inequality. For example, CSO uses consumption as the main measure of economic well-being for poverty analysis but uses income inequality analysis. Using income to measure inequality makes good sense but not when the questions for collecting income data have changed too much over the years rendering comparison of income inequality over those years virtually impossible

McCulloch et al. (2000). Moreover, CSO uses only the Gini coefficient as measure of income inequality. But it is well known that different measures of inequality do capture changes in different parts of a distribution (Cowell, 2000; Dinardo, Fortin and Lemieux, 1996).

Regarding poverty, it is important that the robustness of poverty estimates is ascertained. None of the earlier studies do sensitivity analysis of poverty with respect to poverty lines. Without sensitivity analysis it is not possible to tell whether poverty ranking is sensitive in the neighbourhood of the poverty lines used. In the absence of such sensitivity analysis it is hard to say that poverty has decreased with certainty as is being claimed in government reports.

Nonetheless, stylized facts from early poverty and inequality studies show that in any given year poverty is higher in rural areas than in urban areas (McCulloch et al., 2000; GRZ, 2004) . This is true for the head count, poverty gap ratio and squared poverty gap indices. This illustrates that the majority of the poor actually reside in rural areas. The major differences between the studies comes when looking at whether poverty increased or decreased over time.

The rest of the chapter is organized as follows: Section 2.2 gives the theoretical and empirical approaches to inequality and poverty measurement and dominance analysis; Section 2.3 gives an account of the data used to analyze poverty and inequality; Section 2.4 presents summary measures of inequality and ordinal ranking of inequality and social welfare; Section 2.5 presents summary measures of poverty and results of poverty dominance tests to come up with a robust ordinal ranking of poverty; and section 2.6 concludes.

2.2 Theoretical and Empirical Methods of Poverty and Inequality Measurement and Ranking

Poverty and inequality measurement is important in comparing whether poverty or inequality has increased or decreased between two periods or places. When the question of interest is to find out by how much poverty has increased over time researchers normally use a summary measure. On the other hand, if the interest is to find out if poverty has increased or decreased between two reference points then one has the choice to either use indices or some ordinal ranking. It is important, however, to mention that most of the curves used for making ordinal rankings are also useful for measuring distances between distributions. For example, poverty incidence curves are just a series of poverty headcounts.

Seidl (1988) gives a survey of various poverty indices that can be used to measure poverty. However, in this thesis we use the most common class of poverty indices, the Foster, Greer and Thorbecke (1984) indices (hereafter referred to as FGT poverty Indices). The normalized FGT indices as defined by Duclos and Araar (2006)[1] is:

$$\overline{P}(z;\alpha) = \int_0^1 \left(\frac{g(p;z)}{z}\right)^{\alpha} dp \tag{2.1}$$

and a non-normalized version is

$$P(z;\alpha) = \int_0^1 (g(p;z))^{\alpha} dp \tag{2.2}$$

where $\alpha \geq 0$, $g(p;z)$ is the poverty gap defined as the difference between consumption and the poverty line. The parameter α differentiates the members of this class of poverty. $\overline{P}(z;\alpha=0)$ gives the headcount ratio which is the proportion of the population with consumption that fall below the poverty line, $\overline{P}(z;\alpha=1)$ is the income poverty gap. According to Foster and Shorrocks (1988b) the income poverty gap, $\overline{P}(z;\alpha=1)$, is a normalized sum of the shortfalls of the poor. Lastly, $\overline{P}(z;\alpha=2)$ is the squared-poverty-gap index. In this case the parameter α might be viewed as a measure of poverty aversion: the larger α is the greater the emphasis to the poorest people.

A thorough presentation of different inequality measures and how they differ based on varying ethical judgement is given in Cowell (2000). For comparability with earlier studies we use the Gini index, mean logarithmic deviation (MLD) and the Theil index. The Gini index can be expressed in many ways. For example, Duclos and Araar (2006) shows that using the S-Gini[2] formula, the Gini index can be defined as:

$$I(\rho=2) = \frac{2}{\mu}\int_0^1 (\mu - Q(p))(1-p)\,dp \tag{2.3}$$

The Gini index is more sensitive to redistributive changes around the median of the

[1] The continuous version of the FGT class here is as presented in Duclos and Araar (2006). This is for the continous variable case. Foster et al. (1984) originally define for the discrete variable version as

$$P_{\alpha}(y;z) = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{g_i}{z}\right)^{\alpha}$$

the summation is equivalent to the integral in the continous case while $1/n$ is the dp (Duclos and Araar, 2006).

[2] S-Gini stands for single parameter Gini.

distribution[3].

The mean logarithmic deviation (MLD) and the Theil index are part of the generalized entropy indices of inequality defined as[4]:

$$I(\theta) = \begin{cases} \frac{1}{\theta(1-\theta)} \left(\int_0^1 \left(\frac{Q(p)}{\mu} \right)^{\theta} dp - 1 \right) & \text{if } \theta \neq 0, 1 \\ \int_0^1 \ln \left(\frac{\mu}{Q(p)} \right) dp & \text{if } \theta = 0 \\ \int_0^1 \frac{Q(p)}{\mu} \ln \left(\frac{Q(p)}{\mu} \right) dp & \text{if } \theta = 1 \end{cases} \tag{2.4}$$

where $I(\theta = 0)$ is the Mean Logarithmic Deviation (MLD), $I(\theta = 1)$ is the Theil index and $I(\theta = 2)$ is half the square of the coefficient of variation. The parameter θ captures the sensitivity of a specific GE index to particular parts of the distribution: for θ large and positive, the index is sensitive to changes in the distribution that affect the upper tail; for θ negative, the index is sensitive to changes in the distribution that affect the lower tail. The Generalized Entropy indices are used because they satisfy all the desired axioms of inequality[5] (Cowell, 2000).

2.2.1 Poverty Dominance

Stochastic dominance tests are usually used to establish a robust ordinal ranking of poverty, inequality and welfare based on some social ethical judgement. This is because sensitivity of quantitative indices is not the same at different parts of a distribution. This implies that ranking can be reversed using different indices and for poverty with different poverty lines (Araar, 2006). To conduct poverty dominance tests we follow Ravallion (1994) and Davidson and Duclos (2000). According to these authors, we consider two distributions of consumption, characterized by their cumulative distribution functions, F_A and F_B, with support contained in the nonnegative part of the real line[6]. We then define the distribution of A with order 1 as the cumulative distribution of A i.e., $D_A^1(x) = F_A(x)$ and the s-order distribution as $D_A^s(x) = \int_0^x D_A^{s-1}(y)\, dFy$ for any integer s ≥ 2 and we define $D_B^s(x)$ analogously.

Davidson and Duclos (2000) show that generally $D^s(x) = \frac{1}{(s-1)!} \int_0^x (x-y)^{s-1} dF(y)$. Using this definition we can then say that distribution B stochastically dominates

[3]Duclos and Araar (2006) gives a variant formula of the Gini index which justifies why this index is sensitive to changes in around the median of a distribution.

[4]This is as shown in Cowell (2000) and Duclos and Araar (2006).

[5]These include the Pigou-Dalton transfer principle, scale invariance, population invariance, replication invariance and decomposability.

[6]It has to be noted however that poverty dominance curves do not require incomes or consumption to be non-negative.

distribution A at order s if $D_A^s(x) \geq D_B^s(x)$ for all $x \in \mathbb{R}_{++}$. To apply this to poverty analysis, we suppose that a poverty line is established at some consumption level $z > 0$. Then we say that B stochastically dominates A at order s up to the poverty line if $D_A^s(x) \geq D_B^s(x)$ for all $x \leq z$. This implies that distribution, $D_B^s(x)$, is everywhere to the right of distribution, $D_A^s(x)$(Davidson and Duclos, 2000).

First order poverty dominance entails that the cumulative distribution of A must at least lie above that of distribution B up to the poverty line z (i.e. $F_A(x) \geq F_B(x)$ for all $x \leq z$.). Hence the poverty head count ratio in A is (weakly) greater than that in B for any poverty line not exceeding z. Second order dominance of A by B up to the poverty line z implies that $D_A^2(x) \geq D_B^2(x)$. This entails that for all poverty lines $x \leq z$, the average poverty gap in A, $D_A^2(x)$, is greater than that in B, $D_B^2(x)$. This is generalized to any desired order s (Davidson and Duclos, 2000). Ravallion (1994) and other authors have referred to $D^1(x)$ as the poverty incidence curve, $D^2(x)$ as the poverty deficit curve and $D^3(x)$ as the poverty severity curve. Recall that $D^1(x)$ is the cumulative distribution function and in the case of poverty it is up to the poverty line z. Hence, the poverty deficit curve is defined as the area under the cumulative distribution function up to the poverty line and the poverty severity curve is the area underneath the poverty deficit curve up to the poverty line.

Chen and Duclos (2008) show that poverty indices that are ranked by first order stochastic dominance should meet four properties. They argue that such indices should show a (weakly) fall in poverty when some income increases, everything else being equal (Pareto principle), be invariant to adding an exact replicate of a population to the same population, meet the anonymity principle and must be invariant to marginal changes to those incomes that are above the poverty line, z, everything being equal.

In practice, however, it is not uncommon to find that dominance of one distribution function by another up to a poverty line can not be established because the cumulative distribution functions intersect [7]. If that is the case, then one can resort to restricted poverty dominance. Davidson and Duclos (2006) demonstrate that not only is restricted dominance a used to restrict the ranges of poverty lines where dominance can be established but it also relates to restrictions on the class of allowable poverty indices.

The idea of restricted poverty dominance was first introduced by Atkinson (1987) and its theoretical rigor has been extended by Foster and Shorrocks (1988a) and Foster and Shorrocks (1988b). Davidson and Duclos (2000) extend the analysis of bounds to poverty dominance and Davidson and Duclos (2006) use bootstrap methods to evaluate

[7] See Chen and Duclos (2008) for a number of other arguements why restricted dominance is used in practice.

the statistical properties of various tests of restricted poverty dominance. Restricted poverty dominance entails restricting dominance analysis to bounds i.e., $z \in [z_{\min}, z_{\max}]$ as long as these bounds look reasonable. But how is poverty dominance done in applied works?

Davidson and Duclos (2000) show that given a random sample of size N, the distribution $D^s(x)$ can be estimated as

$$\begin{aligned} \widehat{D}^s(x) &= \frac{1}{(s-1)!}\int_0^x (x-y)^{s-1}\, d\widehat{F}(y) \\ &= \frac{1}{N(s-1)!}\sum_{i=1}^{N}(x-y_i)^{s-1} I(y_i < x) \end{aligned} \tag{2.5}$$

where I is an indicator variable equal to 1 when the statement is true and 0 when false and $\widehat{F}$ is the empirical distribution function. If one assumes independence of the two distributions under consideration, then Davidson and Duclos (2000) shows that the sampling variance of the difference $\widehat{D}_A(x) - \widehat{D}_B(x')$ using two independent samples from distributions A and B is given by:

$$var\left[\widehat{D}_A(x) - \widehat{D}_B(x')\right] = var\left[\widehat{D}_A(x)\right] - var\left[\widehat{D}_B(x')\right] \tag{2.6}$$

Davidson and Duclos (2000) show that the most restrictive of hypotheses that can be tested are the null of no dominance between the two distributions : H_0 : $D_A^s(x) - D_B^s(x) = 0$, the hypothesis of dominance, $H_0 : D_A^s(x) - D_B^s(x) \geq 0$ and a hypothesis that does not impose any restrictions on the distributions. Davidson and Duclos (2006) argue that because of the nature of the hypotheses, rejection of no dominance does not necessarily imply acceptance of dominance. Nonetheless, to test the null of no dominance we follow Kaur, Prakasa Rao and Singh (1994) where we use the minimum over $x \in Z$ of the t-ratios and reject the null of non dominance if that minimum exceeds the critical value.

In section 2.5 we use this framework to deduce whether there has been poverty dominance between 1991 and 2004 in Zambia. Poverty incidence, deficit and severity curves show that there was no poverty dominance between the two years but the restricted dominance approach outlined here shows that it is possible to have first order poverty dominance within a broad range of poverty lines which include the two national poverty lines.

2.2.2 Inequality Dominance

We continue to consider two populations of consumption distribution A and B that are defined over the positive real line and we now define the Lorenz curve for distribution A as $L_A(p)$ and that of B as $L_B(p)$. Then, distribution A Lorenz dominates distribution B if the Lorenz curve of A is nowhere below and somewhere above that of B i.e. $L_A(p) > L_B(p)$ (Foster and Shorrocks, 1988a). Extending this further according to Atkinson (1970), all inequality indices that meet the Pigou-Dalton principle of transfers should indicate that inequality in B is higher than inequality in A when $L_A(p) > L_B(p)$ for all $p \in [0, 1]$. In other words when one non-intersecting Lorenz curve lies above another, the higher Lorenz curve displays less inequality than the lower one (Araar, 2006).

In situations where Lorenz curves intersect there are essentially two ways forward. The first is to supplement restrictions on the class of social welfare functions which means imposing further restriction on the evaluation function. The second is to derive specific unambiguous ranking of inequality based on selected inequality indices (Cowell, 2000). This thesis follows the latter approach where we use the Theil index, the Mean Logarithmic Deviation and the Gini coefficient to deduce whether there has been an increase or a decrease in inequality.

Section 2.4 presents inequality ranking analysis using the dominance approach outlined here. Lorenz curves of 1991 and 2004 intersect making it difficult to assess a robust inequality ranking. However, using the selected inequality measures we do find that inequality did indeed fall over the period.

Inequality and poverty dominance methods offer accurate ranking only when there is good data. Unreliable and incomparable data can certainly lead to misleading rankings. Therefore before doing poverty and inequality analysis we, in the following section, give a full discussion of the data that underlie the subsequent analysis.

2.3 Consumption Aggregation

The process of estimating poverty or inequality over time involves key methodological choices. In the first instance one has to decide whether to use income or consumption as the measure of living standards. Once one chooses a measure of living standards, he/she has to decide on how broad the aggregate measure should be. For example in the case of consumption, the researcher has to decide on whether to use cash consumption only or also include own-consumption and imputed monetary measures of asset usage.

Furthermore, the aggregate measure should take into account economies of scale in order to compare between households. This involves one deciding what equivalence

scales to choose from a myriad of possible forms and values. With regard to poverty measurement, the next decision is to choose the poverty line. And, the final decision comes down to choice of what measure of inequality or poverty to use (Chen and Duclos, 2008; Deaton, 1997).

This chapter uses datasets from four independent nationally representative surveys: the 1991 national priority survey; the 1996 Living Conditions Monitoring Survey; the 1998 Living Conditions Monitoring Survey; and the 2004 Living Conditions Monitoring Survey. When using independent cross-section survey data, one is confronted with the question of whether the data are comparable. We look at aggregate composition of consumption across years to eliminate minor differences that may affect comparability. One advantage of using these surveys is that they were conducted by the same organization and questionnaires content remained similar over the period.

Looking at the design of all the four surveys, one comes to the conclusion that the same design was used. All four surveys were nationally representative covering all of Zambia's 9 provinces. Each survey was conducted during the same period running from October to December of the survey year. Furthermore, census supervisory areas (CSAs) were allocated to provinces and districts proportional to total population. Standard enumeration areas were sampled randomly within the CSAs and finally households were randomly selected in each sampled standard enumeration area. Urban SEAs were stratified according to whether a household is drawn from the low- , medium- or high-cost areas. On the other hand, Rural SEAs were stratified depending on type of agriculture activity small-scale, medium scale, large scale or non-agriculture. The the fact that coverage, design and sampling was similar across these surveys allows for easy usability of the data.

In analyzing these data, we use post enumeration sampling weights supplied by CSO (GRZ, 1991; GRZ, 1997; GRZ, 1998; GRZ, 2004). Ideally this would help in making the surveys representative of the population of interest because non-response issues are assumed to have been taken care of by the producer of the data; namely, the CSO. When merging files to get our data, some sample observations could not be merged which led to samples used in our analysis being slightly smaller than actual CSO samples. The cause of loss of data was minimal but still worth mentioning. In 1991, 10,000 households were interviewed and we managed to build a sample of 9,869 representing a 98.7 percent. In 1996 the total sample for the survey as reported by CSO was 11, 752 but we only managed to come up with a sample of 11,712 which accounts for 99.7 percent of the original sample. In 1998 the CSO sample was 16,710 while we end up with a sample of 16,448 which is 98.4 percent of the original sample . As for 2004, a total of 19,315 households were sampled but we use 18,994 representing

98.4 percent of the data.

All analysis in this chapter and subsequent chapters uses sampling design and weights that allow for inference to be made to the actual population. In most cases, the sampling design including stratification and clustering was taken into account using the svyset command in Stata. However, in instances where it was not possible to survey set the data, we use sampling weights and clustering to ensure the correct standard errors are obtained. For example, when bootstrapping standard errors of inequality and poverty measures we use sampling weights while also taking into account the strata and primary sampling units in the data.

The study uses consumption as the measure of welfare because of several reasons. First, the surveys used consistent and comparable questions on consumption and not income (McCulloch et al., 2000). Income questions changed so much from one survey to another so much that comparability is difficult. Secondly, it is harder to assess income in developing countries such as Zambia where the proportion of the population that is self employed is high. And thirdly, consumption is a better measure of well-being because it is less affected by seasonal fluctuations (Alwang, Mills and Taruvinga, 2003; Deaton and Zaidi, 2002).

Consumption Composition

When constructing the consumption aggregate for each year, the study aims at coming up with a comparable welfare measure so that poverty, inequality and other statistics derived from such a measure could be compared across time. Lanjouw and Lanjouw (2001) show that differences in the definition of consumption may lead to serious differences in measured poverty. In order to compare consumption data across different surveys, the study aggregates expenditures on food, health, education, housing, clothing and footwear for each of the years. We now look at the similarities and differences in the composition of each of these categories from one year to another. The overall goal is to come up with as broad a measure of consumption as is possible. In contrast to McCulloch et al. (2000) who adjust consumption of 1996 and 1998 to conform to 1991 consumption, we adjust 1991 consumption to make it conform with the other years 1996, 1998 and 2004 which have very similar questions and no problem of comparability. We adjust the 1991 consumption by imputing not only own consumption but also missing categories in the 1991 consumption aggregate.

Food expenses

Questions on food expenses did not change much over the different surveys. A recall period of one month was used on the purchase of maize meal. Whereas in 1991 respondents were asked for one category of maize meal, the categories were increased

in subsequent surveys to include different types of maize meal. Since families generally rely on one type of maize meal for a month, it was assumed that this change would not have serious effect on comparability. All other food expenses were collected using questions with a recall period of two weeks.

Own consumption was not collected in 1991, but it was collected in 1996, 1998 and 2004 surveys. The lack of estimates of own produce consumption in 1991 is likely to overstate poverty and inequality measures for that year, especially as most rural households in Zambia rely on small-scale or subsistence agriculture (Deaton and Zaidi, 2002). Despite missing own-produce estimates for1991, (e.g. McCulloch et al., 2000) went ahead to compare 1991 poverty and inequality estimates to those of other years. On the contrary we impute own consumption for 1991 following the method by Skinner (1987). This is explained in detail in appendix A.4.

Expenditures on millet, sorghum and groundnuts are left out in the 1991 survey and we impute this for 1991 along with own consumption. Vegetable expenses were put in a single category in 1991 but split into tomatoes, onions and other vegetables in subsequent surveys. We assumed that this difference would not lead to serious changes. Therefore, no adjustment was done. In 1991, expenses on oranges and bananas are the only fruits accounted for while in other surveys 'fruits' is a general category capturing many more fruits such as mangoes, apples etc. The composition of fruits and vegetables was left as indicated and assumed that was partly corrected for using the imputation of own consumption and other missing categories.

Some categories are completely left out in the 1991 survey. These include cigarettes or tobacco, alcoholic beverages. A category called non-alcoholic beverages is included in all surveys except 1991 when it is shown as tea or coffee. Non-alcoholic beverages in 1998 and 2004 explicitly capture expenditures on juices, soft drinks and munkoyo (a traditional nonalcoholic energy drink). This was indeed a refinement that is presumed to not cause so much distortion. The omitted category for alcoholic beverages and cigarettes is estimated along with own consumption for 1991. The refinements on non-alcoholic beverages were assumed not to cause major distortions.

Whereas meat was indicated as a single category in 1991 and 1996, it is split into cow meat, goat meat, sheep meat, pig meat and game meat in 1998 and 2004. This type of refinement is also assumed not to cause serious distortions because it is possible that the single category does sufficiently capture the other categories.

Education and Health Expenses

The 1991 questionnaire on schooling contains four categories including fees, uniforms, contribution to school Parents Teachers Association (PTA) and private tuition. The data was aggregated into fees and books only. The four categories are included

in the 1996, 1998 and 2004 questionnaires as well. But in addition to these four categories, the 1996, 1998 and 2004 questionnaires also included an additional category for other expenses. We assume that the categories covered were comprehensive enough to warrant no adjustments. The major difference though is the period over which the expenses were collected. In 1991 the expenses were collected over the whole year, in 1996 over two years while in 1998 and 2004 over three terms which covers a full year. We converted all education expenses into a full year and reconverted into a month to conform with the rest of the data. No further adjustment was done to correct for the differences.

The questions on health expenses were comparable in all the surveys. Health expenses included medicine expenses, fees to health providers. The only exception is the prepayment scheme fees which were not there in 1991 but were collected in 1996, 1998 and 2004. No adjustment was done.

Housing, Clothing and Footwear

Questions soliciting expenses on clothing and footwear remained the same throughout the period under consideration. However, recall periods did differ. The 1991 questionnaire used a three month recall period while the 1996 and 1998 questionnaires used a one month period and the 2004 questionnaire uses both a one month and one year period.

On housing expenses the 1991 and 1996 surveys have the same questions. They include expenses on rent, water, electricity, candle, paraffin, charcoal firewood and other expenses. In addition to these categories, the 1998 and 2004 surveys include expenses on telephone, cable or pay television. In a related question, the 1996, 1998 and 2004 questionnaires include a question on own produced charcoal. This was not included in 1991 but is assumed to have been imputed alongside the other imputed missing expenses.

Remittances and Transport

In 1991 and 1996, expenditure on transport was collected through three categories including expenditure to and from work, to and from school and expenditure on other transport in the past one month. Further to the 1991 and 1996 categories, a personal expenses category was included in 1996 and 1998. This focused on expenditure on fuel, vehicle maintenance, motorbike repairs and boat or canoe repairs.

The questions on remittances remained the same over the years capturing remittances paid in cash or in kind to rural or urban areas over a period of one month. In 1996, 1998 and 2004 the remittances to those outside Zambia were also included. These are included in the consumption aggregate. The category on personal services though not in the 1991 questionnaire was included in 1996, 1998 and 2004 surveys.

What is clear is that the 1991 survey had a range of omitted categories which include own produce food consumption, own produce charcoal and telephone expenses. To ensure as broad a consumption aggregate as possible we decided to impute the missing expenditure values for 1991. Although the consumption aggregate should also include imputed values of usage of durable assets this could not be estimated in any of the years and was left out.

Another important issue is the extent of missing values in the data. The data used in this thesis has a low proportion of missing values so that we did not impute missing values. Appendix A.1 shows that the main variables of consumption did not have missing values. And, only a tiny proportion of households had zero consumption. The appendix shows that only 0.03 percent of the households had zero consumption in 1996, 0.08 percent in 1998 and 0.01 percent in 2004. We also conducted checks of variables, such as education of head and spouse of household, employment and age, that are used in the subsequent chapters of the thesis and this reveals that there is no serious problem of missing values.

2.3.1 Price Adjustments, Equivalence Scales and Poverty Lines

In the analysis that follows for the rest of the thesis, nominal values are converted into 1998 real prices regionally disaggregated. The nominal value of consumption was deflated using a regionally disaggregated consumer price index[8] produced by GRZ (2008). Since the surveys are stratified into seven groups, all rural households were stratified into four strata based on the scale of agriculture. On the other hand, urban households were stratified according to type of residence- low, medium and high metropolitan. Rural areas used a different price index from that in urban areas. We used a low metropolitan price index for urban households falling in low and medium metropolitan strata,and used a high metropolitan price index for the remaining urban households.

We used the Latham scale (Dercon and Krishnan, 1998; McCulloch et al., 2000) used by World Health Organization and in case of Zambia by (Dercon and Krishnan, 1998; McCulloch et al., 2000). The Latham[9] equivalence scale takes into account the demographic composition of the household but does not take into account economies of scale. In developing countries such as Zambia, economies of scale are likely to be minimal (Deaton and Zaidi, 2002). However, to ensure that the results do not depend on the Latham equivalence scales (Dercon and Krishnan, 1998; McCulloch et al., 2000), we provide kernel density plots for 1991 and 2004 in appendix A.4.1. The other two

[8] See Appendix A.2 for CPI figures for 1990 to 2004

[9] see Appendix A.3 for a detailed description of Latham Scale.

plots are for kernel density plots of consumption using an equivalent scale that takes into account economies of scale and household composition Deaton and Zaidi (2002) and the CSO scale that is similar to the Latham scale. As can be seen, the plots are very similar implying that the results are not sensitive to choice of equivalence scale.

The study adopts the GRZ (1991) national poverty lines that are based on the cost-of-basic-needs method. Using the National Food and Nutrition Commission constructed basic needs food basket necessary to maintain the nutritional requirements of an average family of six, the GRZ (1991) arrived at lower poverty line of ZMK961 per adult equivalent in 1991 prices. A further 30 percent was added to this amount to account for other basic non-food items giving rise to a second higher poverty line of ZMK 1,380 per month. Following McCulloch et al. (2000), the two poverty lines are adjusted into 1998 prices and also for the Latham equivalence scales to come up with ZMK 32,232.85 and ZMK46,271.39 for the lower and upper poverty lines respectively.

2.3.2 Distribution of Real Consumption and Summary Measures

Kernel density estimates of the distribution of equivalent consumption shown in figure 2.1 reveal that there were changes in the distributions. The Epanechnikov kernel was used in all the density estimation processes in this thesis while the optimal bandwidth was selected using the Sheather-Jones plug-in method. This method is preferred because it is data-based, has a superior theoretical performance and performs reliably well for smooth density simulations (Sheather and Jones, 1991). All kernel density estimations were done using the KDENS programme in Stata.

Graph 2.1shows that there was a shift to the right in 1996 compared to the1991. The 1996 distribution has a higher peaked than that of the 1991. From 1996 to 1998 there was a leftward shift in the distribution with a further leftward shift in 2004. Overall the 2004 distribution has the highest peak followed by the 1998 and 1996 distributions. The thesis seeks to understand if household characteristics may explain these observed changes in the distribution of equivalent consumption.

Table 2.1 shows the mean and median of the real adult equivalent consumption in 1998 prices and respective bootstrapped standard errors. If one compares 1996 and 1998, there is certainly no major justification why consumption between the two years would have such a sharp decline. But comparing 1991, 1998 and 2004 , the data suggests that mean and median of real equivalent consumption declined steadily. Looking at the entire period, the mean real consumption declined from ZMK59,970 per month in 1991 to ZMK44,264 per month in 2004 representing a 26 percent decline

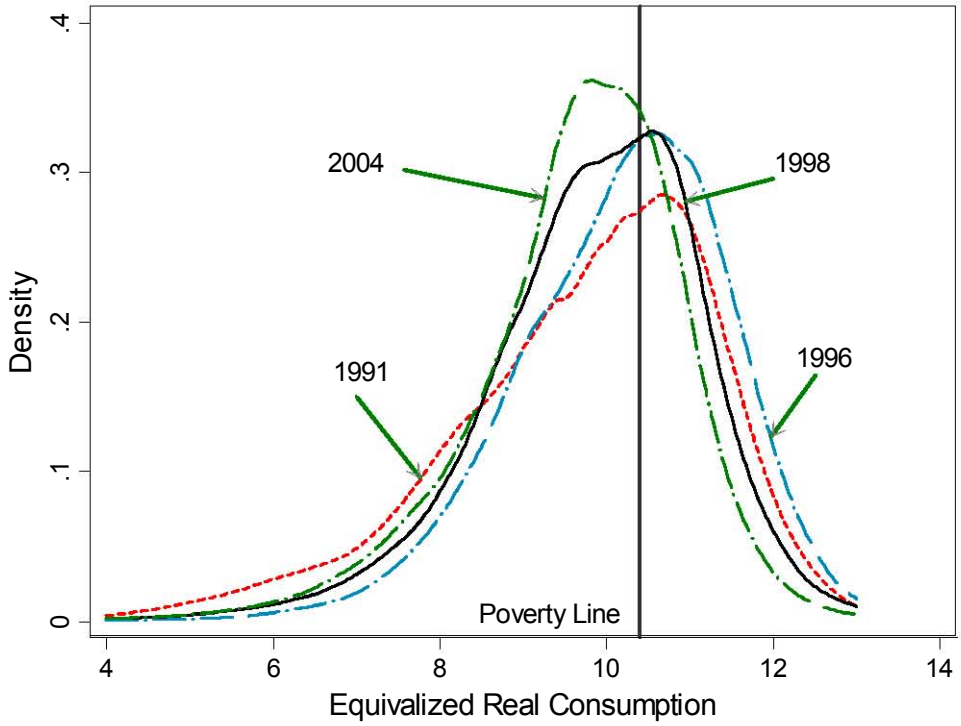

Figure 2.1: The Distribution of Real Consumption Per Adult Equivalent

Table 2.1: Mean and Median Real Consumption 1991, 1996, 1998 and 2004

	Years				Percentage Change			
	1991	1996	1998	2004	96-91	98-96	04-98	04-91
Mean	59,970***	79,918***	56,542***	44,264***	33	-29	-22	-26
s.e.	(3,687)	(4,029)	(2,398)	(2,683)				
Median	47,510***	54,588***	37,583***	30,034***	15	-31	-20	-37
s.e.	(4,017)	(3,840)	(2,210)	(2,442)				

*note: *** significant at 1 percent level*
Bootstrapped standard errors in brackets

over a 15 year period. The decline in the median real consumption is even higher. Median real consumption declined by 37 percent between 1991 and 2004. Analysis of the share of cash consumption in total consumption does suggest that the proportion of own consumption did not change too much from one year to another. The share of cash consumption in total consumption was 83.4 percent, 82.7 percent, 86.1 percent and 85.0 percent in 1991, 1996, 1998 and 2004 respectively. To a large extent this suggests that the estimated own consumption for 1991 was within that of the other years. In addition total food as a percentage of total expenditure was estimated to be 53 percent in 1991, 56 percent in 1996, 61 percent in 1998 and 66 percent in 2004.

Figure 2.2 shows the cummulative distribution functions (CDFs) of the 1991 equivalent real consumption. The continous line shows the CDF of total real consumption including imputed own consumption while the dashed line is the CDF of total consumption without an estimate of own consumption. Clearly at lower levels of consumption the gap between the two lines is wider suggesting that poor families generally rely on own consumption much more than richer ones. This is as expected since most poor people reside in rural areas and depend mostly on subsistence agriculture.

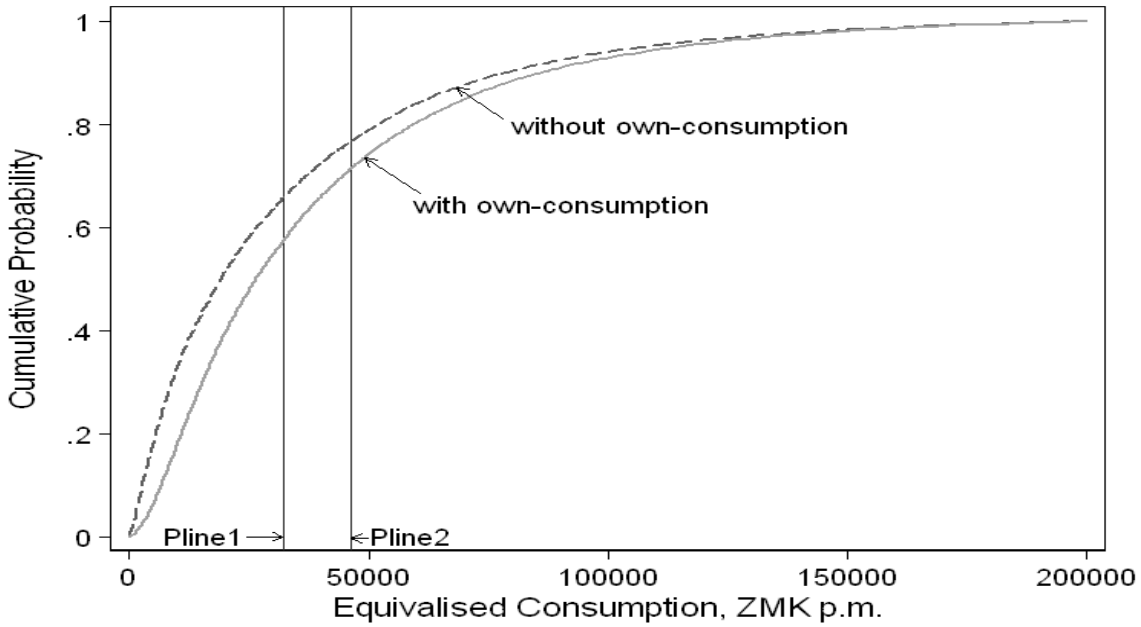

Figure 2.2: 1991 CDFs : with and without own-consumption

2.4 Measurement and Ordinal Ranking of Inequality

Figure 2.3 gives Lorenz curves for 1991, 1996, 1998 and 2004. The Lorenz curves shown do not seem to give much information on the distribution of well-being in the four years because they intersect. But the 1991 distribution lies everywhere below that of the other years suggesting that inequality was far worse in 1991 than during the other years.However, figure 2.4, which shows the difference in the Lorenz curves of 1991 and 2004, clealy reveals that the 1991 Lorenz curve is below that of 2004 up to the 50^{th} percentile thereafter there appears to be no statistical difference at 95 percent confidence interval. Therefore, the question of whether inequality increased or not is resolved below through using selected summary measures of inequality.

Figure 2.5 shows the generalized Lorenz curves for the years. Since Lorenz curves are not affected by the mean of the distribution, they cannot be used to rank distributions in terms of social welfare, only in terms of inequality (Deaton, 1997). This weakness of Lorenz curves is corrected for by using Generalized Lorenz Curves (GLC hereafter). According to Deaton (1997), if the GLC in one period lies everywhere above the GLC in another period (i.e., the higher GLC dominates the lower one), it implies that the poorest $p \in [0, 100]$ percent of the population have more resources in total in the higher GLC which should therefore be preferred by any equity respecting

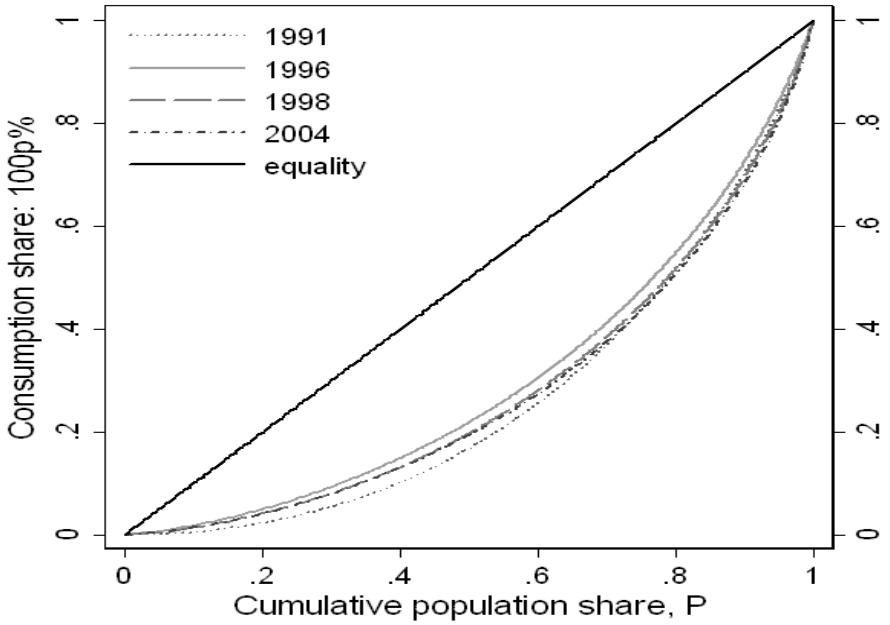

Figure 2.3: Lorenz Curves 1991-2004

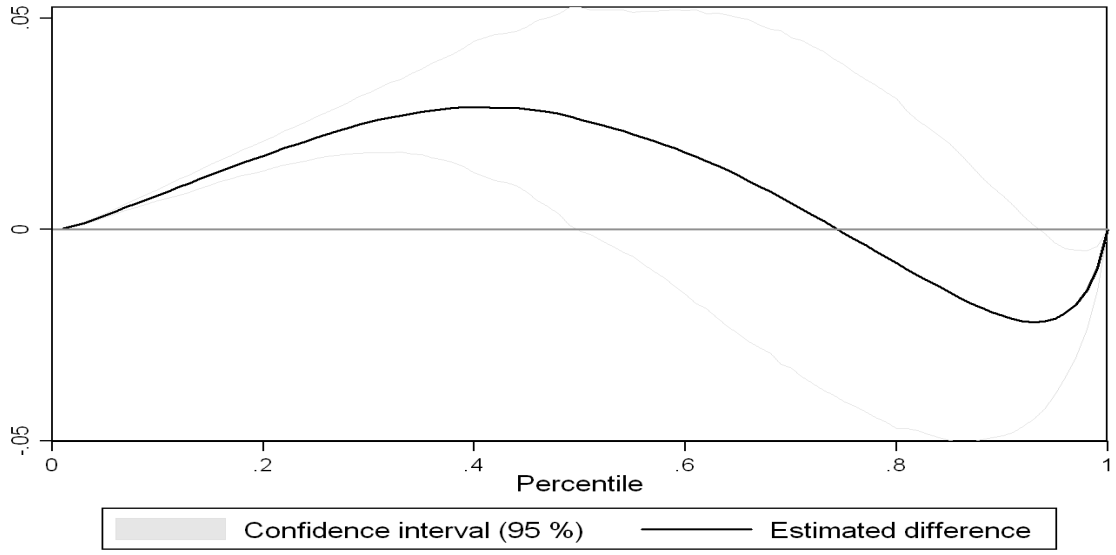

Figure 2.4: Difference in 1991 and 2004 Lorenz Curves

social welfare function.

In figure 2.5, the generalized lorenz curves for 2004 and 1991 intersect so it is not possible to deduce the ranking of welfare based on Generalized Lorenz Dominance criteria. Thus, to rank welfare in the two distributions would depend on specific welfare indices based on specific value-judgements that are built into these indices. The Generalized Lorenz curve of 1996 dominates the Generalized Lorenz Curves for all the other years thereby showing that 1996 had a better social welfare ranking than the other years. Also, the 1998 GLC dominates that of 2004 signifying that social welfare worsened.

Table 2.2 shows selected consumption inequality measures for the period 1991 to 2004. Panel a. of the table shows national inequality measures. It reveals that there has been a decline in inequality in all the measures but the decline was steeper between 1991 and 1996. The Gini index reduced from 0.484 in 1991 to 0.458 in 2004, the Mean Logarithmic Deviation from 0.509 in 1991 to 0.375 in 2004 and the Theil index from 0.40 in 1991 to 0.31 in 2004. In terms of absolute difference over this period 1991 to 2004, the Gini index decreased by 0.023 points, the Mean Logarithmic Deviation by 0.107 points and the Theil index by 0.06 points. All these changes in inequality are statistically significant at 1 percent level. Based on these selected inequality indices it is suggested that inequality reduced over the period.

Unlike in most African countries[10], inequality is higher in rural areas than it is in urban areas in Zambia. This could be attributed to the coexistence of subsistence farmers and large commercial farms in rural areas. Panels b and c of table 2.2 show that consumption inequality declined between 1991 and 1996 in both rural and urban areas. Like at national level, inequality has shown an upward trend from 1996 onwards.

In 2004, the Gini index was 0.46 in rural areas compared to 0.41 in urban areas. During the same year, the Theil index was 0.31 in rural areas compared to 0.25 in urban areas and the Mean Logarithmic index was 0.37 in rural areas compared to 0.29 in urban areas. The overall change in inequality, from 1991 to 2004, in rural areas decreased by 0.004 points according to the Gini index, by 0.032 points according to the MLD and by 0.04 points according to the Theil index. However, the changes in the Gini and Theil indices is not statistically significant while that the MLD is significant only at 10 percent level. Over the same period for urban areas , the Gini increased by 0.055 points, the MLD by 0.016 points but the Theil decreased by 0.02 points. The change in the MLD is not statistically significant. These results suggest that generally in the rural areas inequality may have remained the same while in urban areas there

[10]For a detailed analysis of inequality in Africa see Odedokun and Round (2004). They show that out of 26 Sub-Saharan African countries only 7 have a higher inequality in rural areas than in urban areas. Actually the 7 include Zambia.

Table 2.2: Consumption Inequality Measures 1991-2004

	Actual Measures				**Change**			
Statistic	1991	1996	1998	2004	1991/96	1996/98	1998/04	1991/04
				National				
Gini Coeff.	0.484***	0.465***	0.485***	0.458***	-0.044***	0.022***	-0.001	-0.023***
	(0.005)	(0.006)	(0.007)	(0.002)	(0.006)	(0.006)	(0.005)	(0.005)
MLD: GE(0)	0.509***	0.375***	0.426***	0.375***	-0.147***	0.044***	-0.004	-0.107***
	(0.013)	(0.010)	(0.120)	(0.004)	(0.01)	(0.009)	(0.009)	(0.009)
Theil: GE(1)	0.40***	0.31***	0.35***	0.31***	-1.22***	0.20**	-0.04	-0.06***
	(0.007)	(0.007)	(0.008)	(0.003)	(0.09)	(0.08)	(0.05)	(0.07)
p90-10	17.26***	9.11***	10.06***	9.69***	-0.07***	0.039***	0.001	-0.03***
	(0.74)	(0.31)	(0.39)	(0.20)	(0.009)	(0.008)	(0.007)	(0.009)
p75-25	4.55***	3.18***	3.39***	3.29***	-6.71***	0.74*	0.2	-5.77***
	(0.09)	(0.06)	(0.06)	(0.04)	(0.69)	(0.425)	(0.40)	(0.67)
				Rural				
Gini Coeff.	0.473***	0.444***	0.481***	0.460***	-0.041***	0.033***	0.004	-0.004
	(0.008)	(0.004)	(0.007)	(0.007)	(0.010)	(0.007)	(0.009)	(0.012)
MLD: GE(0)	0.431***	0.334***	0.415***	0.370***	-0.097***	0.061***	0.004	-0.032*
	(0.012)	(0.007)	(0.012)	(0.012)	(0.016)	(0.011)	(0.015)	(0.019)
Theil: GE(1)	0.35***	0.28***	0.34***	0.31***	-0.7***	0.12*	-0.03	-0.04
	(0.008)	(0.005)	(0.007)	(0.008)	(0.12)	(0.07)	(0.09)	(0.13)
p90-40	11.9***	7.54***	9.24***	9.21***	-0.064	0.056	0.009	0.001
	(0.38)	(0.23)	(0.41)	(0.29)	(0.018)	(0.011)	(0.016)	(0.021)
p75-25	3.67***	2.96***	3.29***	3.22***	-3.26***	1.29***	0.51	-1.46***
	(0.14)	(0.02)	(0.06)	(0.08)	(0.45)	(0.50)	(0.48)	(0.43)
				Urban				
Gini Coeff.	0.361***	0.413***	0.436***	0.407***	0.019*	0.029***	0.007	0.055***
	(0.014)	(0.006)	(0.009)	(0.006)	(0.011)	(0.008)	(0.011)	(0.013)
MLD: GE(0)	0.313***	0.292***	0.331***	0.290***	-0.036	0.041***	0.011	0.016
	(0.044)	(0.008)	(0.014)	(0.010)	(0.028)	(0.011)	(0.016)	(0.031)
Theil: GE(1)	0.27***	0.25***	0.28***	0.25***	-0.02	0.03	-0.03***	-0.02**
	(0.032)	(0.006)	(0.010)	(0.007)	(0.05)	(0.06)	(0.01)	(0.01)
p90-10	5.57***	7.05***	7.69***	7.02***	0.009	0.044***	0.066***	0.066***
	(1.10)	(0.24)	(0.50)	(0.41)	(0.013)	(0.011)	(0.017)	(0.017)
p75-25	2.29***	2.74***	2.75***	2.77***	1.13**	0.9**	1.92**	1.92**
	(0.06)	(0.04)	(0.06)	(0.11)	(0.61)	(0.44)	(0.87)	(0.87)

Note: bootstrap standard errors in brackets; *, **, *** significant at 10%, 5% and 1% respectively

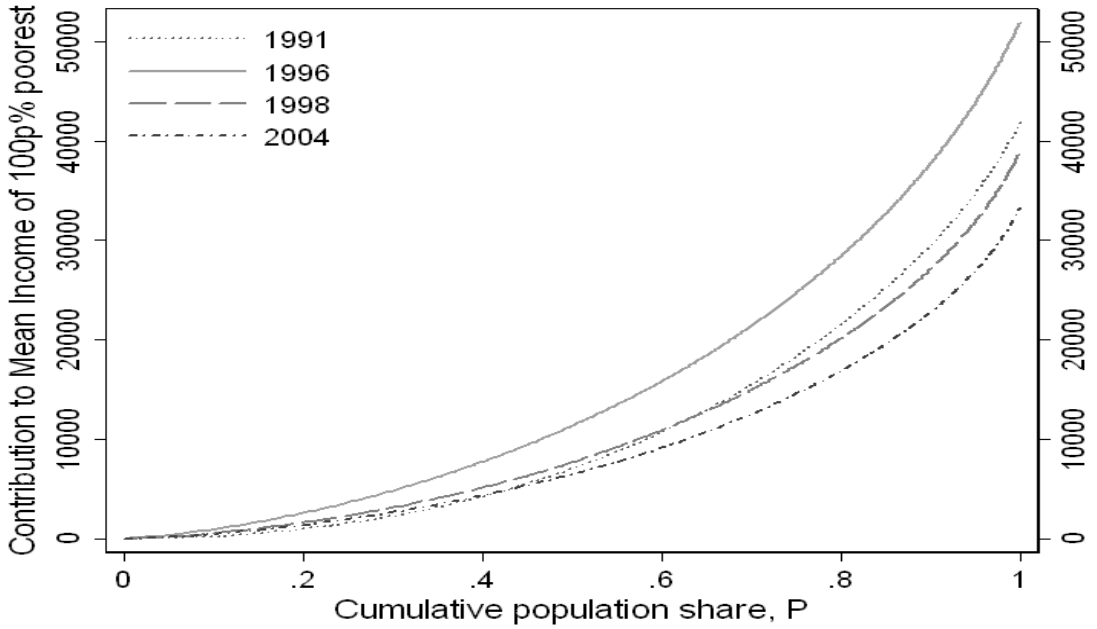

Figure 2.5: Generalized Lorenz Curves 1991-2004

is an increase.

2.5 Measurement and Ordinal Ranking of Poverty

We now move on to examine changes in poverty over time. We show how the distribution of wellbeing has changed over the period in figure 2.6. The figure shows the cumulative distribution functions of equivalized real consumption for households in 1991, 1996, 1998 and 2004. In general, especially around the two national poverty lines of ZMK32232.85 and ZMK 46271.39, there was an improvement in the distribution between 1991 and 1996 since the 1996 cumulative distribution lies below the 1991 cumulative distribution. The cumulative distribution of equivalent real consumption for 2004 lies above that of 1998 and 1996 while that of 1998 lies above the 1996 distribution. It is also clear that at lower levels of the distribution these cumulative distributions do intersect. But within the lower and upper poverty lines, we know that we will record a worsening of measured poverty between 1996 and 1998 and between 1998 and 2004. We use two poverty lines and the FGT class of poverty measures.

The majority of the people in Zambia live below the national poverty line. The depth and severity of poverty as measured by the poverty gap and the squared poverty gap is also high. Table 2.3 shows that poverty initially reduced between 1991 and 1996 and then started to increase. At national level, the head count poverty reduced from 62.8 percent in 1991 to 54.9 percent in 1996 and then increased to 69 percent and 76.4 percent in 1998 and 2004 respectively. The poverty gap, FGT(2), decreased from 35.9 percent in 1991 to 24.5 percent in 1996 then increased to 36 percent and 42.4 percent in 1998 and 2004 respectively. The movement of the squared poverty gap follows that of the other two measures. Looking at the overall period 1991 to 2004, we see that the head count increased by 0.134 points, the poverty gap by 0.078 points and the squared poverty gap by 0.042 points. These differences are all significant at 1 percent level. This clearly shows by how much poverty has increased over the time under consideration. However, as already mentioned earlier these results may be sensitive to choice of index used and also poverty lines used. Hence the need for a more robust analysis done later in this chapter.

Moving on to rural-urban distribution of poverty, we find that poverty in Zambia is largely a rural phenomenon. In 1991, 86.8 percent of the people residing in rural areas lived below the national poverty line while 34.7 percent of those in urban areas were poor. For rural areas, the head count poverty reduced in 1996 but then started increasing in 1998 till 2004. Over the period 1991 to 2004, there is an overall reduction of 2.7 percent in the head count poverty, a 3.6 percent and 3.7 percent decrease in poverty gap ratio and squared poverty ratio respectively. It is important to mention

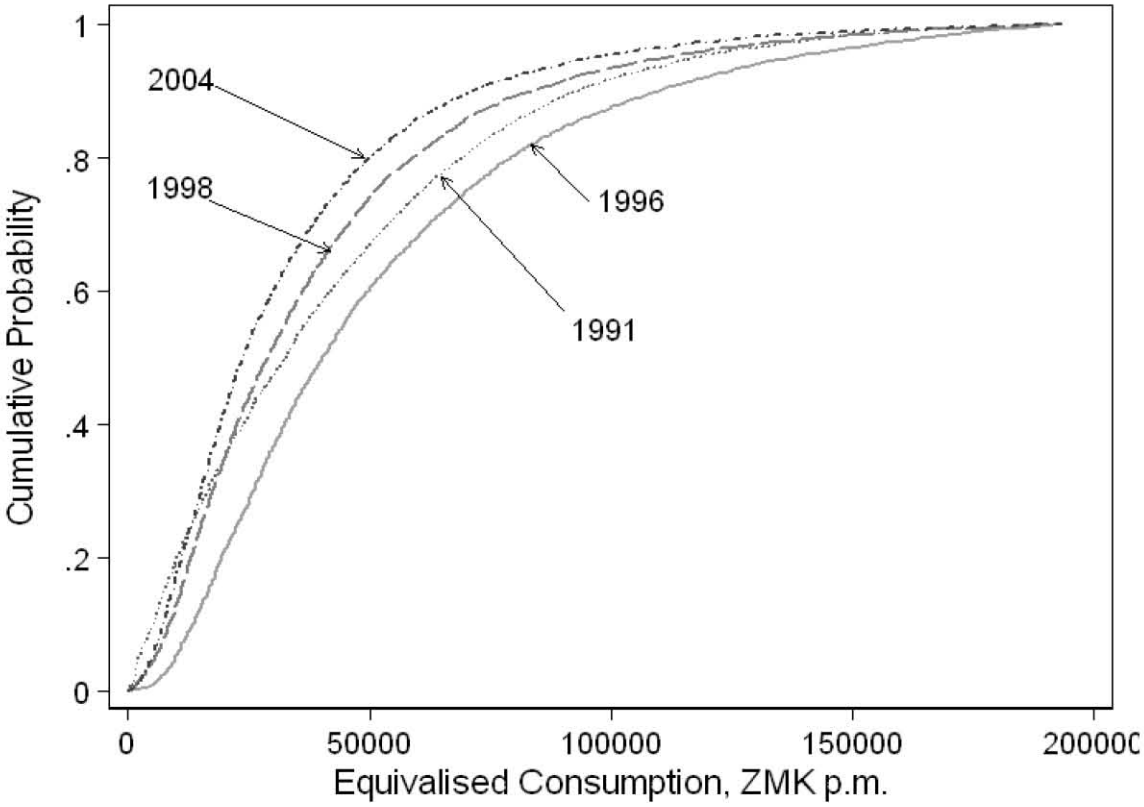

Figure 2.6: Cumulative Distribution Functions 1991-2004

that though the there is an apparent declining trend in rural poverty the changes are statistically insignificant suggesting that rural poverty has essentially remained high over the period.

On the contrary, urban areas have seen an increase in poverty levels over the period 1991 to 2004. Over this period, there is an overall increase of 30 percent in the head count poverty, a 18.5 percent and 11.4 percent increase in the poverty gap and squared poverty gap respectively. This suggests that the structural adjustment and macroeconomic policies of the 1990s affected people in urban areas more than those in rural areas.

2.5.1 Poverty Dominance

Since we are interested in the distribution of poverty between 1991 and 2004, our primary question is whether poverty has increased or not between the two years. We first look at the poverty incidence curve in Figure 2.8. Clearly, the figure shows that there was no first order stochastic dominance because the poverty incidence curves intersect. In a complementary way we see that the FGT($\alpha = 0$) Foster et al. (1984) curves of 1991 and 2004 do intersect. The difference between the curves is shown in Figure 2.9. The FGT($\alpha = 0$) curves of 1991 is below that of 2004 at poverty lines below ZMK15000 and above at higher poverty lines. This suggests that the headcount poverty is higher in 1991 than in 2004 for poverty lines below ZMK15000 and the reverse is true for higher poverty lines. An interesting feature is that, though poverty is higher in 2004 than 1991 at poverty levels higher than ZMK15000, the difference is highest between the two national poverty lines of ZMK32,232 and ZMK46,271. At higher poverty lines than ZMK46,271 the gap between the two headcount poverty narrows. With this, we are unable to rank wether poverty did increase or decrease between 1991 and 2004. Failure to establish first order poverty dominance suggests moving to assess second order dominance. One way of doing this is by examining poverty deficit curves. If these intersect, then one would go on to examine third order dominance by looking at whether poverty severity curves do intersect or not. Alternatively to examining curves one would carry out formal poverty dominance tests as presented in Appendix A.5. In that appendix, it is found that poverty dominance between 1991 and 2004 is not achieved up to third order.

Table 2.4 shows the results of the poverty dominance tests of order 1 for 1991 and 2004 distributions, as explained in section 2.2. The first column shows the selected poverty lines from a minimum of ZMK7, 788 to a maximum of ZMK100,000 in 1998 prices. This range was chosen because both the national (lower) food poverty line and the higher poverty line fall in this range. Additionally, the usually quoted US$1/day

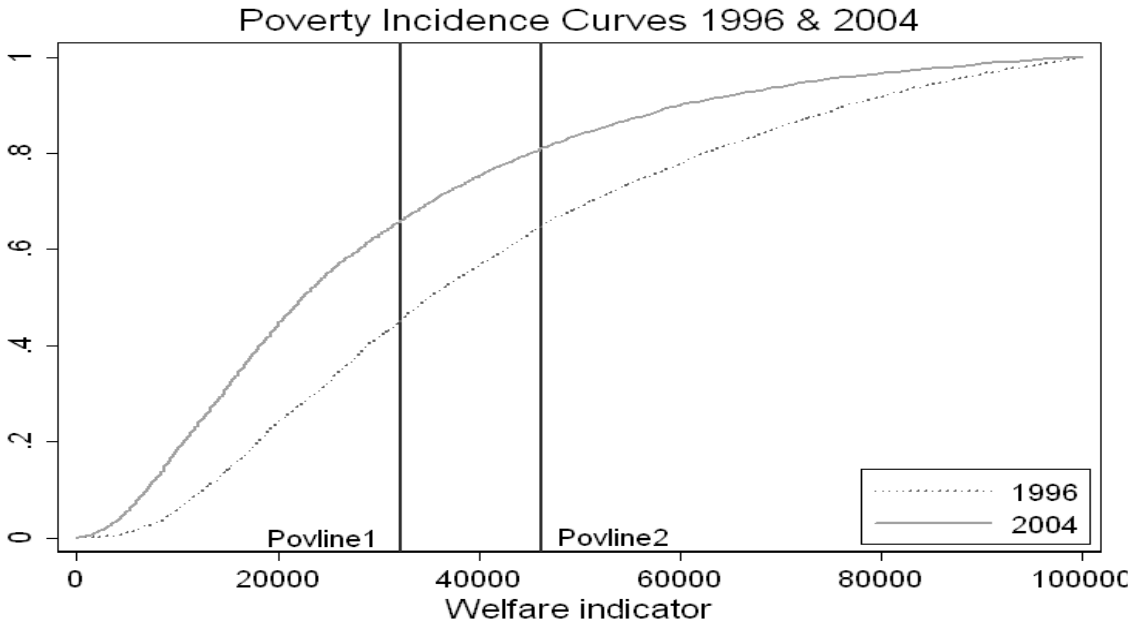

Figure 2.7: Cumulative Distribution Functions 1991-2004

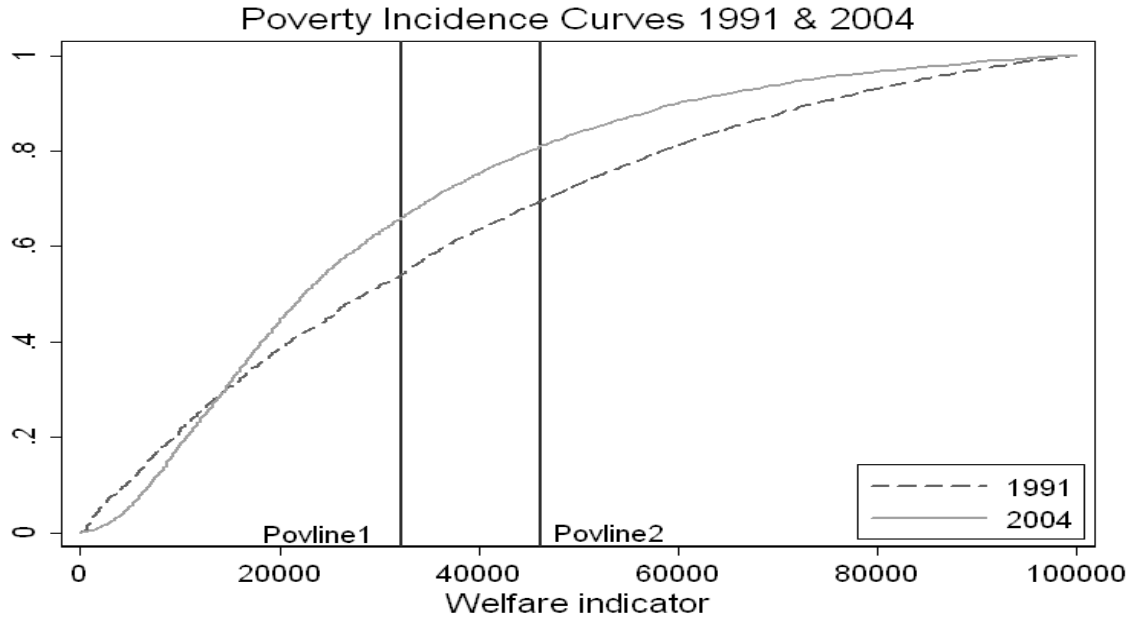

Figure 2.8: Cumulative Distribution Functions 1991-2004

Table 2.3: Poverty Measures 1991-2004 the Poverty Line- ZMK46271.49 in 1991 prices

	Actual Measures				**% Change**			
Statistic	1991	1996	1998	2004	1991/96	1996/98	1998/04	1991/04
National								
FGT (0)	0.628	0.549	0.686	0.764	-0.070***	0.100***	0.104***	0.134***
	(0.009)	(0.014)	(0.016)	(0.013)	(0.017)	(0.021)	(0.019)	(0.015)
FGT(1)	0.359	0.245	0.360	0.424	-0.103***	0.088***	0.093***	0.078***
	(0.007)	(0.0078	(0.014)	(0.012)	(0.010)	(0.015)	(0.017)	(0.013)
FGT(2)	0.254	0.140	0.233	0.282	-0.106***	0.072***	0.076***	0.042***
	(0.006)	(0.005)	(0.011)	(0.010)	(0.006)	(0.011)	(0.014)	(0.011)
Rural								
FGT(0)	0.868	0.678	0.786	0.851	-0.182***	0.079	0.076	-0.027**
	(0.008)	(0.007)	(0.006)	(0.008)	(0.011)	(0.446)	(0.446)	(0.012)
FGT(1)	0.549	0.319	0.450	0.515	-0.224***	0.101***	0.087***	-0.036***
	(0.006)	(0.003)	(0.007)	(0.010)	(0.006)	(0.008)	(0.014)	(0.013)
FGT(2)	0.399	0.186	0.303	0.359	-0.208***	0.091***	0.08	-0.037
	(0.004)	(0.003)	(0.006)	(0.010)	(0.005)	(0.007)	(0.100)	(0.100)
Urban								
FGT(0)	0.347	0.294	0.520	0.633	-0.043*	0.181***	0.162***	0.3***
	(0.013)	(0.017)	(0.012)	(0.013)	(0.025)	(0.025)	(0.014)	(0.015)
FGT(1)	0.137	0.099	0.212	0.287	-0.025*	0.095***	0.115***	0.185***
	(0.015)	(0.007)	(0.008)	(0.008)	(0.014)	(0.011)	(0.011)	(0.014)
FGT(2)	0.085	0.047	0.116	0.166	-0.026**	0.06***	0.08***	0.114***
	(0.014)	(0.004)	(0.005)	(0.006)	(0.012)	(0.007)	(0.009)	(0.013)

Note: 1) Own calculations using 1991 priority survey, 1996, 1998 and 2004 Living Conditions Monitoring Surveys

2) Bootstrap standard errors in brackets

*3) * Significant at 10 %, ** significant at 5 %, *** significant at 1%*

Figure 2.9: Difference in FGT(alpha=0) Curves 1991-2004

poverty line would translate to slightly over ZMK55,000 in 1998 prices.

Column 2 gives the head count poverty in 1991 at designated poverty lines while column three shows the poverty headcounts for 2004. The fourth column gives the t-statistic of the difference between the two poverty head counts at the designated poverty line. Columns five to eight are a continuation of the table from poverty line ZMK55,076 to ZMK100,000. If we set the minimum level of significance to 5 percent which gives us a standard normal critical value of -1.65. Based on this, we can conclude that in the range [ZMK24,339 ZMK100,000] the poverty incidence curve of 2004 dominates that of 1991 which implies that the head count poverty in that range is unambiguously higher in 2004 than it was in 1991. What is interesting is that this range where poverty in 2004 dominates poverty in 1991 also encompasses the range of national poverty lines which is ZMK32, 232.85 and ZMK46, 271.39. We can thus conclude that poverty unambiguously increased in this range [11].

An interesting period is that between 1996 and 2004. As we have observed above, the FGT indices show that poverty increased from 1996 and 2004. The poverty incidence curves are shown in Figure 2.10. These curves do not intersect which suggests that the poverty incidence curve of 1996 stochastically dominates that of 2004. The tests in table 2.5 show that indeed there is first order dominance. This implies that

[11] In Appendix A.5 we show that there is no poverty dominance up to third order for the distribution of welfare between 1991 and 2004.

Table 2.4: First order poverty dominance tests 1991 and 2004

Poverty line	$\widehat{F}_{1991}(z)$	$\widehat{F}_{2004}(z)$	$t_{\widehat{F}_{1991}(z)-\widehat{F}_{2004}(z)}$	Poverty line	$\widehat{F}_{1991}(z)$	$\widehat{F}_{2004}(z)$	$t_{\widehat{F}_{1991}(z)-\widehat{F}_{2004}(z)}$
7,788	0.15	0.11	1.52	55,076	0.70	0.82	-2.59***
10,152	0.20	0.18	0.56	57,441	0.71	0.83	-2.58***
12,517	0.24	0.23	0.06	59,805	0.73	0.85	-2.65***
14,881	0.27	0.29	-0.37	62,169	0.75	0.86	-2.60***
17,246	0.31	0.35	-0.83	64,534	0.76	0.87	-2.61***
19,610	0.34	0.41	-1.06	66,898	0.77	0.87	-2.61***
21,974	0.37	0.46	-1.40	69,263	0.79	0.88	-2.59***
24,339	0.40	0.51	-1.74*	71,627	0.80	0.89	-2.50**
26,703	0.43	0.55	-1.75*	73,991	0.81	0.90	-2.48**
29,068	0.46	0.58	-1.89*	76,356	0.82	0.90	-2.47**
31,432	0.48	0.61	-2.06**	78,720	0.83	0.91	-2.40**
33,796	0.51	0.64	-2.11**	81,085	0.84	0.91	-2.39**
36,161	0.54	0.67	-2.13**	83,449	0.85	0.92	-2.36**
38,525	0.56	0.69	-2.16**	85813	0.86	0.92	-2.24**
40,890	0.58	0.72	-2.29**	88,178	0.87	0.93	-2.23**
43,254	0.60	0.74	-2.39**	90,542	0.88	0.93	-2.23**
45,619	0.62	0.76	-2.43**	92,906	0.88	0.93	-2.16**
47,983	0.64	0.78	-2.50**	95,271	0.89	0.94	-2.14**
50,347	0.66	0.79	-2.53**	97,635	0.90	0.94	-2.09**
52,712	0.68	0.81	-2.54**	100,000	0.90	0.94	-2.04**

note: * significant at 10 percent

** significant at 5 percent

*** significant at 1 percent

Table 2.5: First order poverty dominance tests 1996 and 2004

Poverty line	$\widehat{F}_{1996}(z)$	$\widehat{F}_{2004}(z)$	$t_{\widehat{F}_{1996}(z)-\widehat{F}_{2004}(z)}$	Poverty line	$\widehat{F}_{1996}(z)$	$\widehat{F}_{2004}(z)$	$t_{\widehat{F}_{1996}(z)-\widehat{F}_{2004}(z)}$
7,788	0.03	0.11	-5.10***	55,076	0.61	0.82	-5.08***
10,152	0.05	0.18	-4.98***	57,441	0.63	0.83	-5.22***
12,517	0.08	0.23	-4.88***	59,805	0.64	0.85	-5.29***
14,881	0.12	0.29	-4.88***	62,169	0.66	0.86	-5.22***
17,246	0.15	0.35	-4.98***	64,534	0.68	0.87	-5.26***
19,610	0.19	0.41	-4.86***	66,898	0.69	0.87	-5.20***
21,974	0.23	0.46	-5.15***	69,263	0.71	0.88	-5.17***
24,339	0.26	0.51	-5.39***	71,627	0.72	0.89	-5.25***
26,703	0.30	0.55	-5.41***	73,991	0.73	0.90	-5.20***
29,068	0.34	0.58	-5.20***	76,356	0.74	0.90	-5.11***
31,432	0.36	0.61	-5.34***	78,720	0.76	0.91	-5.06***
33,796	0.40	0.64	-5.29***	81,085	0.77	0.91	-5.06***
36,161	0.43	0.67	-5.12***	83,449	0.78	0.92	-4.94***
38,525	0.45	0.69	-5.09***	85813	0.79	0.92	-4.95***
40,890	0.48	0.72	-5.22***	88,178	0.79	0.93	-5.02***
43,254	0.51	0.74	-5.18***	90,542	0.80	0.93	-5.02***
45,619	0.53	0.76	-4.98***	92,906	0.81	0.93	-5.05***
47,983	0.56	0.78	-4.95***	95,271	0.81	0.94	-5.09***
50,347	0.57	0.79	-5.07***	97,635	0.82	0.94	-5.10***
52,712	0.59	0.81	-5.10***	100,000	0.83	0.94	-5.04***

note: *** significant at 1 percent

Dominance achieved at order 1

Therefore the poverty incidence curve for 1996 dominates that of 2004 for poverty lines ZMK 7,788 to ZMK100,000

the head count, poverty gap and squared poverty gap indices will all be higher in 2004 than in 1996. It also implies that poverty generally increased from 1996 to 2004 and it gives the basis for the poverty modelling in chapter 4 which focuses on the period 1991 to 2004. Two reasons underpin the focus on 1991 and 2004. The first reason is that the year 1991 is when Zambia had its first nationally representative survey capturing living conditions. The second reason is that looking at the trends in poverty laid out in this chapter, one concludes that there was an upward trend in poverty over the entire period even though minor fluctations could be seen from one year to another.

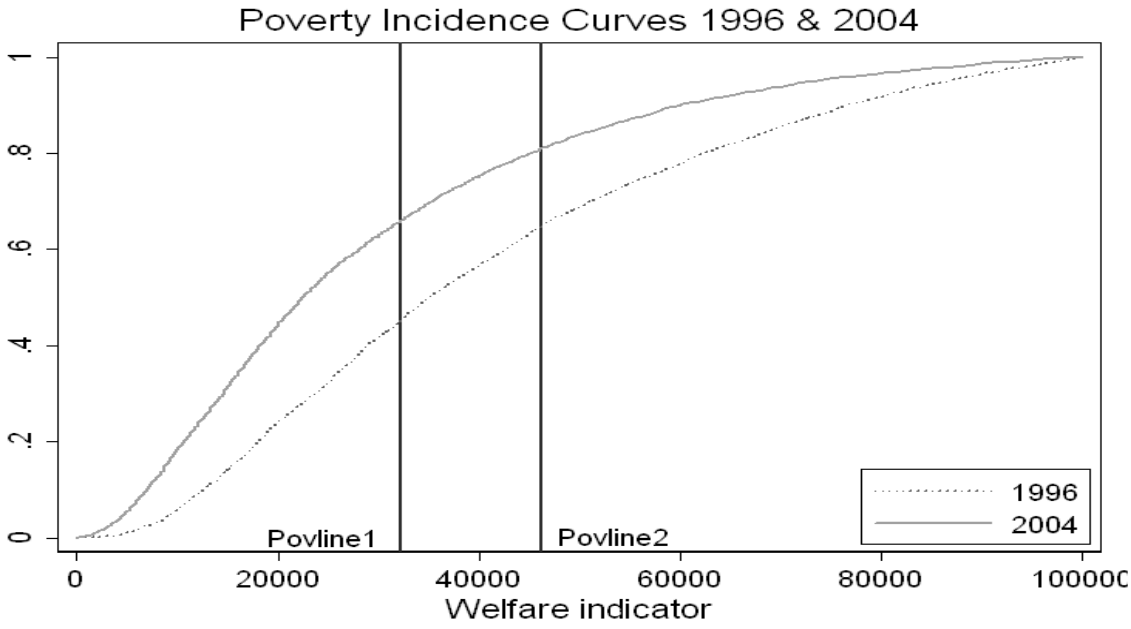

Figure 2.10: Cumulative Distribution Functions 1991-2004

2.6 Conclusion

Zambia is a dual economy that has a traditional agricultural sector and an advanced industrial sector that relies heavily on the copper sector. The over reliance of the country on the copper sector has caused the economy to swing with the fluctuations in the copper prices and production. Poverty reduction remains a central part of development policy but this will only be achieved if the agricultural sector is modernized to the extent that it can provide livelihoods for the majority of the poor who currently reside in the rural area.

The chapter shows the profile of poverty and inequality in Zambia for 1991 to 2004. Using comparable survey data, it is found that inequality at national level decreased while poverty increased over the period. The Gini coefficient, the Mean Logarithmic Deviation (MLD) and the Theil index all show a statistically significant decline over the period 1991 to 2004. On the other hand, the head count (FGT(0)), the poverty gap (FGT(1) and the squared poverty gap (FGT(1)) all show an increase between 1991 and 2004. In between the period, it is found that poverty reduced slightly between 1991 and 1996. It has since shown that poverty has had an upward trend despite the sustained economic growth the country registered for 2002 onwards. Although poverty dominance could not be established up to third order, using restricted poverty dominance it is found that poverty increased between 1991 and 2004 within reasonable bounds which include the lower and upper national poverty lines.

Furthermore, it is found that poverty is largely a rural phenomenon with over 86.8 percent of the rural people living below the poverty national poverty line. Like poverty, inequality is shown to be higher in rural than in urban areas. This could be attributed to the coexistence of commercial farms and peasants in most rural parts especially those along the line of rail. Over time rural poverty has been declining while urban poverty has been on the increase.

In sum then, in this chapter we have presented the data sets that form the basis for comparison of changes in Zambian inequality and poverty over time. Money-metric well-being is measured using monthly consumption and we have spelt out the assumptions necessary to make the key consumption variable comparable over time. Then, on the basis of these comparable data sets we have shown that inequality has decreased and poverty has increased within reasonable bounds of poverty lines. We established that these changes are robust. This is the first robust profile of changes in Zambian inequality and poverty from 1991 to 2004. In the remainder of this thesis we will go on to interrogate the factors driving the decrease in inequality in chapter 3, and the increase in poverty in chapter 4.

Chapter 3

The Effect of Changes in Education and Employment on Inequality

3.1 Introduction

This chapter examines the effect of education and employment on the distribution of economic well-being in Zambia. As we discussed in detail in the previous two chapters, following a period of structural adjustment and macroeconomic reform in the 1990s, the country experienced an increase in poverty and a decrease in inequality (McCulloch et al., 2000). The decrease in inequality was particularly substantial between 1991 and 1996 and then more moderate between 1996 and 2004. Poverty has shown a continued increase despite the economy registering sustained growth from the year 1998.

Earlier research on inequality in Zambia was largely focused on these measurement issues at both national and regional levels (McCulloch et al., 2000; GRZ, 2004). There is also a literature analyzing the relationship between inequality, growth and poverty (Mulenga and Campenhout, 2008; Thurlow and Wobst, 2004). However, there continues to be a gap in the analysis of sources of this decline in inequality. The main purpose of this chapter is to bridge this gap and give indications of the key factors that have driven this inequality.

To explain changes in inequality, empirical studies rely on decomposition methods. There are several of these methods. For example, one can decompose inequality measures by population subgroup or by income source (Shorrocks, 1984; Shorrocks, 1982) or can use regression-based decompositions that allow to distinguish across the contributions of multiple and correlated determinants. All these methods however suffer from one major setback- they rely on the decomposition of a particular inequality measure such that, in certain instances, different inequality measures can result in different conclusions. Moreover, it is hard to tell how different explanatory factors affect

different parts of the whole distribution(Cameron, 2000).

With this weakness of decomposition methods that rely on summary measures of inequality, other methods based on density decomposition have been developed. These include the semi parametric kernel density re-weighting method (Dinardo et al., 1996) and the density decomposition by population subgroups (Jenkins and Kerm, 2004). This chapter uses the semi parametric method first introduced by Dinardo et al. (1996). The method allows for visual results on how each explanatory factor impacts on the distribution of real equivalent consumption.

The analysis in this chapter focuses on the period 1991 to 2004 for several reasons. Firstly, 1991 is taken as the base year because this was when government changed from a one party state to a multi party democratic system. The change in government meant major shift in policy orientation from a command-driven economy to a liberalized economy that became largely market-driven. Secondly, a decline in inequality and increase in poverty is observed between 1991 and 1996 and then a moderate decline in inequality with continued rise thereafter.

Structural adjustment programmes of the 1990s involved a wide range of policies including liberalization of agriculture through removal of subsidies and introduction of private-driven marketing, liberalization of external trade through harmonization and reduction of tariffs, privatization of state-owned enterprises, public sector downsizing through retrenchments and the introduction of user fees for education and health (McCulloch et al., 2000). All this was done with the goal of promoting economic growth and development but might have been done too fast to allow a smooth transition thereby resulting in job losses, reduced access to education and health services and increased poverty.

The chapter proceeds as follows: Section 3.2 introduces the data used in this chapter and borrows heavily from chapter 2; Section 3.3 outlines the decomposition methodology used in the chapter; Section 3.4 presents the results of the analysis in this chapter; And finally section 3.5 summarizes and concludes the chapter.

3.2 Data and Household Characteristics

The chapter uses data from three nationally representative household surveys generated by the central statistical office. These surveys include the 1991 Social Dimension of Adjustment (SDA) Priority Survey, the 1996 living conditions monitoring survey I, and the 2004 living conditions monitoring survey IV.

As discussed in detail in chapter 2, consumption questions in the three surveys remained generally the same but the 1991 survey did not collect data on own con-

sumption. So when comparing consumption between 1991 and 2004 , only cash consumption is used in the decomposition. The same applies to the sub-period decomposition between 1991 and 1996. On the other hand, the sub-period decomposition between 1996 and 2004 uses a consumption aggregate that includes own consumption and cash consumption. This is justified on account that there is comparable cash and own consumption data for the period. Nonetheless sensitive results using only cash consumption yielded very similar results.

Before looking at changes in average household education and the proportion of household members involved in the formal sector, we look at household characteristics of the head of household since these are closely related. Table 3.1 shows individual household head and household characteristics for each of the years 1991, 1996 and 2004. There are several observed changes in characteristics that are worth noting and that may be key in explaining the changes in the distribution of well-being in Zambia. The first is that the proportion of households with heads that have tertiary education has increased with a difference of 4 percent between 1991 and 2004. And, the proportion of primary education and lower decreased by 6 percent. However, the proportion of primary education or lower still remains over 50 percent. An analysis of the mean number of years of schooling of the household head by consumption deciles shows that the average years of schooling of household heads in the first decile decreased by 7 percent from 6.4 years in 1991 to 6.0 years in 2004. For the second, third and fourth consumption deciles the mean years of schooling for household heads increased by 18.2 percent, 22.4 percent and 22.4 percent for 1991, 1996 and 2004 respectively. In the four upper consumption deciles average years of schooling in each increased by less or equal to 10 percent.

These education distribution changes may have had an effect on consumption distribution. Nielson and Westergard-Nielson (2001) found that returns to primary schooling in Zambia were positive in rural areas and nil in urban areas. Given that the majority of the households in the bottom 3 deciles live in the rural areas and acquire primary education, a positive return would improve their welfare. This may not be true in urban areas (Nielson and Westergard-Nielson, 2001). Therefore the improvement in the average years of schooling in the lower deciles could have contributed to reduced consumption inequality. Depending on how big the return to primary education is in rural areas, it would be plausible to hypothesize that the changes in the distribution of education with large increases in the lower tail of the consumption distribution and less so in the upper tail would contribute to inequality reduction.

Looking at increases during two sub periods, 1991 to 1996 and 1996 to 2004, gives further insights into how education changed in relation to the consumption distribu-

tion. There was not much difference in terms of changes in the education proportions in the lower and top deciles, between 1991 and 1996. In the bottom and second bottom deciles, the average years of schooling declined by 1.9 and 2.3 percent respectively. Similarly in the top decile, education fell by 3.1 percent while for the third decile education increase was close to zero. Looking at the changes in the same education categories between 1996 and 2004 and by quintiles we generally see a similar pattern. Households in the 4 lower deciles recorded increases in average years of schooling of not less than 14 percent while the three of the top four deciles showed an increase in education of not more than 5.8 percent.

The proportion of household heads engaged in self-employment increased from 59.7 percent in 1991 to 68.4 percent in 1996 and further to 72.2 percent in 2004. This accounts for a total increase of 12.5 percentage points. On the contrary, the proportion of household heads employed in government and parastatal sectors each declined while the private sector proportion increased marginally. These changes reflect the structural changes the economy went through during the period. With intensified implementation of structural adjustment from 1991, the Zambian economy registered a reduction in formal employment largely due to the liquidation of some key parastatal firms, retrenchments in the public sector and employment restructuring in most firms so as to cope with increased competition resulting from trade liberalization.

To gain a further understanding of the possible effects of employment on welfare, the study looks at employment patterns across consumption quintiles and over the three years of interest. The first striking finding is that the majority of households in the lower quintiles are engaged in self employment while less than 50 percent of those in the top quintile are in self employment. Of the households in the lower quintile, 76.9 percent had a household head in self employment in 1991. This proportion increased to 93.3 percent in 1996 and further to 95.4 percent in 2004. There was a steady increase in self employment in the upper quintile. Of the households in the 5^{th} consumption quintile, the proportion of self employed increased from 26.4 percent in 1991 to 37.7 in 1996 and further to 41.3 in 2004. The proportion of household heads employed in the public sector declined in all the quintiles. However, the decline was higher in the bottom quintile than in the top quintile. Between 1991 and 1996 the proportion of public sector employed heads decreased by 82.1 percent in the 1^{st} quintile and by 32.3 percent in the 5^{th} quintile. But between 1996 and 2004, the decline was just about the same.

Although the proportion of household heads employed in the private sector is a small proportion, there are some important changes that are worth noting. The proportion of privately employed household heads showed a decreasing trend in the 1^{st}

quintile, no trend for the 2^{nd} quintile and an increasing trend in the 4^{th} and 5^{th} quintiles. Nielsen and Rosholm (2001) found that between 1991 and 1996, wages in Zambia were higher in the public sector than in the private sector and that the public sector wage premium increased the most in the bottom percentiles. This may entail an improvement in the welfare of a number of households in the upper quintile with worsening conditions for most households who were losing jobs in the public and private sectors.

Furthermore, there was a significant increase in the number of households residing in rural areas and this increase is higher between 1991 and 1996. The change in movement of people from urban to rural area especially between 1991 and 1996 is cited by Mulenga and Campenhout (2008) as a key mitigating factor for the majority of households whose heads lost jobs during the economic restructuring period.

In terms of capturing the education endowment of adult members of a household, we get the average years of education in the household and then partition that into years 1-7 years, 8-12 years and above 12 years of average education endowment in the household. Also the employment variable is redefined in line with the aim of capturing the household employment endowment. In this regard, we take the number of household members employed in the formal sector which includes private and public sector. Since much of the change is in the proportion of employees in the public sector, this variable captures more of the variability in public sector employment. From this new employment variable, we include a new dummy variable of employment which is equal to 0 if the household has no one employed in the formal sector, 1 if only one is employed, 2 if only two employed and 3 if 3 or more members of a household are employed in the formal sector. Results of these new education and employment dummy variable are shown in Table B.1.1 in appendix B.1. From the table we see that the proportion of households with average education below 7 years decreased by 13 percent between 1991 and 2004. Over 60 percent of these households reside in rural areas and are in the first and second deciles. In contrast, households with average education between 8 and 12 years increased by 9 percent while those with over 12 years increased by 4 percent. Thus, like the education level of the household head, we see a decrease of households with low average education endowments and an increase in those with high endowments. In case of the distribution of average education of households, we find that average education in the 1^{st} quintile increased more than those in the 4^{th} and 5^{th} quintiles.

Table B.1.1 also shows that the proportion of households with no member working in the formal sector increased from 61 percent in 1991 to 75 percent in 2004. This represents an increase of 14 percent. On the other hand, the proportion of households

with one household member employed in the formal sector decreased by 15 percent over the same period. The proportion of households with two members engaged in the formal sector increased marginally by 1 percent.

This section identifies key changes in education and employment variables that might have an effect on the distribution of household welfare and likely explain the changes in the decline of inequality over the years. The next subsection presents the decomposition method the study uses in this chapter.

Table 3.1: Changes in Household Head and Household Characteristics 1991-2004

	Actual Proportions			**Differences**		
	1991	1996	2004	1996-1991	2004-1996	2004-1991
Education of household head						
Primary	0.576	0.588	0.499	0.012	-0.089	-0.077
	(0.043)	(0.040)	(0.047)	(0.059)	(0.062)	(0.064)
Secondary	0.388	0.348	0.425	-0.04	0.077	-0.037
	(0.037)	(0.032)	(0.035)	(0.049)	(0.047)	(0.051)
Tertiary	0.036	0.064	0.077	0.028	0.013	-0.041
	(0.009)	(0.010)	(0.106)	(0.013)	(0.106)	(0.106)
Employment of household head						
Self Employed	0.595	0.681	0.716	0.086	0.035	0.121
	(0.056)	(0.049)	(0.052)	(0.074)	(0.071)	(0.076)
Public Sector	0.271	0.164	0.108	-0.107	-0.056	-0.163
	(0.045)	(0.028)	(0.019)	(0.053)	(0.034)	(0.049)
Private Sector	0.105	0.134	0.129	0.029	-0.005	0.024
	(0.017)	(0.022)	(0.027)	(0.028)	(0.035)	(0.032)
Other	0.029	0.021	0.047	-0.008	0.026	0.018
	(0.005)	(0.003)	(0.008)	(0.006)	(0.008)	(0.009)
Area						
Rural	0.571	0.652	0.614	0.081	-0.038	0.043
	(0.087)	(0.083)	(0.110)	(0.120)	(0.138)	(0.140)
Urban	0.429	0.348	0.386	-0.081	0.038	-0.043
	(0.429)	(0.083)	(0.110)	(0.437)	(0.138)	(0.442)

Note: standard errors in brackets

3.3 Explaining Inequality: Methodology

The literature on inequality and poverty decomposition is so vast that it is not possible to give a review in this chapter[1]. One strand of literature decomposes income inequality by factor components to deduce the contribution of each factor to total inequality (Fei and Kuo, 1978; Pyatt, Chen and Fei, 1980; Shorrocks, 1982). Since this chapter focuses on decomposing consumption, this method is not appropriate here. A more relevant method to our problem is the one that decomposes a welfare measure by population subgroups following for example Shorrocks (1984). Under this method an index of inequality is decomposed into what is due to changes in the relative mean of various predetermined groups of individuals or households, what is due to changes in their population weights and a residual attributed to inequality within those groups (Bourguignon, Ferreira and Lustig, 2005). In recent literature these two methods have been found to be inadequate due to several reasons. First, the analysis in the two methods relies on summary measures of inequality that are likely to give different results with different inequality measures used (Cameron, 2000). Second, both methods fail to allow for controls. Third, in the case of decomposition by population subgroups, it is not possible to distinguish between changes in inequality due to the distribution of a particular attribute or due to market returns of the same attribute (Bourguignon et al., 2005).

Fields (2003) and Morduch and Sicular (2002) are some of the studies that have applied regression-based decomposition methods in order to overcome some of these weaknesses. However, the method used in this chapter falls in the broad category of studies that seek to decompose the whole distribution. This method can be done parametrically for example Bourguignon et al. (2005) or by non- or semi-parametric methods, for example Dinardo et al. (1996).

Due to a number of reasons, this study uses the semi parametric re-weighting method following Dinardo et al. (1996) hereafter referred to as the DFL method. Unlike other methods, the DFL does not rely on a specific measure of inequality which sometimes may lead to varying results depending on the inequality measure used (Cameron, 2000). In addition, using DFL, the analyst is able to determine how different factors affect different parts of a distribution of interest (Dinardo et al., 1996). Further, the analysis does not rely on the imposition of any functional form allowing the data to speak for itself. Nonetheless, using the DFL re-weighting method has one major disadvantage. DFL re-weighting requires a parsimonious model thereby limiting the number of explanatory factors that can be analyzed individually. Despite

[1]For a recent survey of inequality decomposition see Heshmati (2004).

this limitation, the method still gives good insights on how explanatory factors may affect a distribution of interest rendering some relevant policy options.

The appeal of the DFL method has led to its widespread use in wage and income distribution analysis and poverty analysis[2]. While the DFL method has found increased application in developed countries, its application in less developed countries particularly in Africa remains limited. Notable among the studies on Africa are the studies by Leibrandt, Levinsohn and McCrary (2010) which analyses the distribution of earnings in South Africa and Alwang et al. (2003) who study factors affecting the distribution of well-being as proxied by consumption in Zimbabwe. This study stands to contribute more evidence in this regard.

3.3.1 Changes in Consumption between 1991 and 2004

Following DFL, we define an individual observation as a vector (Y, Z, t), consisting of household equivalent consumption Y, a vector of characteristics Z and a year, t. Equivalent consumption in year t is expressed as:

$$f_t(Y) \equiv f(Y; t_Y = t, t_Z = t) \tag{3.1}$$

Each observation belongs to the joint distribution, $F(Y, Z, t)$ of equivalent consumption, attributes and date. The joint distribution of consumption and attributes at one point in time is the conditional distribution, $F(Y, Z|t_Y = t, t_Z = t)$. Then, the density of equivalent consumption in a given year is expressed as the integral of the density of equivalent household consumption conditional on a set of individual and household characteristics and on a date $t_Y = t$, $f(Y|Z, t_Z = t)$ over the distribution of individual and household characteristics, $F(Z|t_Z = t)$, at a date $t_Z = t$.

$$\begin{aligned} f(Y|t_Y = t, t_Z = t) &= \int_{Z \in \Omega_Z} f(Y|Z, t_Y = t)\, dF(Z|t_Z = t) \\ &\equiv f(Y; t_Y = t, t_Z = t) \end{aligned} \tag{3.2}$$

where Ω_Z is the domain of individual and household attributes, Z. In our application, Z is a vector of explanatory variables including education, employment states and socio-demographic attributes. Our estimation of counterfactual densities will be based on the last expression in 3.2. For example, $f(Y; Z, t_Z = 04, t_Z = 04)$ is the observed density of household equivalent consumption in 2004 but can equally be looked at as

[2] An example of the DFL use in income distribution globally are Hyslop and Mare (2005), Cameron (2000) and Daly and Valletta (2006)

A recent application on child poverty analysis in the USA is that by Chen and Corak (2008).

the density of equivalent consumption that would have prevailed in 2004 if the vector of attributes, Z, remained as in 2004. The same reasoning applies to the density $f(Y; Z, t_Z = 91, t_Z = 91)$ for 1991.

The vector of characteristics, Z, is divided into four explanatory variables including education (denoted E), employment states (denoted W), economic returns, (R) and socio-demographic attributes, a sub-vector X of exogenous continuous and discrete variables. With this sub-division of the Z matrix, the density of equivalent consumption in 2004 is:

$$f_{04}(Y) \equiv f\left(Y; t_Y = 04, t_{R|W,E,X} = 04, t_{W/E,X} = 04, t_{E|X} = 04, t_X = 04\right) \tag{3.3}$$

And that of 1991 is:

$$f_{91}(Y) \equiv f\left(Y; t_Y = 91, t_{R|W,E,X} = 91, t_{W/E,X} = 91, t_{E|X} = 91, t_X = 91\right) \tag{3.4}$$

Using these two densities, the changes between the two densities is the difference defined as:

$$\nabla f(Y) = f_{04}(Y) - f_{91}(Y) \tag{3.5}$$

Figure 3.1 presents the kernel density estimates of the distribution of equivalent real consumption over the period 1991 and 2004. Each density plot includes a 95 percent confidence interval. This shows that the two distributions are statistically different. Both distributions are skewed to the right. However the distribution of equivalent consumption in 2004 has a higher peak which can be a rough indication that inequality reduced over the two periods. The figure reveals that the left tail of the 2004 distribution has less mass compared to that of 1991. This may suggest that the proportion of people in extreme poverty in 2004 reduced (when the poverty line is below the mode).

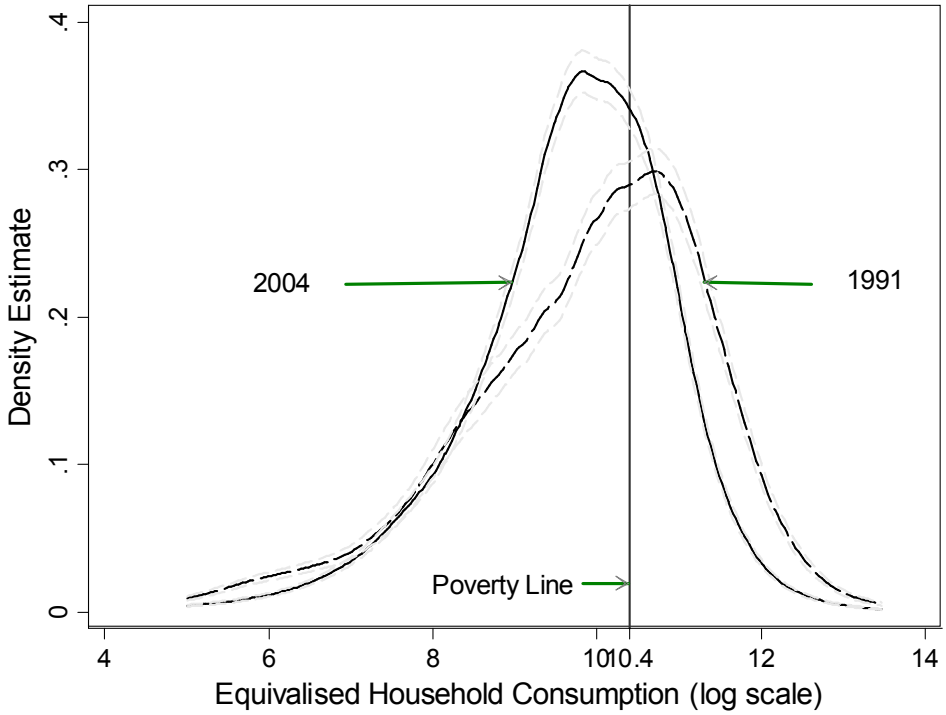

Figure 3.1: The Distribution of Real Consumption Expenditure 1991 and 2004

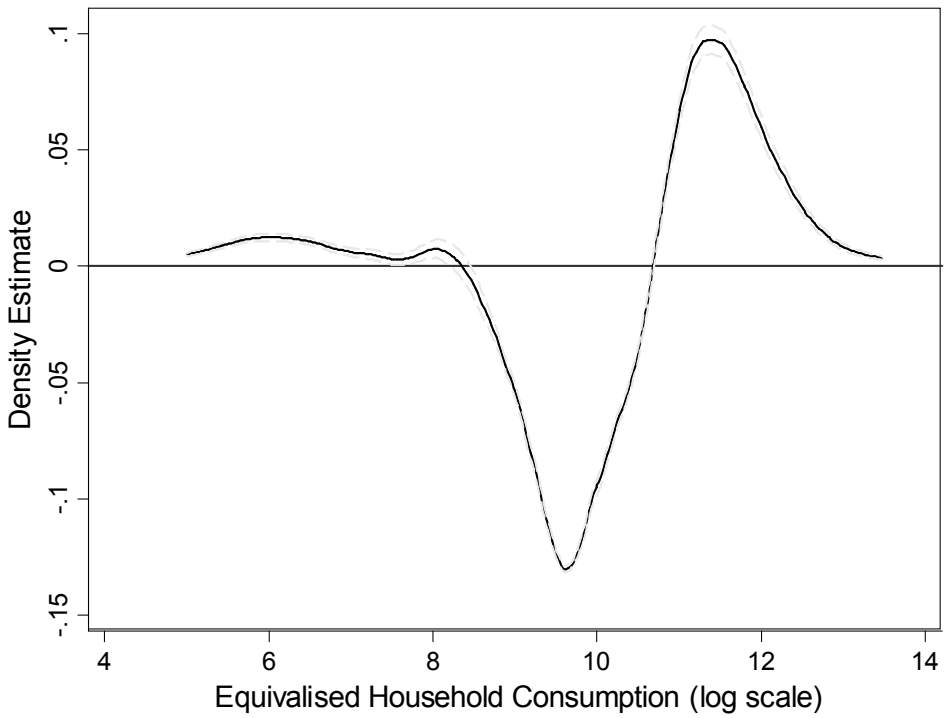

Figure 3.2: Real Consumption Expenditure Difference between 1991 and 2004

Figure 3.2 shows the difference between the two densities. It shows that slightly above 7.5 in log equivalent consumption, the 2004 density is below the 1991 density and between 7.5 and 10 the 2004 density is above the 1991 one. This is the difference that we seek to explain using density decompositions.

3.3.2 Decomposing Changes in Household Consumption: Primary Order

To do semi-parametric decompositions, studies have either made the explanatory variable into discrete categories or swapped the explanatory variable by ensuring rank preservation for example of wages between the two years of interest. As explained above, our key variables of education and employments are changed into categorical variables while the combined effect of other household attributes are continuous and dicrete. In addition, we analyze the combined effect of returns to these variables on the distribution of equivalent consumption. In the previous section, we showed that there have been notable changes in the distribution of consumption. But at the same time, we observe changes in the distribution of average education and the number of household members working in the formal sector. We now go further to define how we capture these key explanatory variables. We focus on these three due to parsimony in that more explanatory variables may make the analysis difficult.

- Education (E): The effect of changes in education is captured by looking at the average years of schooling of adult household members. Once this average for each household is calculated, we make the education variable discrete by forming a dummy variable with three categories as follows: category 1- the average education of adult household members is 7 years or below; category 2 - average adult household education is between 8 years and 12 years inclusive; and 3 average household education is above 12 years. We assume that capturing education in this manner makes the variable capture the education endowments of the whole household as opposed to the head of household alone. Nonetheless, in the course of this study we also composed education as only the level of schooling of the head of household. Glewwe (1991) argues that education like other household composition variables are a predetermined factor and so not a strictly exogenous factor with respect to household welfare. We thus can only interpret the changes in welfare distribution conditional on education which is a predetermined factor.

- Employment sector (W): The effect of employment is captured by looking at employment in the formal and informal sector. The formal sector includes the

government sector, parastatal sector and the formal private sector. All jobs that are offered outside these three sub-sectors are considered as being in the informal sector. To capture the household effects, the chapter focuses on the number of household members engaged in the formal sector. We thus make discrete the employment variable into four categories as follows: Category 1 - there is no one in the household employed in the formal sector; category 2 - there is one household member engaged in the formal sector; category 3 - there are two household members engaged in the formal sector and category 4 - there are 3 or more members of the household engaged in the formal sector.

- 'Economic returns' (R); Our formulation of the effect of economic returns follows Hyslop and Mare (2005). This variable accounts for the combined affect of returns to all our explanatory variables including education and employment sector. Later in section 3.3.2 we show how we compose changes in this variable. We feel that this variable may be important in explaining changes in welfare especially that changes in explanatory variables can be transmitted through two channels, endowments or returns. The only drawback is that it is not easy to separate the influence of changes in economic returns to a single variable.

To account for the marginal impact of each explanatory factor, the study follows Daly and Valletta (2006) by sequentially decomposing the changes in the difference between the two densities:

$$f_{91}(Y) - f_{04}(Y) = \left[\begin{array}{c} f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E|X} = 91, t_X = 91\right) \\ -f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E|X} = 91, t_X = 04\right) \end{array} \right] \tag{3.6a}$$

$$+ \left[\begin{array}{c} f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E|X} = 91, t_X = 04\right) \\ -f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E|X} = 04, t_X = 04\right) \end{array} \right] \tag{3.6b}$$

$$+ \left[\begin{array}{c} f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E|X} = 04, t_X = 04\right) - \\ f\left(Y; t_Y = 91, t_{W/E,X} = 04, t_{E|X} = 04, t_X = 04\right) \end{array} \right] \tag{3.6c}$$

$$+ \left[\begin{array}{c} f\left(Y; t_Y = 91, t_{W/E,X} = 04, t_{E|X} = 04, t_X = 04\right) - \\ f\left(\widehat{Y}^r; t_Y = 91, t_{W/E,X} = 04, t_{E|X} = 04, t_X = 04\right) \end{array} \right] \tag{3.6d}$$

$$+ \left[\begin{array}{c} f\left(\widehat{Y}^r; t_Y = 91, t_{W/E,X} = 04, t_{E|X} = 04, t_X = 04\right) \\ -f\left(Y; t_Y = 04, t_{W/E,X} = 04, t_{E|X} = 04, t_X = 04\right) \end{array} \right] \tag{3.6e}$$

Parts 3.6a to 3.6e show the way the decomposition is done. Simply put the decomposition involves replacing one explanatory variable in the 1991 welfare distribution by that in 2004. As is indicated the preceding equations, the replacement is done in

a sequential manner focusing at one variable at a time until all explanatory factors are accounted for. Part 3.6a shows the effect of changes in household attributes other than education and employment. Part 3.6b shows the impact of changes in education on household welfare. The effect of changes in formal employment sector composition of the household is captured in 3.6c. And finally, the effect of changes in 'economic' returns is captured by 3.6d. The remainder in 3.6e accounts for the residual effect after all explanatory factors above are accounted for. Column one of Panel A of table 3.2 shows sequentially the actual kernel density for the distribution of equivalent consumption in 1991 and 2004 and counterfactual densities generated in the decomposition. In addition, we show respective weighting functions in column three. These weights are used to generate densities. Since the results may be path-depedent, we also do the decomposition in reverse order as indicated in panel B of this same table.

While in the preceding paragraph and table we have shown the counterfactual densities of interest we now show how we derive the weights used to generate each counterfactual density shown above in equations 3.6a to 3.6e. In deriving these weights we follow the counterfactual densities as sequentially as shown in table 3.2.

Effect of Socio-Demographic Factors (X)

Since there are more household characteristics that influence the distribution of household wellbeing, we lump these key variables under socio-demographic attributes. The vector of socio-demographic factors, X, includes age, squared, land, fraction of male adults above 18 years, fraction of female adults above 18 years, fraction of children less than 7 years and fraction of children between 8 and 17 years, fraction of adults above 65 years old. To evaluate the effect of changes in social demographic factors, the simulation involved obtaining the density of equivalent consumption and conditioning it on the 1991 distribution of education, employment, and returns while replacing social demographic factors of 2004 into the 1991 distribution. Ideally this would require integrating the 1991 density over the social demographic factors which is not easy to achieve. Therefore, the counterfactual density of what the distribution of equivalent consumption would have been in 1991 had the socio demographic factors been as in 2004 is the first line of equation 3.7. The second line is arrived at by finding an appropriate re-weighting function in equation 3.8:

Table 3.2: Order of decomposition and weights

Density Description	Aggregate	Weight
A. Primary Order Decomposition		
1. 1991 distribution $f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E\|X} = 91, t_X = 91\right)$	Y	θ_{91}
2. (1) with 2004 - attributes $f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E\|X} = 91, t_X = 04\right)$	Y	$\theta_{91}\widehat{\Psi}_X$
3. (2) with 2004 education composition $f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E\|X} = 04, t_X = 04\right)$	Y	$\theta_{91}\widehat{\Psi}_X\widehat{\Psi}_{E/X}$
4. (3) with 2004 employment attributes $f\left(Y; t_Y = 91, t_{W/E,X} = 04, t_{E\|X} = 04, t_X = 04\right)$	Y	$\theta_{91}\widehat{\Psi}_X\widehat{\Psi}_{E/X}\widehat{\Psi}_{W/E,X}$
5. (4) with change in economic returns $f\left(\widehat{Y}^r; t_Y = 91, t_{W/E,X} = 04, t_{E\|X} = 04, t_X = 04\right)$	$\widehat{Y}^R$	$\theta_{91}\widehat{\Psi}_X\widehat{\Psi}_{E/X}\widehat{\Psi}_{W/E,X}$
6. 2004 distribution $f\left(Y; t_Y = 04, t_{W/E,X} = 04, t_{E\|X} = 04, t_X = 04\right)$	Y	θ_{04}
B. Reverse Order Decomposition		
1. 1991 distribution $f_{91}(Y) \equiv f\left(Y; t_Y = 91, t_{X\|E,W} = 91, t_{E\|W} = 91, t_W = 91\right)$	Y	θ_{91}
2. (1) with 2004 employment sector $f_{91}(Y) \equiv f\left(Y; t_Y = 91, t_{X\|E,W} = 91, t_{E\|W} = 91, t_W = 04\right)$	Y	Ψ_W
3. (2) with 2004 education attributes $f_{91}(Y) \equiv f\left(Y; t_Y = 91, t_{X\|E,W} = 91, t_{E\|W} = 04, t_W = 04\right)$	Y	$\Psi_W\Psi_{E/W}$
4. (3) with 2004 demographic attributes $f_{91}(Y) \equiv f\left(Y; t_Y = 91, t_{X\|E,W} = 04, t_{E\|W} = 04, t_W = 04\right)$	Y	$\Psi_W\Psi_{E/W}\Psi_{X/E,W}$
5. (4) with change in economic returns $f_{91}(Y) \equiv f\left(\widehat{Y}^r; t_Y = 91, t_{X\|E,W} = 04, t_{E\|W} = 04, t_W = 04\right)$	$\widehat{Y}^R$	$\Psi_W\Psi_{E/W}\Psi_{X/E,W}$
6. 2004 distribution $f_{91}(Y) \equiv f\left(Y; t_Y = 91, t_{X\|E,W} = 91, t_{E\|W} = 91, t_W = 91\right)$	Y	θ_{04}

$$
\begin{aligned}
& f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E|X} = 91, t_X = 04\right) \qquad (3.7)\\
= & \int\int\int f\left(Y|W, E, X, t_Y = 91\right) dF\left(W|E, X, t_{W|E,X} = 91\right) \times \\
& dF\left(E|X, t_{E|X} = 91\right) dF\left(X, t_X = 04\right) \\
= & \int\int\int f\left(Y|W, E, X, t_Y = 91\right) dF\left(W|E, X, t_{W|E,X} = 91\right) \times \\
& dF\left(E|X, t_{E|X} = 91\right) \Psi_X dF\left(X, t_X = 91\right)
\end{aligned}
$$

The re-weighting function for these factors is:

$$
\begin{aligned}
\Psi_X\left(X\right) & \equiv \frac{dF\left(X, t_X = 04\right)}{dF\left(X, t_X = 91\right)} \qquad (3.8)\\
& = \frac{pr\left(t_X = 04|X\right)}{pr\left(t_X = 91|X\right)}
\end{aligned}
$$

where the last line of Equation 3.8 is derived through Bayes' rule. The probability, $pr\left(t_X = t|X\right)$, is estimated using the pooled sample of both 1991 and 2004 data set. A dummy variable was constructed equal to 1 if year 2004 and 0 otherwise . A standard logit model was used to estimate these probabilities. If the probabilities are too small it may lead to misleading results in the simulations. Therefore if close to one (equal to 0.99) or zero (equal to 0.01) the predicted probabilities were removed meaning that these sample points were not used in creating weights.

Effect of Changes in Education Levels

Under this section the main question addressed is: 'what would have been the distribution of adult equivalent consumption in 1991 had the levels of education of household heads been as in 2004?' This implies getting a counterfactual density of equivalent consumption for 1991 but with education and social demographic attributes held to their 2004 levels. The idea of keeping social demographic attributes to their 2004 as well as education levels is due to the sequential nature of the decomposition. It helps to give the net effect of education when this counterfactual density and the previous one are subtracted. Therefore the counterfactual for education is defined in the first line of equation 3.9. The the second equation is arrived at

by having an appropriate re-weighting function:

$$
\begin{aligned}
& f\left(Y; t_Y = 91, t_{R|W,E,X} = 91, t_{W/E,X} = 91, t_{E|X} = 04, t_X = 04\right) \qquad (3.9)\\
= & \int\int\int f\left(Y|R,W,E,X,t_Y = 91\right) dF\left(R|W,E,X,t_{R|W,E,X} = 91\right) \times \\
& dF\left(W|E,X,t_{W|E,X} = 91\right) dF\left(E|X,t_{E|X} = 04\right) dF\left(X,t_X = 04\right) \\
= & \int\int\int f\left(Y|R,W,E,X,t_Y = 91\right) dF\left(R|W,E,X,t_{R|W,E,X} = 91\right) \times \\
& dF\left(W|E,X,t_{W|E,X} = 91\right) dF\left(E|X,t_{E|X} = 91\right) \Psi_{E/X} dF\left(X,t_X = 91\right) \Psi_X
\end{aligned}
$$

Where Ψ_X is the re-weighting function due to social demographic attributes explained earlier and $\Psi_{E/X}$ is the re-weighting function for education. This re-weighting function is derived as follows:

$$
\begin{aligned}
\Psi_{E|X}\left(E,X\right) &\equiv \frac{dF\left(E|X,t_{E/X} = 04\right)}{dF\left(E|X,t_{E|X} = 91\right)} && (3.10)\\
&= \sum_{j=1}^{J} I_j \frac{pr\left(E = j|t_{E/X} = 04\right)}{pr\left(E = j|t_{E/X} = 91\right)} && (3.11)
\end{aligned}
$$

In the re-weighting function 3.10, I_j is an indicator variable that is 1 if E=j and 0 otherwise. Since education has three categories, J=3. The conditional probabilities in the re-weighting function are estimated using an ordered logit model, using household sampling weights.

Effect of Changes in Employment States

From 1991 to 2004, there was a notable shift in employment of household heads from government and parastatal to the private and self employment sectors of the economy. This structural transformation of 1990s necessitates this investigation. Therefore, the question of interest is: 'what would have been the distribution of equivalent consumption in 1991 had the employment levels of households remained as in 2004?' The 1991 distribution adjusted for socio demographic attributes and education is then further adjusted for changes in employment attributes. The resulting counterfactual represents the effect due to changes in

employment states. The first line of equation 3.12 represents this counterfactual:

$$\begin{aligned} & f\left(Y; t_Y = 91, t_{W/E,X} = 04, t_{E|X} = 04, t_X = 04\right) \\ = & \int\int\int f\left(Y|W, E, X, t_Y = 91\right) dF\left(W|E, X, t_{W|E,X} = 91\right) \times \\ & dF\left(E|X, t_{E|X} = 04\right) dF\left(X, t_X = 04\right) \\ = & \int\int\int f\left(Y|W, E, X, t_Y = 91\right) dF\left(W|E, X, t_{W|E,X} = 91\right) \times \\ & \Psi_{W|E,X} dF\left(E|X, t_{E|X} = 91\right) \Psi_{E/X} \Psi_X dF\left(X, t_X = 91\right) \end{aligned} \tag{3.12}$$

where $\Psi_{E/X}$ and Ψ_X remain as previously defined while $\Psi_{W|E,X}$ is the re-weighting function for the density derived just like the education re-weighting function in the previous section. An ordered logit was was used to estimate the propensities for each employment category. This is in conformity of how the household employment variable was constructed where higher categories reflect a higher number of household members employed in the formal sector.

Effect of Changes in 'Economic Returns'

We analyse the effect of changes in 'economic returns' to socio demographic attributes, education, and employment on the distribution of consumption following Hyslop and Mare (2005). Contrary to common practice where the effect of economic returns is captured through replacing regression coefficients of one year with coefficients from a regression of another year, we analyze the effect of economic returns by taking the difference in regression coefficients and using that difference to deduce the change in log consumption attributed to the difference in the coefficients. So this can be interpreted as the change in the 1991 distribution due to the difference in the beta coefficients which are linked to changes in returns to household demographic composition, education and employment. Specifically, the regressions of log-consumption on education, employment, industry and socio demographic attributes as follows:

$$\widehat{Y}_{ti} = X'_{ti}\beta_t + \varepsilon_{ti} \tag{3.13}$$

The change in predicted returns is $\Delta\widehat{Y}_i = X'_{91i}\left(\widehat{\beta}_{04} - \widehat{\beta}_{91}\right)$ while the log household consumption adjusted for the change in economic returns is $\widehat{Y}^r_{91} = Y_{91} + \Delta\widehat{Y}_i$. To get the counterfactual density which captures the changes in the 'omnibus' economic returns, the study uses the adjusted consumption $\widehat{Y}^r_{91}$ as the measure of welfare while the other weights remain as shown in 3.8 and 3.10. Thus, the counterfactual density that captures the changes in economic returns between the two periods of interest is:

$$
\begin{aligned}
& f\left(Y; t_Y = 91, t_{W/E,X} = 91, t_{E|X} = 04, t_X = 04\right) \qquad (3.14)\\
= & \int\int\int f\left(\widehat{Y}^r | W, E, X, t_Y = 91\right) dF\left(W|E, X, t_{W|E,X} = 04\right) \times \\
& dF\left(E|X, t_{E|X} = 04\right) dF\left(X, t_X = 04\right) \\
= & \int\int\int f\left(\widehat{Y}^r | W, E, X, t_Y = 91\right) dF\left(W|E, X, t_{W|E,X} = 91\right) \times \\
& \Psi_{W|E,X}\Psi_{E/X} dF\left(E|X, t_{E|X} = 91\right) \Psi_X dF\left(X, t_X = 91\right)
\end{aligned}
$$

3.3.3 Reverse Order Decomposition

It is important to note that results in this type of decomposition may depend on the order of decomposition due to the possibility of general equilibrium or endogenous relations between the explanatory variables (Daly and Valletta, 2006). As a result of this, we conduct the decomposition in reverse order as well. The second panel of Table 3.2 shows the decomposition in reverse order. The representation of the underlying general distribution in reverse conditioning sequence is:

$$
f_t\left(Y\right) \equiv f\left(Y; t_Y = t, t_{X|E,W} = t, t_{E|W} = t, t_W = t\right) \qquad (3.15)
$$

Now, the re-weighting function of employment states, W, is not conditioned on any other variable and it can be written as:

$$
\begin{aligned}
\Psi_W\left(W\right) & \equiv \frac{dF\left(W|t_W = 04\right)}{dF\left(W, t_W = 91\right)} \qquad (3.16)\\
& = \frac{pr\left(t_W = 04\right) pr\left(t_W = 04|W\right)}{pr\left(t_W = 91\right) pr\left(t_W = 91|W\right)}
\end{aligned}
$$

Then the estimated weight is a simple function of the employment structure estimated using individual sampling weights in both years. The next in the decomposition sequence is education conditioned on employment states. The re-weighting function for education is derived as shown below:

$$
\begin{aligned}
\Psi_{E|W}\left(E, W\right) & \equiv \frac{dF\left(E|W, t_{E/W} = 04\right)}{dF\left(E|W, t_{E|W} = 91\right)} \qquad (3.17)\\
& = \sum_{j=1}^{J} I_j \frac{pr\left(E = j|t_{E/W} = 04\right)}{pr\left(E = j|t_{E/W} = 91\right)}
\end{aligned}
$$

Where the estimate of this re-weighting function is estimated using cell-by-cell estimate of the 2004 work and education categories to that of 1991. And lastly, the re-weighting

function for the social demographic variables was derived using basic probability theory. From probability theory it is known that $F(W,E,X) = F(W|E,X)F(E|X)F(X) = F(X|W,E)F(E|W)F(W)$. Therefore the complete set of reverse-order weights is equal to the product of the complete set of primary order weights. This is used to obtain the weighting function of the social demographic attributes as follows:

$$\Psi_{W|E,X}.\Psi_{E|X}.\Psi_X = \Psi_{X|W,E}.\Psi_{E|W}.\Psi_W \tag{3.18}$$

$$\Longrightarrow \Psi_{X|W,E} = \frac{\Psi_{W|E,X}.\Psi_{E|X}.\Psi_X}{\Psi_{E|W}.\Psi_W} \tag{3.19}$$

The last exercise in the reverse order decomposition is to conduct the counterfactual of economic returns. Since this is assumed not to depend on the 'endowments' decomposition, the counterfactual for economic returns to attributes was obtained the same way as in the primary order decomposition.

3.4 Results

The findings are divided into two distinct subsections. The first subsection focuses on presenting decomposition results for the whole period, 1991-2004. Primary order results are presented on re-weighted kernel densities and their respective differences to visually depict the effect of each explanatory factor on the distribution of household welfare. Also, quantitative measures are derived from the simulated densities in order to compare results of one period from another and deduce the implications for inequality and poverty. The second subsection looks at decomposition results focusing on two sub-periods, 1991 to 1996 and 1996 to 2004. This is because inequality decreased sharply from 1991 to 1996 and only marginally from 1996 to 2004 (McCulloch et al., 2000).

3.4.1 Equivalent Consumption Decomposition : 1991-2004

Figure 3.3 displays the impact of explanatory factors on the distribution of real equivalent household consumption. The factors are presented in sequence. Each panel presents a factor adjusted to its 2004 level and examines the effect of this adjustment compared to the prior distribution. Sub-figure a. shows the effect of changing social demographic attributes to their 2004 level while holding all other factors to their 1991 level. The adjusted distribution labeled +Attributes and represented by a solid line, shows the distribution of equivalent real consumption of 1991 with household socio demographic attributes of 2004 holding all other factors constant. It is clear to see that changes in household socio demographic attributes affect the whole distribution by increasing the number of households below the poverty line (Pline) and reducing those above the poverty line . The distribution of equivalent real consumption adjusted for attributes lies above the 1991 distribution for the portion where

household consumption is below the poverty line and vice versa above the poverty line. This result suggests that changes in household demographic factors had an adverse effect on household welfare for both 'poor' and 'rich' households.

Panel b shows the distribution due to changes in attributes and education, labeled +Education and represented by a solid line. In the same panel we also show the distribution (dashed line) adjusted for attributes only, labeled +Attributes. The panel reveals that the effect of changes in education affect the whole distribution except for the lower tails. The distribution adjusted for education has a higher peak than that adjusted only for attributes. This can be a crude indication that changes in education composition resulted in reduced spread in the distribution of equivalent consumption. If the peak in the distribution adjusted for education was after the poverty line, this would likely mean reduced head count poverty but this is not the case because the peak is below the poverty line. On both sides of the distribution, changes in education reduce the number of households in the sides of the distribution. The result, therefore, suggests that education changes might have contributed to observed changes in the distribution of real equivalent household consumption.

The effect of changes in household employment is shown in panel c. The counterfactual density of what the distribution of real equivalent consumption would have been if household employment, the education level and socio demographic attributes were as in 2004 holding all other factors to 1991 level is labelled +Employment (dashed line). Also shown in the figure is the distribution +Education. Comparing the two distributions we find that despite major shifts in the proportion of household members employed in the formal sector, changes in employment did not have a significant impact on the distribution of household welfare. It is almost hard to distinguish between the education adjusted real equivalent consumption distribution to that additionally adjusted for sector of employment. One reason could be that the effect of employment was mainly through changes in ' economic returns' to employment as opposed to changes in 'endowments' being analyzed here. Since we can not separate the effect of economic returns, this technique cannot help us much here. But we will try to assess how in reverse the sequence employment changes will impact the distribution after employment precedes education.

Finally panel d shows the effect of changes in 'economic returns', labeled +Returns (dashed line). Results show that changes in 'economic returns' affect the entire distribution except in the tails. Real equivalent consumption distribution adjusted for 'economic returns' has a higher peak though the distribution affects many other parts of the entire density. These results indeed show that changes in returns partly explain the changes in the distribution of household welfare. The effect of all four factors collectively is shown in panel e. The density of consumption adjusted for all factors sits almost on top of the 2004 distribution. This is a good indication that the decomposition is able to account for a considerable proportion of the difference in distribution. However, the distribution due to all factors labelled +Returns does not coincide with the 2004 distribution of consumption. Since the distribution adjusted for all factors is has a higher peak, it suggests that the combined effect of all

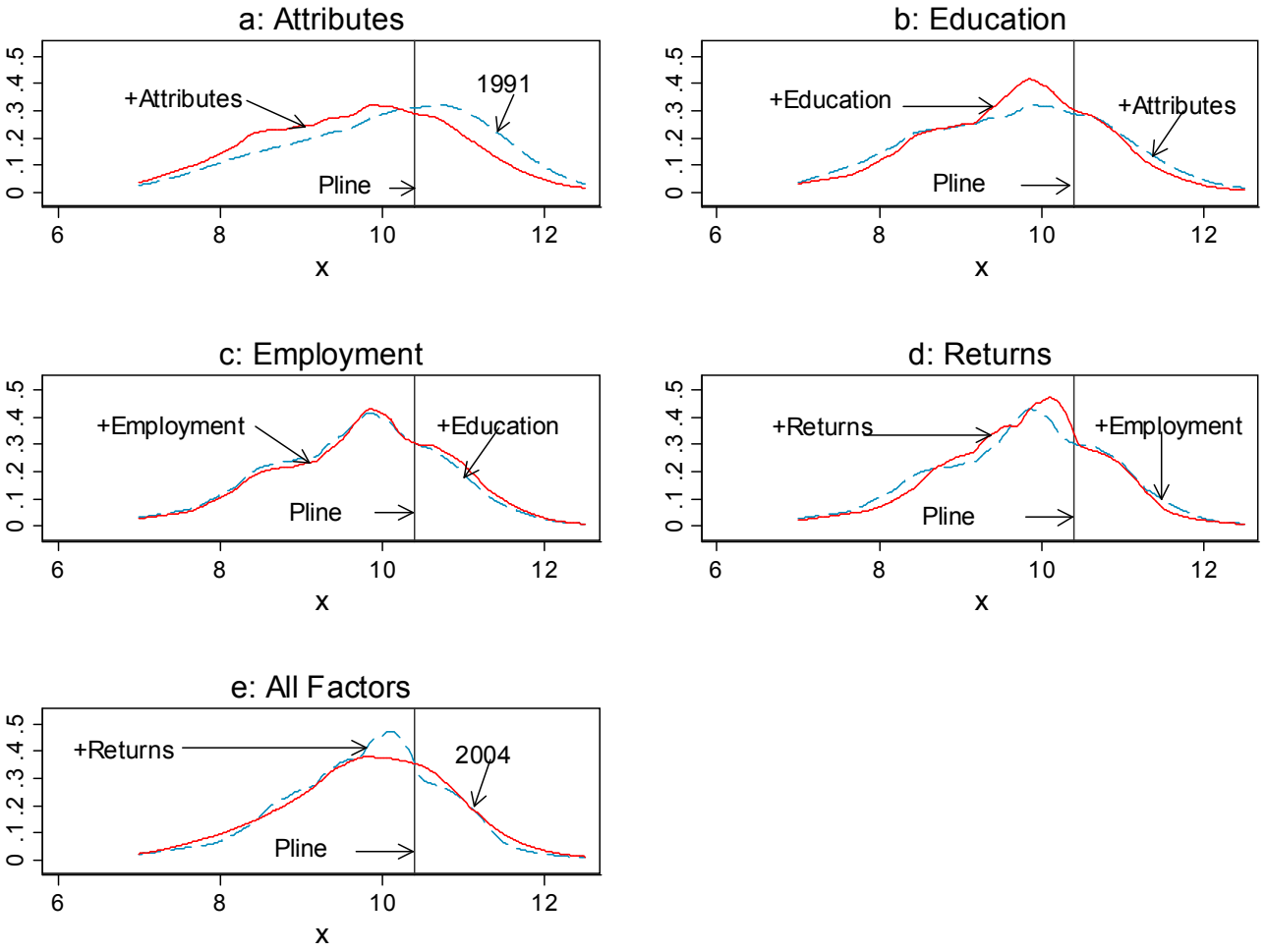

Figure 3.3: Consumption Decomposition 1991 and 2004

explanatory factors led to increased peaking with a slightly exaggerated effect.

This suggests that there are factors that the decomposition has not taken into account and these would be reflected as residuals in the analysis. It is indeed likely that changes in the taxation structure influenced the distribution of welfare. The whole agricultural policy shifted during the period 1991 to 2004. During 1994, government provided agricultural markets largely for Zambia's stapple, maize, but during the years of adjustment there was a rather fluctating policy where in some years the private sector was allowed to participate but once government realized private sector failure, government moved back in but without predictability. It is therefore likely that these policies affected the distribution of welfare. On the question of endogeneity, there does not seem to be a high likely that this would have affected the rate at which old people aquired education. Thus the relationship is likely to be weak given that the decision of an adult to pursue education is mainly to do with the education policy itself.

Figure 3.4 shows complementary representation of the density decomposition. In this figure, the marginal impact of each explanatory factor is represented as the difference in the two densities for each respective panel in figure 3.3. In each panel of figure 3.4, the difference between the densities in the corresponding panel in figure 3.3 and the total difference as derived from the 1991 and 2004 densities are presented. This type of analysis gives an alternative view of how each of the factor accounts for the total change in the distribution of consumption in the two periods.

Panel a of figure 3.4 shows that the changes in demographic composition account for much of the changes in the distribution of household welfare. This is deduced from the way the difference in attributes almost mirrors that of total change. Changes in education have a large partial effect on the distribution of household welfare. As can be seen the marginal impact of education accounts for the change in the total distribution of the whole period. As opposed to attributes, education changes account for total change without missing certain parts or going counter to the main change. Changes in sector of employment are represented as almost a horizontal line in panel c. This is an indication that changes in the sector of employment do not affect the distribution of welfare in a significant way. The marginal impact of economic returns is reflected in panel d. It shows that changes in economic returns explain a large part of the changes in consumption distribution except in some places. The weakness here is that we can not separate the effect of economic returns to specific individual factors. Because of the counter movement of the effect of attributes, panel e shows that the effect of all the factors together explains part but also does not do well in explaining the whole distribution.

To analyze the implications of the decomposition on poverty and inequality measures, quantitative measures of statistics derived from the re-weigthed densities are presented in table 3.3 and appendix B.2.4. Analyzing the percentiles from the table in appendix B.2.4 provides a general view on how each of the explanatory variables impacts the distribution of consumption. The table shows that household attributes affected all percentiles by reducing

Figure 3.4: Differences in Decomposed Densities

the amount of equivalent consumption in each percentile. For example in the 10th percentile consumption reduced from ZMK2,098 in 1991 to ZMK1,870 , a reduction of ten percent. The median reduced from ZMK23,430 to ZMK15,666 a reduction of 33 percent. This clearly suggests that changes in economic attributes had a negative effect on welfare for all households. After the negative effect of household attributes, education changes in education improve the lower percentiles while worsening the upper percentiles. As a result of changes in education, the 10th percentile improves from ZMK1870 to ZMK2098, an improvement of 10 percent which counters the effect of changes in attributes. As a result of education changes, the 25th percentile increases from ZMK5,260 to ZMK5,900 while the median remains constant. In contrast, changes in education reduce the 75th and 90th percentile by 15.5 percent and 20.5 percent respectively. Therefore the change in education is one of the likely explanations of the observed narrowing of household welfare in Zambia over the period.

Interestingly, changes in the sector of employment affect the whole distribution. However, this should be looked at in the light of the distributions. If the differences occur at percentile points it is possible to conclude that employment sector changes led to increases in welfare but if the two distributions keep coinciding in many places, such a conclusion might be misleading as is the case here. Changes in economic returns have a similar effect to that of changes in education. The 10th and25th percentiles and the median of welfare increase while 75th and 90th percentiles decrease. Finally, the difference between the last two columns in appendix B.2.4 is the residual change that is not explained by the decomposition exercise. These two columns reveal that the change in consumption at the 75th percentile is fully accounted for by the decomposition while the change at 10th percentile is over estimated by 25 percent. The median and 75th percentiles are underestimated by 25 percent and the 90th percentile by 29 percent.

Table 3.3 shows the marginal impact of each explanatory factor. Each statistic in this table is calculated as the difference between the statistics presented in panel a of appendix B.2.4. Furthermore, the shares of each marginal impact as a percentage of the total change in the statistic between 1991 and 2004 is shown in square brackets in this same table 3.3. The first column of this table shows the total change in selected inequality indices, percentile ratios and poverty indices. There are a number of points that come out of Table 3.3. Firstly, from the first column, it is shown that all inequality measures indicate a decline while there was an increase in all poverty measures. Although poverty measures are shown in this results table, our primary concern is to look at the impact of changes in each explanatory factor on inequality which is here captured by changes in selected inequality measures including the Gini-coefficient, Theil index and mean logarithmic deviation (MLD)[3]. We compliment this analysis by looking at the 90th-to-10th and 75th to 25th percentiles.

Second, changes in the distribution of household education and economic returns were

[3]Poverty decomposition is the focus of the chapter 4. Here all that comes out is that education and employment changes help reduce poverty while changes in economic returns and other household attributes are contribute to increased poverty.

the main factors driving a reduction in inequality. The contribution of these factors to the changes in the Gini coefficient, Theil index and mean log deviation is statistically significant. Specifically, changes in education accounted for 80 percent of the total change in the Gini coefficient and Theil index, 60 percent of the Mean Logarithmic deviation, 64 percent of the 90-10 percentile ratio and 68 percent of the 75-25 percentile ratio. Changes in economic returns account for 48 percent of the change in the Gini coefficient, 54 percent of the Theil index and 32 percent in the mean logarithmic deviation. Combining the effect of education and economic returns goes beyond 100 percent in Gini and MLD this is because the decomposition overestimates the middle part of the distribution and the Gini and Theil indices pick that up very well. Nonetheless it is assumed that residual factors are counteracting this effect. Changes in employment have significant results except for the Gini index. However the magnitude is extremely low. Changes in attributes counter the changes in the inequality measures. This implies that changes in the household demographic attributes lead to increased inequality countering the effect of the other factors.

Third, the contribution of all explanatory factors is shown in the last column of table 3.3. The column shows that the decomposition was useful with all factors accounting for a significant part of the change in inequality measures. However, in some cases the estimated measure overestimates the actual consumption distribution but this is assumed to be countered by residual factors. Most important are the proportions shown in square brackets in the table. looking at the Theil index, for instance, the 92 suggests that all the factors in our decomposition account for 92 percent of the total change in the index. In a same way, all explanatory factors account for 88 percent of the change in the mean logarithmic deviation and 96 percent of the change in the 90th-to-10th percentile ratios. As indicated earlier, all factors account for 114 percent of the change in the Gini coefficient and 108 percent of the 75th-to-25th percentile. Certainly, this has to do with the middle of the distribution where the change is overestimated and easily picked by the Gini and 75th-to-25th percentile ratio. On the overall, we can be confident that the decomposition is able to explain a substantial amount of the change in the distribution of consumption over the period.

One of the key concerns relates to whether the explanatory variables are indeed exogenous. In our model the key question is whether education, employment and attributes are indeed not related to the residuals to such an extent that endogeneity becomes an issue. We note first that education is largely a predetermined variable and can fairly be considered exogenous. The second is the way the employment variable is captured to include the number of people in the household that are employed in the formal sector. This composition of the employment variable is likely not to be related to consumption. Attributes include variables such as age of household and area of residence, which are assumed exogenous.

The basis of the simulation in this chapter is that changes in the distribution of education, employment and attributes are capturing the effect of policies such as privatization, retrenchments and removal of user fees. Therefore, an understanding of how education, employment and attributes affect the distribution of welfare is the first step while other analysis

not carried in this thesis for lack of time and resources would be an investigation into how policy changes during the 1991 period affected the distribution of household characteristics. Thus, it is assumed that the explanatory variables used in this model do not suffer from a serious endogeneity problem.

It is also worth stating that formulating the education and employment variable differently based on the education level and employment state of the household head resulted in very similar result. But these results are not included in this paper because we wanted to focus purely on household variables which encompass all members of the household.

3.4.2 Sub-Period Analysis

Earlier, we saw that the aggregate 1991 to 2004 change was the total outcome of two sub-periods. In this section the paper explores whether the effects of education and employment remain the same during the sub-periods 1991 to 1996 and 1996 to 2004. Doing the analysis into sub-periods is important in order to capture phenomenon that may be unique to a sub period but not to the whole period. From 1991 to 1996 inequality decreased sharply(McCulloch et al., 2000). On the other hand, the period after 1996, Zambia's economy started improving even to the extent of posting positive growth in per capita incomes by the early 2000s. In contrast to the earlier period, consumption inequality decreased slightly between 1996 and 2004. This period signifies Zambia's return to growth in national output. So what is interesting would be to find out if the changes in education would either be inequality increasing or remain inequality decreasing as in the simulations for the whole period.

Sub-Period : 1991-1996

This is a sub period characterized by significant changes in inequality. Table 3.4 shows the decomposition results of the period. During the period there was a decline in inequality. These results suggest that changes in education and economic attributes were the main 'drivers' of changes in inequality of economic welfare. Changes in education contributed to reducing all the inequality measures as is seen in the negative sign. The same applies to the effect of changes in economic returns. What is noticeable here and perhaps different from the 1991-2004 decomposition is that the change in inequality measures between 1991 and 1996 is small and thus the proportional effect of education and economic returns is higher. Over this period, household attributes did not affect the distribution of consumption as is evidenced by statistically insignificant changes. The same applies to changes in the employment variable. So the main results of this sub-period do not differ much from the main period, 1991-2004. As in the main period, education changes and changes in economic returns are the main factors accounting for declining in inequality.

Sub-Period: 1996-2004

Table 3.5 shows the decomposition results for the period 1996-2004. The first column of the table shows the total change in inequality and poverty measures. The Gini coefficient, the mean logarithmic deviation and the two percentile ratios show a change that is statistically insignificant. Only the change in the poverty measures, which is not this chapter's focus, and change in the Theil index are statistically significant. Thus, we limit the finding in this sub-period to the change in the Theil index. Two variables contribute to the change in the Theil index. These include household attributes and employment. Changes in the sector of employment over the period contributed to the decrease in the index and accounted for 22 percent of the change in the index. Factors which were key in driving the reduction in inequality and the general distribution of household welfare for the whole period, 1991 to 2004, are found not to have any influence during this period. Although this is the case, changes in education are still found to have impacted on the Gini coefficient and the mean logarithmic deviation just like in the other periods. Given the smallness of the change in inequality measures, the decomposition for this period is found not to be accounting for much. And the results for all factors are generally insignificant.

Table 3.3: Marginal Contribution: Primary Order Decomposition 1991-2004

Statistic	Total Change	Effect of				All Factors
		Attributes	Education	Employment	Returns	
Mean	-19272***	-13420***	-7200***	1437***	-2635***	-21819***
	(2342)	(1390)	(1148)	(293)	(430)	(2653)
		[70]	[37]	[-7]	[14]	[113]
Gini Coeff.	-0.08***	0.02*	-0.07***	-0.008**	-0.04***	-0.09***
	(0.020)	(0.012)	(0.010)	(0.004)	(0.006)	(0.023)
		[-24]	[80]	[10]	[48]	[114]
Theil's GE(1)	-0.30***	0.13***	-0.24***	-0.006	-0.16***	-0.28***
	(0.069)	(0.032)	(0.041)	(0.021)	(0.027)	(0.063)
		[-45]	[80]	[2]	[54]	[92]
MLD: GE(0)	-0.35***	0.02	-0.21***	-0.01	-0.11***	-0.30***
	(0.051)	(0.034)	(0.021)	(0.009)	(0.014)	(0.054)
		[-7]	[60]	[3]	[32]	[88]
90-10	-31.6**	-5.7	-20.5	1.56	-5.7	-30.4***
	(13.28)	(9.62)	(7.93)***	(3.03)	(3.78)	(10.59)
		[18]	[64]	[-5]	[18]	[96]
75-25	-3.0*	-0.4	-2.1**	0.29	-1.09	-3.2*
	(1.60)	(1.69)	(0.97)	(0.56)	(0.67)	(1.61)
		[13]	[68]	[-10]	[36]	[108]
Poverty: FGT(0)	0.12***	0.12***	0.03***	-0.03***	0.02***	0.15***
	(0.009)	(0.008)	(0.008)	(0.003)	(0.015)	(0.015)
		[100]	[27]	[-21]	[18]	[125]
Poverty: FGT(1)	0.04***	0.09***	-0.004	-0.02***	-0.01	0.06***
	(0.014)	(0.007)	(0.006)	(0.002)	(0.005)	(0.013)
		[200]	[-11]	[-44]	[-14]	[130]
Poverty: FGT(2)	0.01	0.07***	-0.02***	-0.01***	-0.01***	0.02**
	(0.008)	(0.006)	(0.005)	(0.002)	(0.004)	(0.011)
		[562]	[-140]	[-123]	[-114]	[185]

Notes: a) Bootstrapped standard errors: *** , **, * significant at 1 %, 5 % and 10 % respectively
b) percent share in square brackets

Table 3.4: Primary Decomposition: 1991-1996

Statistic	Total Change	Effect of				All Factors
		Attributes	Education	Employment	Returns	
Mean	14,783	-25,678***	1992***	-22,037***	-1783***	-25,472****
	(1896)	(2583)	(537)	(1673)	(472)	(2709)
		[-173]	[13]	[-0.02]	[-12]	[-172]
Gini Coeff.	-0.03***	-0.01	-0.07***	0.005**	-0.05***	-0.10***
	(0.007)	(0.027)	(0.009)	(0.002)	(0.007)	(0.032)
		[-49]	[247]	[-18]	[180]	[350]
Theil: GE(1)	-0.05***	0.18**	-0.20***	-0.0004	-0.26***	-0.28***
	(0.023)	(0.077)	(0.032)	(0.007)	(0.045)	(0.081)
		[-350]	[385]	[1]	[489]	[524]
MLD: GE(0)	-0.22***	-0.07	-0.19***	-0.01	-0.10***	-0.35***
	(0.035)	(0.071)	(0.022)	(0.006)	(0.018)	(0.067)
		[30]	[86]	[–7]	[46]	[156]
90-10	-30.5**	-27.7**	-9.7**	3.18	0.00	-34.2**
	(13.74)	(13.35)	(4.72)	(2.71)	(2.58)	(12.3)
		[90]	[32]	[-10]	[-6]	[112]
72-25	-2.5	-1.86	-2.34**	-0.21	-0.40	-4.40**
	(1.72)	(2.29)	(1.14)	(0.26)	(0.42)	(1.87)
		[75]	[94]	[-8]	[0]	[177]
Poverty: P0	-0.09***	0.25***	-0.009	0.001	0.002	0.25***
	(0.010)	(0.025)	(0.006)	(0.002)	(0.004)	(0.023)
		[-280]	[10]	[-0.7]	[-2]	[-273]
Poverty: P1	-0.10***	0.20***	-0.06***	0.005**	-0.011*	0.14***
	(0.009)	(0.019)	(0.009)	(0.003)	(0.005)	(0.019)
		[-204]	[65]	[-5]	[11]	[-132]
Poverty: P2	-0.10***	0.17***	-0.08***	0.005**	-0.01*	0.08***
	(0.009)	(0.016)	(0.011)	(0.002)	(0.006)	(0.016)
		[-171]	[83]	[-4]	[12]	[-81]

Notes: in brackets are bootstrapped standard errors

Table 3.5: Primary Decomposition: 1996-2004

Statistic	Total	Effect of				All
	Change	Attributes	Education	Employment	Returns	Factors
Mean	-37217	52333	5076	-137499	-85539	-29700
	(4143)	(8025)	(1250)	(13156)	(11753)	(5245)
		[45]	[–33]	[-2.4]	[99]	[19]
Gini Coeff.	-0.02	0.02**	-0.01**	-0.01**	0.02	0.01
	(0.017)	(0.009)	(0.006)	(0.002)	(0.017)	(0.019)
		[96]	[-70]	[34]	[-109]	[522]
Theil: GE(1)	-0.15**	0.05**	0.02	-0.03***	0.05	-0.003
	(0.05)	(0.016)	(0.014)	(0.009)	(0.050)	(0.048)
		[29]	[-15]	[22]	[-34]	[183]
MLD: GE(0)	-0.02	0.057	-0.03**	0.01**	0.08**	0.05
	(0.04)	(0.017)	(0.011)	(0.004)	(0.038)	(0.044)
		[244]	[-126]	[55]	[-370]	[2036]
90-10	1.39	-2.64**	1.04	-0.36	3.35	1.39
	(2.22)	(1.16)	(0.88)	(0.57)	(2.37)	(2.52)
		[-190]	[74]	[-26]	[241]	[-3390]
75-25	0.29	-0.26	0.12	0.13	3.82	0.28
	(0.74)	(0.54)	(0.32)	(0.22)	(0.29)	(0.94)
		[-92]	[45]	[46]	[100]	[-941]
Poverty: P0	0.19***	0.12***	-0.06***	0.002	0.22***	0.28***
	(0.02)	(0.015)	(0.004)	(0.005)	(0.030)	(0.016)
		[-76]	[-33]	[-1.1]	[115]	[5]
Poverty: P1	0.13***	0.03***	-0.03***	-0.006**	0.18***	0.18***
	(0.01)	(0.004)	(0.003)	(0.002)	(0.020)	(0.015)
		[-145]	[-20]	[-4.3]	[140]	[-29]
Poverty: P2	0.10***	0.004*	-0.02***	0.004***	0.15***	0.13***
	(0.01)	(0.003)	(0.002)	(0.001)	(0.015)	(0.013)
		[-195]	[-15]	[-4.0]	[147]	[-66]

3.5 Conclusion

A major contribution of this chapter is the use of a semi-parametric decomposition method to understand the effect of changes in education, employment, household composition and economic returns to these factors on the distribution of household welfare. Unlike other methods, the semi-parametric method used here gives a visual result on where in the distribution of household welfare changes in the explanatory factors impact. This chapter also extends inequality literature in Zambia by looking at decomposition to understand how microeconomic factors affect inequality. Existing literature focuses on poverty and inequality measurement and an understanding of the link between growth, inequality and poverty (McCulloch et al., 2000; Thurlow and Wobst, 2006; Mulenga and Campenhout, 2008). In Africa, literature of decomposition of whole distribution is rare except in South Africa.

The general results from current literature on inequality in Zambia is that there has been a decline in inequality between 1991 and 2004. Findings in this thesis confirm this. The key task in this chapter, however, was to find out if changes observed in education endowments of households would explain the observed inequality decline. Results suggest that improvements in education of households in the lower than median percentiles may explain the change in the distribution of household welfare as measured by equivalent consumption. Thus these improvements in education are to a large extent explaining the observed decline in consumption inequality between 1991 and 2004. Empirical literature on the effect of education changes on income distribution are mixed. For example, Cameron (2000) found that in Java increased education attainment of heads of household increased income inequality while Gunatilaka, Chotikapanich and Inder (2006) found that increased educational attainment of principle income earners in Sri Lanka had minor income distributional impact but with increased impact around the middle and lower end of the distribution than at the upper end of the distribution. In a developing country context, Alwang et al. (2003) found that increased education attainment by heads of households helped to offset the declining effects of deteriorating economic conditions on Zimbabwe. This study however did not do a sequential decomposition and also did not look at the implications of the decompositions for specific poverty and inequality indices.

Another factor that we presumed would have an impact on the distribution of consumption is the expansion of the informal sector whereby by 2004 there more households with most members deriving their livelihoods from the informal sector either small-scale agriculture or other industries. These changes in sector of employment from formal to informal were found not to drive changes in the distribution of con-

sumption. A likely reason could be that there are some informal sector jobs or self employment that may end up paying a better return than a formal job. But another reason is that the effect of changes in the sector of employment could impact on household welfare through economic returns and not endowments. Indeed it was found in this chapter that returns to education, sector of employment and household composition explained part of the changes in the distribution of consumption and inequality decline. The individual influence of returns to each factor could not be established using this methodology.

The main policy implication of this finding relates to access to education for the poor households most of which reside in rural areas. Education improvement of such households will help reduce rural inequality and by so doing improve household welfare for most rural households. UNDP (2008) found that Zambia has made good progress in meeting her Millennium Development Goal of having universal primary education by 2015. However, the same study notes that there are still serious constraints with regard to access to education of poor households especially those residing in rural areas. This lack of access is due to inadequate schools so that people have to travel long distances to go to school and there is lack of sufficient bursaries for students from poor households. Moreover, secondary education remains inaccessible because infrastructure has stagnated since the 1970s (GRZ, 2006). It is therefore important that the government improves access to education of rural households by providing enough schools and other infrastructure. Along with increased schools, government should increase funding towards providing bursaries to children from poor households. This will improve education levels and, as a consequence, increase welfare of these households through improved production and consumption.

Chapter 4

Understanding Poverty: A Parametric Decomposition Applied to Zambia

4.1 Introduction

In chapter 2, we showed at an aggregate level how poverty has increased over time. Using restricted dominance tests, we showed that within a fairly large range it can be concluded that poverty in Zambia increased between 1991 and 2004. This chapter extends that analysis of chapter 2 by looking at how household characteristics, in particular education and employment, influence changes in poverty. Interestingly, earlier studies on poverty in Zambia have not investigated this area. Moreover, a large volume of applied and theoretical work, both in developed and developing countries, has been devoted to measuring poverty across nations and , within countries over time (Biewen and Jenkins, 2005; Pudney, 1999). In developing countries, applied development literature has focused on macro issues such as the link between poverty, growth and inequality and the effect of structural adjustment policies on poverty[1]. In Zambia, studies have focused on either the link between poverty, growth and inequality (e.g. Thurlow and Wobst, 2006; Mulenga and Campenhout, 2008) or merely on poverty trends (e.g. McCulloch et al., 2000). Chapter 2 of this thesis also gives poverty trends and builds on the work of McCulloch et al. (2000)e.g. but does so in a rather more robust way by not only doing a sensitivity analysis of poverty lines but also looking at an ordinal ranking of poverty.

[1]For a detailed survey of studies focusing on poverty growth and inequality in Sub-Saharan Africa in Africa see for example Fields (2000). On the other hand Killick (1998) gives a good review of studies related to poverty and structural adjustment in Africa.

While these studies present a good account on how poverty in Zambia has moved over time, there is very little that is known about the multivariate relationship between poverty and personal characteristics such as education, employment and family size. Information about this relationship is important because it helps identify individuals who are vulnerable to poverty and can therefore be targeted in poverty reduction policies. In addition, this method brings out a clear understanding of factors impacting poverty trends over time and can help investigate whether poverty has been driven by differences in population characteristics from one period to another or by changes in the poverty function itself (Biewen and Jenkins, 2005).

Using the kernel density re-weighting semi parametric method in the previous chapter, we found that the key determinants of changes in the distribution of equivalized real consumption were changes in the levels of education and changes in economic returns to education, employment and other household attributes. It was particularly observed that improvements in the levels of education in the lower quintiles were key in explaining reduced inequality between 1991 and 2004. In addition most studies on determinants of poverty in African countries have concluded that education, labour markets and household size play a key role as determinants of poverty (e.g. Datt, Simler, Mukherjee and Dava, 2000; Appleton, 1995; Geda, de Jong, Kimenyi and Mwabu, 2005; National Economic Council of Malawi and IFPRI, 2001).

Therefore, we seek to prove the assertions that improved education leads to an increased economic wellbeing and reduced poverty, increased household size increases poverty risk and that the higher the number of people in a household engaged in formal sector employment the higher the household wellbeing and the lower the poverty risk faced by that household. We also test the assertion that changes in the distribution of household characteristics explain much of the change in poverty between 1991 and 2004.

This poverty analysis can be done using the semi parametric decomposition method by Dinardo et al. (1996) used in the previous chapter. However, the aim of this chapter is to investigate the effect of household variables on poverty of different household types, particularly those that are seen to have high poverty rates for example female headed households. In this context, we consider the method used in this chapter as complementing the DFL analysis of the previous chapter. Despite the advantage that the DFL method does not rely on a specific functional form and can give a visual representation of results, it is normally difficult to implement when the data is partitioned into many cells as fewer and fewer observations remain in each cell.

Therefore, the analysis in this current chapter uses the parametric approach proposed by Biewen and Jenkins (2005) to study the relationship between poverty and

personal characteristics over time in Zambia. This method provides a shift-share approach to account for poverty differences over time. The basic problem is to model an individual's probability of being in poverty conditional on that individual's observable characteristics. The common method used to deal with this problem is by using either a probit or Tobit analysis of a dummy dependent variable acting as an indicator of poverty. The logit or probit approach is however not statistically efficient in general since it fails to use the full set of sample information and it therefore leads to the undesirable property that higher poverty lines need not lead to higher poverty rates (Biewen and Jenkins, 2005; Pudney, 1999). This can be avoided if income or consumption distribution conditional on characteristics can be modelled directly. In this chapter, we model consumption conditioned on household characteristics by fitting a two-parameter lognormal distribution (Aitchinson and Brown, 1957). The reason for this is partly that consumption has been found to generally follow a lognormal distribution (Battistin, Blundell and Lewbel, 2007). Also, the kernel density estimates of log equivalent expenditure that were plotted in the previous chapters seem to support this assertion.

The rest of the chapter is organized as follows : Section 4.2 presents the method and also looks briefly at the data used in the modelling; Section 4.3 presents the key results of the study in two subsections, the first focusing on the relation between poverty and its correlates while the second gives an over time decomposition of poverty into the poverty function and its correlates. Section 4.4 concludes.

4.2 Methodology

4.2.1 Data

In line with the findings in chapters 2 and 3, this chapter focuses on the period 1991 and 2004. Therefore, we use the 1991 priority survey and the 2004 living conditions survey as the basis for our analyses. Both surveys are fairly comparable in terms of design and coverage. They are both nationally representative and involved a two stage sampling process. The questions on consumption did not vary much over the period. The major exception was that the 1991 data did not include imputed own consumption. In chapter 2 we show how we estimated own consumption for 1991. The resulting poverty and inequality figures do indeed show comparability between the two data sets used. The aggregate consumption used to measure poverty is as detailed in chapter 2. In that chapter, we show that the proportion of people living below the poverty line increased from 62.8 percent in 1991 to 76.4 percent in 2004.

As a way of looking at what happened between the periods, we also use the data for the mid-point 1996. This data is comparable in terms of design but poverty measures obtained look to be too low. Thus analysis for this year is meant to show how robust the results are over the period and whether there were any changes in the period. During the first stage, a base household is chosen based on certain characteristics of education and employment status of household head and spouse and the number of children in the household. In the second stage, each of these characteristics is changed and the poverty risk for doing so is deduced. In another set of analysis we focus on deducing the impact of changing the number of household members employed in either the public or formal private sectors.

Sample characteristics used in the estimations of this chapter are shown in the table 4.1. The sample means do indeed show comparability of the data from the three years. The mean number of formal sector employment among in households is falling in line with the falling number of formal sector employees. In any year, the average years of education for heads is higher than that of their spouses.

Table 4.1: Variables and Sample Means 1991, 1996 and 2004

Variables	**1991**	**1996**	**2004**
Headcount Poverty	0.628	0.549	0.764
	(0.009)	(0.014)	(0.013)
Household Characteristics			
female	0.19	0.24	0.22
	(0.008)	(0.007)	(0.006)
# of formal sector employees	0.48	0.378	0.349
	(0.071)	(0.057)	(0.062)
Household size	5.47	6.06	5.34
	(0.080)	(0.049)	(0.042)
education years of head	7.56	6.22	7.18
	(0.29)	(0.36)	(0.41)
education years of spouse	4.84	5.08	5.88
	(0.31)	(0.34)	(0.35)

note: standard errors in brackets

4.2.2 Parametric Modelling of Consumption and Poverty

There are different ways of modelling poverty. One common way is to construct a poverty profile in the form of a regression of the individual poverty measure against a variety of household characteristics. In this case one can postulate the model

$$y_i/z = \beta x_i + \varepsilon_i \tag{4.1}$$

where β is a vector of parameters, ε_i is the error term and x_i is a characteristic vector of observed household characteristics and y_i is the consumption of household i and z is the poverty line. Then one defines a binary variable $h_i = 1$ if $y_i/z < 1$ and $h_i = 0$ otherwise. This method then assumes that consumption is a latent variable by modelling

$$\Pr ob\left[y/Z < 1|X\right] = F\left[1 - \beta x\right] \tag{4.2}$$

where F is the cumulative density function. So a probit or logit is used to estimate this model (Ravallion, 1996). This method can be extended to analyze the poverty gap or squared poverty gap by introducing a censored model for instance a Tobit model[2]. The main disadvantage of this approach is however that it throws away relevant data by modelling directly either a binomial or a Tobit model.

As a solution to this problem, particularly when it involves an estimated poverty line that depends on the data, we adopt the model by Biewen and Jenkins (2005). We model the relationship between the poverty status and social economic characteristics

[2]See Appleton (1995) for an example of modelling the poverty gap by employing a Tobit model.

by using an econometric model that directly specifies consumption as a function of household characteristics. Unlike Biewen and Jenkins (2005) who use a 'Generalized Beta of the second type' to model income, we use a lognormal parametric model which in practice has been found to fit consumption better (Battistin et al., 2007). The two parameter lognormal distribution function (Aitchinson and Brown, 1957) is

$$\begin{aligned} F(x) &= \int_0^X \frac{1}{\sigma x\sqrt{2\pi}} e^{-\left(\frac{1}{2\sigma^2}\right)(\log(x)-\mu)} dx \\ &= 1 - \Phi\left(\left(\log(x) - \mu\right)/\sigma\right) \end{aligned} \tag{4.3}$$

Where in the second line Φ is the standard normal cumulative distribution function, σ and μ are the standard deviation and mean of the $\log(x)$.

In order to ensure that the fitted model of consumption (and therefore poverty) varies with characteristics, we introduce heterogeneity in each model parameter. We therefore assume that:

$$\sigma = w_i'\beta_1 \tag{4.4}$$

$$\mu = w_i'\beta_2 \tag{4.5}$$

Where w_i is a $K \times 1$ vector of of household characteristics, $i = 1, 2, ..., n$ and β_1 and β_2 are $K \times 1$ parameter vectors.

This approach follows closely the work of Biewen and Jenkins (2005) who modelled income distribution using a parametric model. They used a Beta model which is more flexible given that it takes into account the scale, location and shape parameters. In our case, the scale parameter is deemed not necessary because we assume that our variable of interest, consumption, is greater than zero which thus can easily be modelled using a two-parameter lognormal distribution. In an earlier work Pudney (1999) used a similar method but chose a semi-parametric approach that was less dependent on functional form but more data hungry. To ensure goodness of fit, we use graphical tests to see whether the lognormal distribution gives a better fit of consumption. As a graphical check we use quantile plots (Q-Q plots) to assess whether the lognormal distribution fits consumption distribution well as purported in other literature.

After conducting goodness of fit tests, the lognormal distribution is fitted to the data and a number of poverty statistics are estimated. Of interest is the headcount poverty rate among individuals sharing the same characteristics w which is defined as

$$p(t, w) = F(t|\beta, w) \tag{4.6}$$

given the poverty line t and a parameter vector $\beta = (\beta_1, \beta_2)'$ and $F(.)$ the lognormal

cumulative distribution function.

The parameters β have no interpretation in themselves, but they can be used to shed more light on the relationship between poverty and individual characteristics via comparisons of the predicted poverty rates which in this case depend on β. Following Pudney (1999) and Biewen and Jenkins (2005), we consider individuals with a set of benchmark characteristics w and investigate whether a different set of characteristics w^* is associated with a higher or lower poverty rate, and by how much. This is equivalent to calculating marginal effects in the logit and probit models. For example to find out the effect or poverty risk of increased education from primary to secondary level of female headed households with no one engaged in formal sector employment, one can examine the poverty risk as the level of education of the household head is increased from primary to secondary. This is referred to as the poverty differential and is defined as:

$$d\left(t, w^*, w\right) = p\left(t, w^*\right) - p\left(t, w\right) = F\left(t|\beta, w^*\right) - F\left(t|\beta, w\right) \tag{4.7}$$

We use the maximum likelihood estimation method to estimate model parameters and poverty differentials and standard errors. Details are in appendix C.1.

4.2.3 Decomposing Poverty Differences Over Time

This section aims to demonstrate that the difference in conditional poverty between any two periods can be decomposed into two separate quantities, the difference due to the poverty function and the difference due to changes in the characteristics. This is important in directing policy attention onto the factors that seem to have the greatest impact on poverty reduction. The decomposition followed here is that of Biewen and Jenkins (2005) which applies in a modified way the original decomposition idea of Oaxaca (1973) and Blinder (1973). Biewen and Jenkins (2005) generalize the Oaxaca-Blinder decomposition in the following manner:

Aggregate poverty can be written as

$$P\left(t\right) = \int_{w} F\left(t|\beta, w\right) dG\left(w\right) \tag{4.8}$$

where $F\left(t|\beta, w\right)$ is the conditional poverty function (i.e. the poverty rate of sub-population with characteristics w), t the poverty line, and $G\left(.\right)$ is the distribution of characteristics in the population. Using this notation, the difference in the poverty

rates between year 1 and year 2 can be expressed as

$$
\begin{aligned}
P_1(t_1) - P_2(t_2) &= \int_w F_1(t_1|\beta, w)\, dG_1(w) - \int_w F_2(t_2|\beta, w)\, dG_2(w) && \text{(4.9a)}\\
&= \underbrace{\int_w F_1(t_1|\beta, w)\, dG_1(w) - \int_w F_2(t_2|\beta, w)\, dG_1(w)}_{\text{differences in conditional poverty function}} && \text{(4.9b)}\\
&\quad + \underbrace{\int_w F_2(t_2|\beta, w)\, dG_1(w) - \int_w F_2(t_2|\beta, w)\, dG_2(w)}_{\text{differences in distribution of characteristics}} \\
&= [P_{11} - P_{21}] + [P_{21} - P_{22}] = C_I + D_I && \text{(4.9c)}\\
&= [P_{11} - P_{12}] + [P_{12} - P_{22}] = D_{II} + C_{II} && \text{(4.9d)}\\
&= [0.5(C_I + C_{II})] + [0.5(D_I + D_{II})] = C_S + D_S && \text{(4.9e)}
\end{aligned}
$$

According to equation 4.9c, the difference in poverty rates between year 1 and year 2 is decomposed into a contribution due to cross-period differences in the conditional poverty function, $C_I = [P_{11} - P_{21}]$ and a contribution due to differences in the distribution of household characteristics between the two periods, $D_I = [P_{21} - P_{22}]$. This is done by asking the counterfactual question: what would the change in the poverty rate between year 1 and year 2 have been in the population if the poverty function had been that prevailing in year 2 and vice versa? Alternatively decomposition of equation 4.9d uses the same idea in a reverse order, leading to D_{II} and C_{II}. A third decomposition, equation 4.9e, is the Shapley value decomposition[3] for which each contribution is the simple average corresponding contributions in the first two decompositions.

The quantities in 4.9c and 4.9d can be estimated by replacing β_1 and β_2 by their estimates $\widehat{\beta}_1$ and $\widehat{\beta}_2$ and the population distribution function $dG(w)$ by the distribution of characteristics in the sample

$$\widehat{G}(w) = \left(\sum_{i=1}^{n} \theta_i\right)^{-1} \sum_{i=1}^{n} \theta_i 1\{w_i = w\} \qquad (4.10)$$

where θ_i is the sample weight of individual i and $1\{.\}$ is an indicator variable which is equal to one if the statement is true and zero otherwise. Recall that w_i is a particular household characteristic and w is a predefined set of attributes. Thus if the attribute of household i belongs to the predefined set of attributes then the statement is true and false otherwise.

[3]For details on Sharpley value decomposition see Shorrocks (1999).

4.3 Results

4.3.1 Fitting a Lognormal Distribution to Consumption Data

We fitted the lognormal distribution to the real equivalent consumption data taking into account the sampling design. The results of the estimated lognormal distribution are shown in appendix C.2. The results show that the estimates of β_1 are statistically significant in all three years 1991, 1996 and 2004 and the majority of estimates of β_2 are also significant for most regressors in 2004, some regressors in 1996 and only the intercept in 1991.

The variables of interest in this chapter include education, employment and household size. Education and employment were the key focus of chapter 3 and it was found there that changes in education levels have an impact on inequality while changes in economic returns to education and employment were also found to be statistically significant. Household composition is the dimension which is added in this chapter. This is because generally the household composition and size in particular has been found to have impact on poverty by increasing it. The effect of these variables are analyzed within different categories of households. This is to see if the effect differs by different household set ups.

Therefore, we partitioned the households according to policy relevant variables based on education levels of the household head and the spouse, household employment states of the head and spouse, the number of household members employed in the formal sector and female headed households. Although it is generally agreed among researchers that consumption follows a lognormal distribution, we show how 'good' the lognormal distribution fits the consumption data used. We therefore fitted the lognormal distribution to each category of data and used a graphical approach to measure 'goodness of fit'. Although formal tests do exist to do this, these would fail to capture the fit as we require it; i.e., a good fit at lower levels of the distribution below the poverty line. Thus a graphical assessment would suffice. Below we show how good the lognormal fit is using quantile-quantile (Q-Q) plots. In each figure we show quantile plots for a base category household for 1991, 1996 and 2004. Each sub-figure shows the theoretical quantile plots for the lognormal distribution represented by the straight line while the quantile plots for the consumption of a base household is shown as the bold line. In some cases this bold line diverges from the lognormal plot but this is usually at higher levels of consumption than the poverty line. Generally, this suggests a good fit for purposes of poverty modelling which focuses on the lower part of the distribution.

Figure 4.1 shows the Q-Q plots for a household where both the head and the spouse

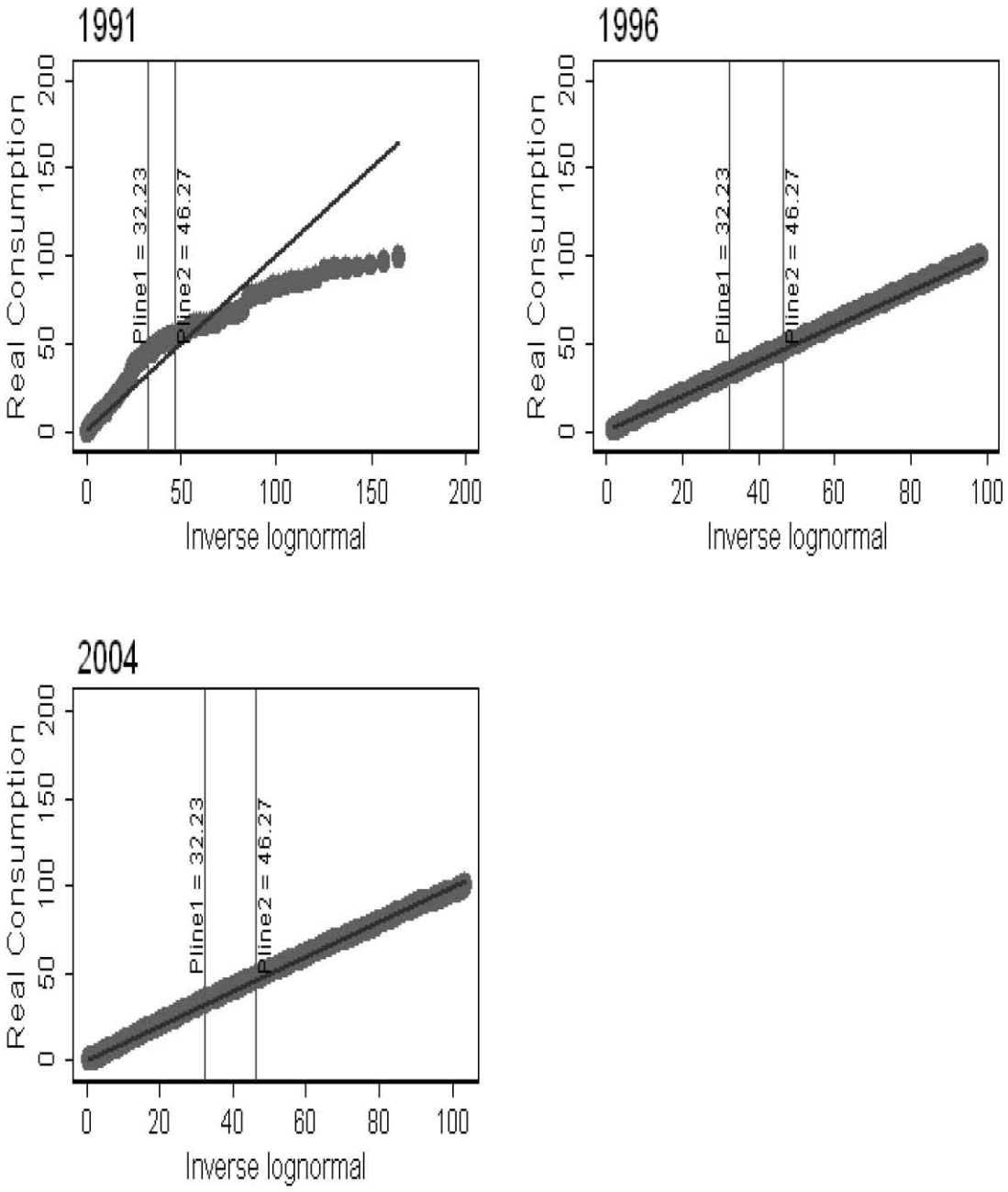

Figure 4.1: Q-Q plots for male-headed household with at most 3 kids; head and spouse with primary education, and both unemployed

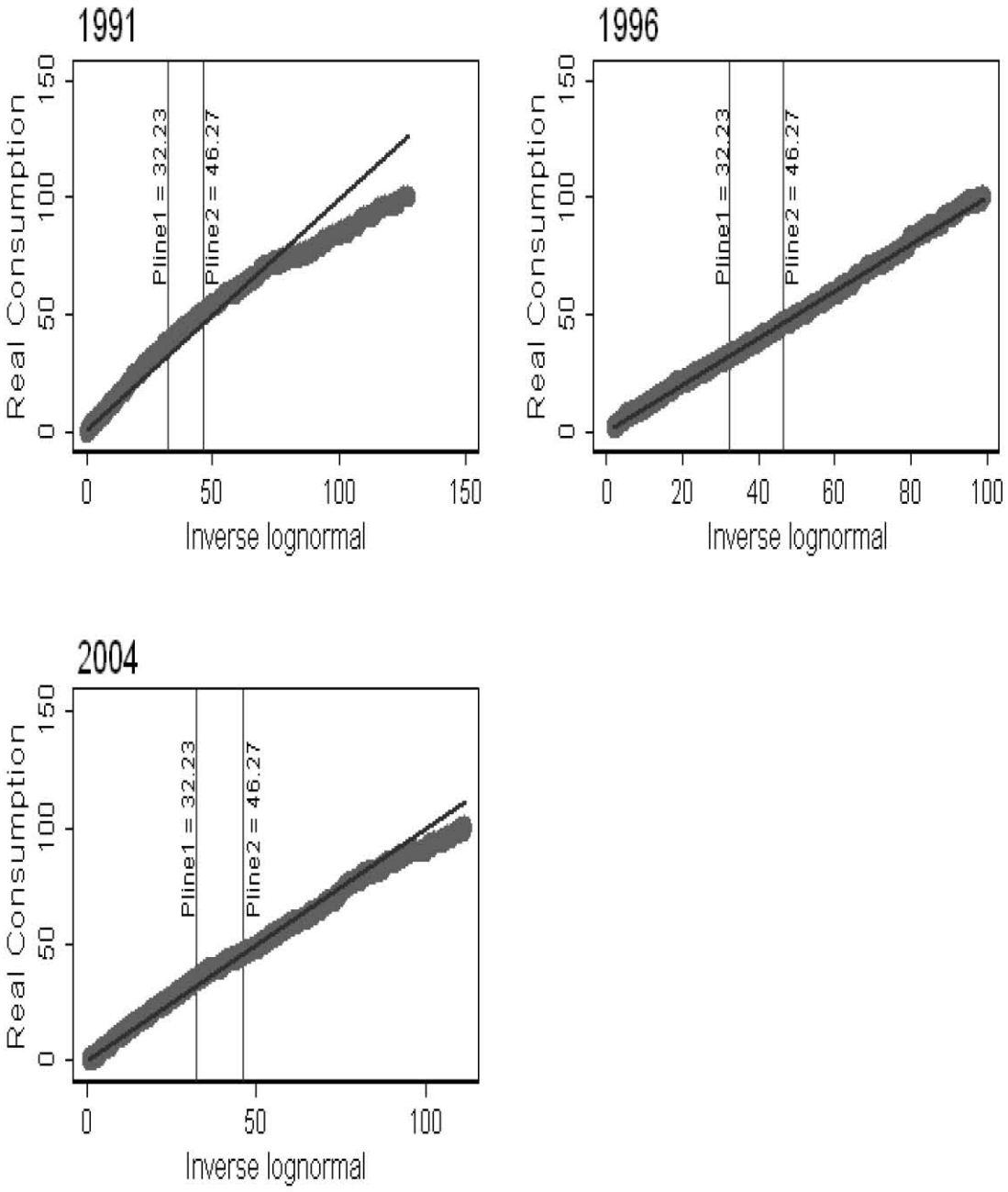

Figure 4.2: Q-Q Plot for lognormal fit of female headed household, selfemployed, with primary education and at most 3 kids

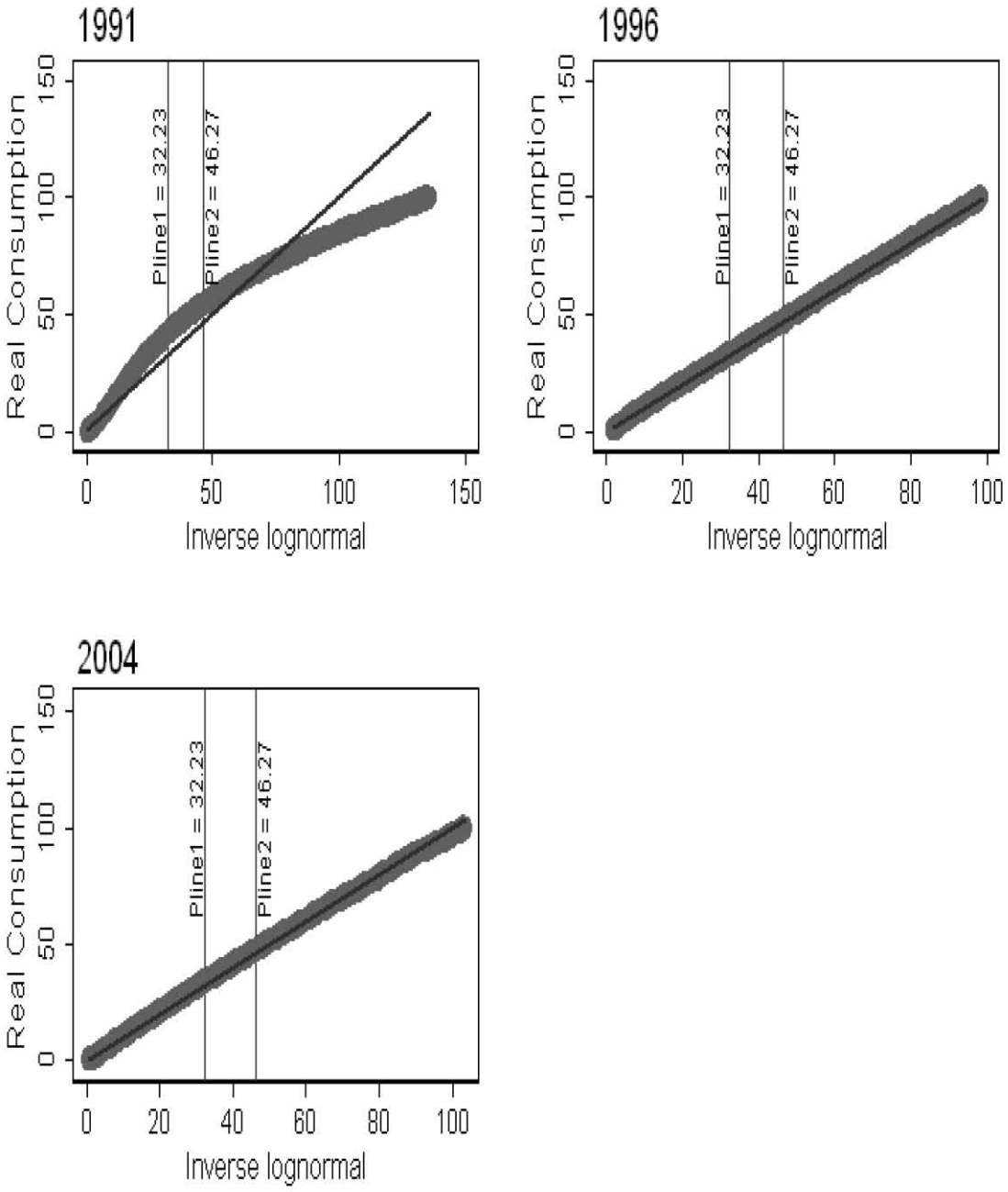

Figure 4.3: Q-Q plots of Lognormal fit of household with 1 member employed in formal sector, both spouse and head with secondary education and with at most 3 kids

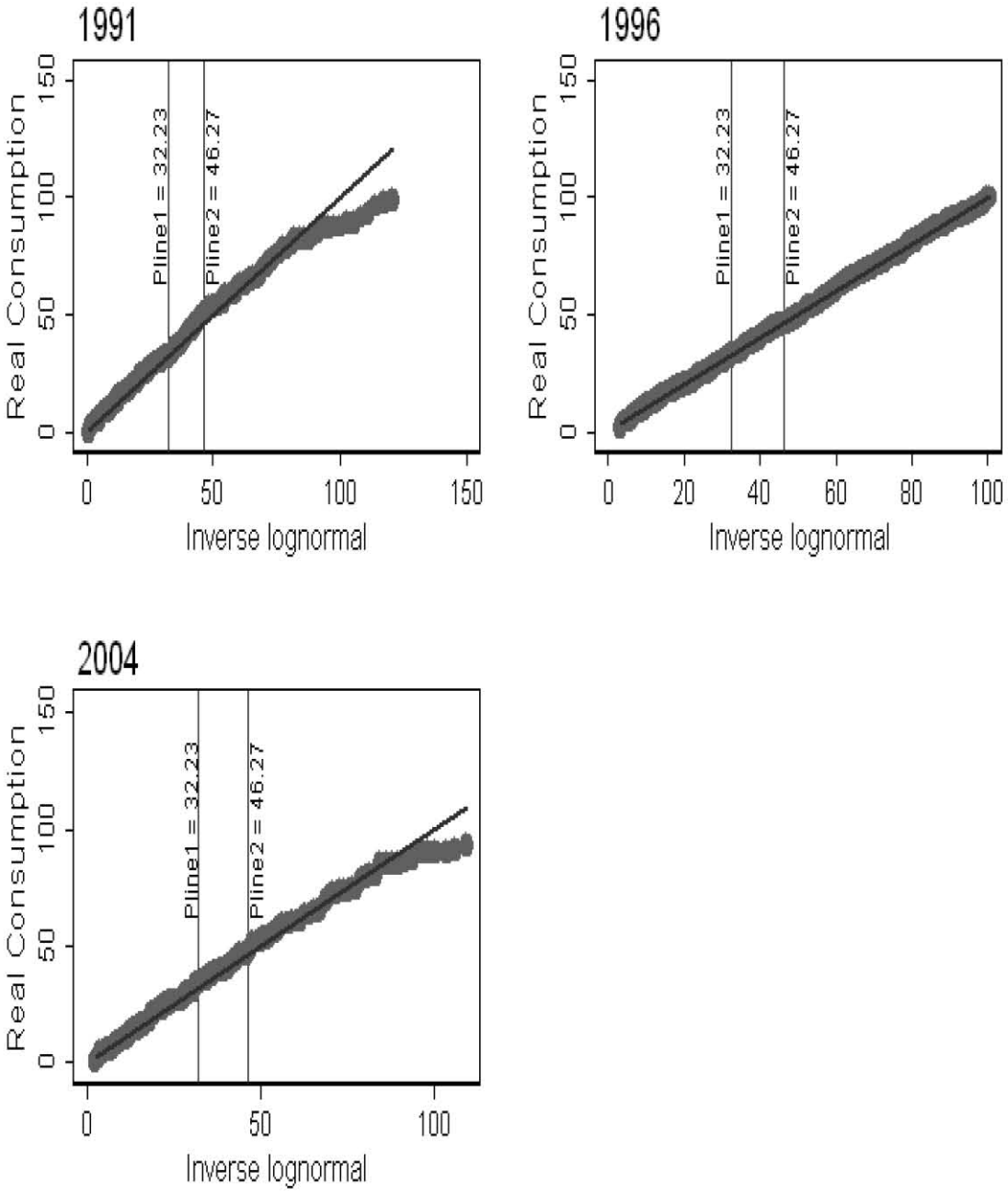

Figure 4.4: Q-Q plots for household like in Figure 1 but now with more than 3 children

have primary education or less, are unemployed and have less than three children. The figure shows that below the poverty line, the lognormal fit was 'good' for 1991, 1996 and 2004. For 1991 data there is a marked departure from lognormal but this is only true above the poverty line. This is however not cause of concern because poverty modelling takes into account only the lower part of the distribution. The figure is for the base category because that is the data where the lognormal distribution is fitted and β_1 and β_2 parameters are estimated. These estimates are then used to predict poverty levels (risk) for the other household types by changing some of the characteristics one at a time.

Figure 4.2 shows the Q-Q plots of a fit of lognormal distribution to a consumption of female headed households where the head is self employed, has attained primary education and has less than three children. Again, the Q-Q plots for all the years show that below the higher poverty line (Pline2), the fit is 'good' except for divergences above that line in 1991 and 2004. we re-emphasize the point that this is no cause for concern because poverty modelling is concerned with modelling consumption of households below the poverty line.

Figure 4.3 presents a lognormal fit to consumption of households where only one household member is employed in the formal sector, both head and spouse have a secondary level education and there are at most three children in that household. The fit is very good for 1996 and 2004 and barely good for 1991 because there is a slight departure from lognormal below pline2. We still go ahead to use the model for predictions because the divergence is not excessive.

Figure 4.4 shows a very good fit for of the lognormal distribution for 1996 but a good fit for 2004 data only for the lower than poverty line consumption levels. The figure shows a fit of the lognormal distribution to consumption of households where both the household head and spouse are self employed each having attained utmost primary education. Also this household type has at most three children.

4.3.2 The Influence of Household Characteristics on Poverty

We investigate the effect of covariates on poverty by first estimating poverty probabilities for a hypothetical base-case household, and the effects on these probabilities (also referred to as the poverty risk) of changing some of the household's characteristics. For results presented in table 4.2 the base category is a household that has both the household head and spouse with at most primary education, unemployed and with at most three children. We then get the poverty differential by changing one of the household characteristics and then comparing to the base category. Since the aim of this chapter is to see how education, employment and household size impact on poverty, we change

these household characteristics and compare the poverty risk faced by such households to that of the base category. We call this the poverty differential. For example, we consider a household similar to the base but different in that the head is engaged in self employment rather than being unemployed. Then, we consider where the head is self employed and with secondary education instead of being unemployed and with primary education. We further consider a case where the head is self employed, both head and spouse have secondary education spouse unemployed with at most 3 children. Then we consider a situation where both the head and the spouse are engaged in self employment but still with less than 3 children and a primary level education. We then look at the effect of household size by looking at a household similar to the base category but with more than three children. This benchmark was chosen to coincide with the estimated average household size in Zambia which is slightly above 5. Lastly, the effect of having the head engaged in the formal sector instead of being unemployed is analyzed.

Before considering the simulation results, it is important to discuss the issue of the endogeneity of household size in our model. In the Zambian case is household size endogenous in the model of income or consumption? It is highly unlikely that this could be the case because of two reasons: The first reason is that the 'number of kids' used in our model includes all children in the household below a certain age. This implies that for a considerable number of households the variable number of kids includes both the children of the household head and dependants. This is very common to most households given the number of orphans that Zambia faces due to the HIV/AIDS pandemic. The second reason is that most households particularly, those in remote rural places, may not have access to modern family planning methods thereby putting into question the argument that such families would 'choose' their family size based on income levels. Given these observations, it is highly unlikely that causality would run in reverse from the consumption level to household size.

The estimated results in table 4.2 show that the poverty level associated with households of the base case reduced from 76 percent in 1991 to 61 percent in 2004. The table shows that a household with a self employed head has a slightly higher poverty rate than the base case. This could imply that self employment of a household head with primary education is as good as that of unemployed. But a more plausible explanation would be that some of the household heads indicated as self employed may have been miss-classified. Poverty difference is not statistically significant in 1991 and 1996 but it was in 2004. Changing the employment status of household head from being unemployed to being self employed and allowing both the head and spouse to attain secondary education leads to a lower level of poverty risk. This implies that

the interaction between education and self employment is a good way of reducing poverty for households. Results for this category of households is associated with a significantly lower poverty risk. This difference is statistically significant in all three years. Further the category where both the head and spouse are in self employment and with primary education or less is again associated with a higher poverty risk. Again the reason could be that self employment for households with parents that have low education does not go far enough in reducing poverty of such households. Self employment for such households is as good as unemployment perhaps due to high illiteracy levels and lack of skills associated with such households. A key result from the table is that households with more than three kids are associated with a higher poverty risk during both years and the difference is statistically significant at 1 percent level. This entails that household size has a significant impact on the poverty risk of a household. Finally, a household identical to the base case but with a head engaged in the formal private or public sector is associated with a lower poverty risk. The difference is significant for 1991 and 2004, and the magnitude higher in 1991. This shows that expansion of formal sector employment would have a key poverty reducing effect.

Table 4.3 presents a second simulation for households that are female headed. In almost all Zambian Living Conditions Surveys, it has generally been found that female headed households are associated with higher poverty levels compared to male headed households. The base category comprises female headed households where the female head is self-employed, has primary level education or less and has at most three children. For such households the level of poverty was 0.84 in 1991, 0.79 in 1996 and 0.66 in 2004. Changing the base case from self employed to unemployed results in reduced poverty risk in 1991 and 1996 but increases the poverty risk in 2004. The 2004 result appears more plausible where self employment results in lower poverty risk than being unemployed. If the coding of households was done properly and if self employment is different from disguised unemployment, one would expect that apriori the household with an unemployed head would face a higher poverty risk as found in 2004. Being employed in the formal sector rather than engaging in self employment results in significant reduction in the poverty risk in all three years. Employment in the formal sector with secondary education has even a higher poverty reduction magnitude. The poverty differential for such a household was 0.63 in 1991, 0.34 in 1996 and 0.50 in 2004. This is because such households are associated with better positions due to higher education levels. A female headed household with more than three children is associated with a higher level of poverty. In all three years, the poverty differential associated with such households is positive and statistically significant. From these

Table 4.2: The Influence of Covariates on Headcount Poverty Index (P0) : Poverty Line ZMK46271

Household type	1991	1996	2004
1) Headcount poverty: unemployed head and spouse	0.76	0.77	0.61
with primary education and less than three kids	(0.037)	(0.042)	(0.032)
Poverty differentials (in percentage points)			
2) self-employed head instead of unemployed	0.03	0.01	0.11***
	(0.049)	(0.052)	(0.036)
3) Self employed head with secondary education	-0.11***	-0.01	-0.05
(instead of unemployed with primary education)	(0.062)	(0.052)	(0.048)
4) Self employed head with both head and spouse	-0.34***	-0.16***	-0.24***
with secondary education (instead of unemployed)	(0.067)	(0.057)	(0.074)
5) both head and spouse self-employed	0.12***	0.05	0.06
(instead of unemployed)	(0.037)	(0.046)	(0.050)
6) with more than three kids	0.14***	0.14***	0.18***
(instead of less than three kids)	(0.041)	(0.044)	(0.049)
7) head employed in the formal sector	-0.21***	-0.02	-0.11***
(instead of unemployed)	(0.046)	(0.050)	(0.052)

note: standard errors in brackets
** Significant at 10 percent level*
*** Significant at 5 percent level*
**** Significant at 1 percent level*

findings it can be argued that better education and employment in the formal sector have a poverty reducing effect for female-headed households. While having more than three children (i.e., higher than average family size) increases poverty.

In line with the inequality simulations in chapter 3, we conduct simulations to see what the effect the number of household members employed in the formal sector has on poverty. Table 4.4 shows a base category for households that have a head and spouse with secondary education, one household member is employed in the formal sector (private or public) and the household has at most three children. Head count poverty associated with such households was 0.29 in 1991, 0.45 in 1996 and 0.22 in 2004. For such households compared to the base category, having more than three children instead of less, both head and spouse having primary instead of secondary education and having no one employed in the formal sector is associated with a higher poverty risk. On the other hand, a household similar to the base category but with two or three members employed in the formal sector was found to be associated with a lower poverty risk than the base category. The exception is that a household with two members employed in the formal sector is found to have a higher poverty risk in 1996 but the result is not statistically significant. In sum, we see that having more

Table 4.3: The Influence of Covariates on Headcount Poverty Index (P0) in Female Headed Households : Poverty Line ZMK46271

Household type	1991	1996	2004
1) Headcount poverty: Self-employed with	0.84	0.79	0.66
primary education and less than three children	(0.017)	(0.013)	(0.013)
Poverty differentials (%)			
2) Unemployed female head instead	-0.07**	-0.07**	0.12***
of self-employed	(0.038)	(0.032)	(0.026)
3) employed in the formal sector	-0.24***	-0.18***	-0.38***
(instead of self employed)	(0.070)	(0.067)	(0.040)
4) employed in formal sector with secondary	-0.63***	-0.34***	-0.50***
instead of primary education and self-employed	(0.097)	(0.033)	(0.021)
5) with more than three children	0.05**	0.10***	0.24***
(instead of less than three children)	(0.023)	(0.018)	(0.053)
6) With secondary education	-0.16***	-0.06**	-0.24***
(instead of primary education)	(0.035)	(0.024)	(0.021)

note: standard errors in brackets
** Significant at 10 percent level*
*** Significant at 5 percent level*
**** Significant at 1 percent level*

Table 4.4: Assessing the Influence of Household Covariates on Headcount Poverty Index (P0) : Poverty Line ZMK46271

Household type	1991	1996	2004
1) one person employed in the formal sector spouse and	0.29	0.45	0.22
head secondary education and less than three kids	(0.028)	(0.027)	(0.023)
Poverty differentials (in percentage points)			
2) with two employed in the formal sector	-0.27**	0.01	-0.07**
(instead of one)	(0.045)	(0.041)	(0.038)
3) With three employed in the formal sector	-0.03	-0.14***	-0.14***
(instead of one)	(0.114)	(0.051)	(0.046)
4) with more than three children	0.23***	0.30***	0.41**
(instead of less than three children)	(0.044)	(0.051)	(0.177)
5) with no one employed in the formal sector	0.11***	0.50***	0.12***
(instead of one employed in formal sector)	(0.060)	(0.040)	(0.052)
6) both head and spouse with primary education	0.40***	0.16***	0.48***
(instead of secondary education)	(0.035)	(0.043)	(0.068)

note: standard errors in brackets
** Significant at 10 percent level*
*** Significant at 5 percent level*
**** Significant at 1 percent level*

people employed in the formal sector reduces the poverty risk associated with such a household. The result also suggests that having higher number of children leads to higher poverty risk.

4.3.3 Poverty Decomposition : Accounting for Poverty Differences Over Time

In this section, we show results of decomposing the poverty differential for 1991 and 2004 into two parts. The first part is due to change in the distribution of household characteristics and the second is due to the change in the conditional poverty function which may indirectly reflect changes in the factor markets; for example, changes in the wage structure. Although we showed in chapter 2 that poverty increased between 1991 and 2004, here we show this change as negative because we subtract the headcount poverty of 2004 (P_{22}) from that of 1991 (P_{11}). Thus the overall difference is represented in row 1 and column 2 of table 4.5. It shows that poverty increased between 1991 and 2004 that is $P_{11} - P_{22} = -0.0326$. Following Biewen and Jenkins (2005) we decomposed this difference into a change due to the conditional poverty function and due to the distribution of household characteristics. Although Biewen and Jenkins (2005) did this decomposition for different countries, we adapt it to differences in poverty over time for the same country. This is done to shed more light on whether changes in attributes between the two years account for a significant change in poverty over time. The second column of table 4.5 shows that out the total change in poverty between 1991 and 2004, a change of $C_I = -0.0378$ (116.0 %) is attributed to a change in the poverty function between the two periods while only $D_I = 0.0052$ (-16.0%) is attributed to changes in the distribution of household characteristics.

The contribution due to differences in the conditional poverty function was negative because poverty in 2004 would have been lower if the 1991 poverty function had been applied in 2004 ($P_{11} < P_{21}$). This then verifies the point that conditional poverty was lower in 1991 than in 2004. In brackets are differences in the decomposed poverty as a percentage of the total change. The results indicate that the change due to the conditional poverty function accounts for 102.6 percent of the total change in poverty in the period. This underscores the fact that almost all the change in poverty between 2004 and 1996 is due to the change in the poverty function. Since the actual total change is only 100 percent, the contribution of differences in the distribution of household characteristics is negative 2.62 percent. It is negative because poverty in 1991 would have been lower if the distribution of household characteristics had been as prevailing in 2004 ($P_{21} < P_{22}$).

This suggests that the distribution of poverty-relevant characteristics was more favourable in 2004 than in 1991 (Biewen and Jenkins, 2005). These results might be potentially sensitive to the choice of base year. Therefore, we check for this sensitivity by doing the decomposition in reverse by interchanging the base year. The results are shown in columns five and six of table 4.5 and are pretty much the same. In addition, we get the average of these effects in order to come up with the Shapley representation in columns seven and eight. The results remain very similar.

Another period of interest for sensitivity analysis is the period between 1996 and 2004. This period is associated with a sharp increase in poverty where poverty is found to have increased by 18.5 percent. Although the 1996 data may raise comparability questions because of a sharp decrease in poverty from 1991 and a sharp increase in poverty when compared to 2004, the poverty decomposition results for 1996 and 2004 still give a similar outcome. About 102.5 percent of the change in observed poverty is attributed to the change in the conditional poverty function while household characteristics account for -2.6 percent.

Table 4.5: Decomposition of poverty defference , 1991 and 2004

	$P_{11}-P_{22}$	$\underbrace{P_{11}-P_{21}}_{C_I}$	$\underbrace{P_{21}-P_{22}}_{D_I}$	$\underbrace{P_{12}-P_{22}}_{C_{II}}$	$\underbrace{P_{11}-P_{12}}_{D_{II}}$	C_S	D_S
1991 & 2004	-0.0326	-0.0378	0.0052	-0.0351	0.0025	-0.0365	0.0038
	(100)	(115.95)	(-15.95)	(107.67)	(-7.67)		
1996 & 2004	-0.1853	-0.1902	0.0049	-0.1946	0.0093	-0.1924	0.0071
	(100)	(102.62)	(-2.62)	(105.03)	(-5.03)		

Notes: In brackets are percent of total change
C_I,C_{II} is the part of the poverty difference accounted for by the differences in the conditional poverty function
D_I, D_{II} is the part of the poverty difference accounted for by the differences in the differences of characteristics
C_S(Shapley decomposition) is the average over C_I and C_{II}
D_S(Shapley decomposition) is the average over D_I and D_{II}

4.4 Conclusion

This chapter has fitted a two parameter lognormal distribution to consumption data and used the fitted model to estimate the effect of household characteristics on poverty. The paper has also used an Oaxaca-Blinder type of decomposition of the poverty difference over time in order to evaluate the influence of changes in the conditional poverty function and in the distribution of characteristics on overall poverty change. This research advances poverty analysis in Zambia in two directions. The first direction is that it goes beyond the current body of research, which focuses mainly on establishing the link between poverty, growth and inequality, by demonstrating how various household characteristics actually impact on poverty. The second direction is that it clearly attributes the major factor driving change in poverty between 1991 and 2004 as being due to changes in the conditional poverty function.

This kind of analysis is important in informing poverty reduction efforts that Zambia has committed in its pursuit of meeting the Millennium Development Goal of halving the people in poverty by 2015. Key findings from this study are relevant to that process. One main result from the poverty simulation is that household structure has a significant effect of poverty across different households. It was found that households with higher numbers of children are likely to have higher poverty risks than those with less children. A policy recommendation emanating from this finding is that as part of the poverty reduction plan there should be strategies to ensure that family sizes are controlled by availing family planning services at affordable cost so as to ensure that even families in low income brackets can access and utilize such services. Another key finding is that formal sector employment has a poverty reducing effect in

almost all household types. This makes it all the more worrying that there has been a steady decline in formal sector employment since the times of structural adjustment in the 1990s. As a result there has been an increase in self employment largely in the informal sector. In a related result, we find that households with members engaged in self employment had almost the same risk as households with unemployed members. Whereas this may point to wrong coding where self employed persons might actually appear as unemployed and vice versa it is plausible to assume that a similar result may be obtained when much of the self employment is actually disguised unemployment. In terms of policy, government should put in place measures that will ensure expansion of formal sector employment as a strategy to reducing poverty.

In addition, it is found that primary education interacted with self employment had little effect on poverty for all household types. On the contrary secondary education interacted with self employment had a significant poverty reduction effect. Those households with head and spouse with secondary education had lower poverty risk than those with head and spouse with only primary education level. More interesting was the fact that households that had the head and spouse with secondary education and engaged in self employment had lower poverty risk than those with primary education and unemployed. This implies that secondary education has a poverty reducing effect for households that are involved in self employment. This could mean that such households had better literacy and numeracy skills enabling them to conduct their business properly. The government should put in place measures that ensure that poor households have access to secondary education or higher. This will enable a greater number of such households to escape poverty even when they remain engaged in self employment.

Furthermore, the decomposition of the poverty differential between the two years, 1991 and 2004, was accounted for by higher conditional poverty rates in 2004. This effect was partly ameliorated by the more than favourable distribution of household characteristics in 2004. Changes in the conditional poverty function reflects changes in both the structure of wages as formed in the labour market and also intervention of the state through the tax and transfer system (Biewen and Jenkins, 2005). The suspension of agricultural subsidies in the 1990s coupled with an ill funded social safety net and losses of jobs with unions being weakened over time because of low member numbers and fragmentation translates into a worse conditional poverty function for 2004 than 1991.

Chapter 5

Conclusion

Structural adjustment policies and macroeconomic reforms of the 1990s led to profound changes in Zambia's education and employment distribution. Retrenchment of workers in the public sector and the liquidation of companies due to increased competition as the country liberalized led to a reduced public and formal private sector employment. On the other hand access to education became increasingly difficult for poor households due to user fees. Although restructuring of the economy was inevitable due to an unsustainable external debt and a blotted public and parastatal sector, it reduced the wellbeing of most Zambians. As a result, poverty increased while inequality reduced. The reduction in inequality is largely on account that most of the people in high income quintiles were adversely affected largely due to job losses while those on the lower part of the distribution were not as badly affected.

Therefore, this thesis investigated the effects of changes in education, employment and household structure on inequality and poverty. To carry out this investigation the thesis looked at two questions. The first question was to find out whether poverty and inequality increased between 1991 and 2004. The second question looked at how education, employment and household structure changes impacted on poverty and inequality. To answer these questions, consumption was chosen as the measure of wellbeing and careful steps were taken to ensure that the consumption aggregate was comparable over time. Adjustments were done to assure comparability in the consumption, particularly when questions changed slightly over time. Of noteworthy, is the fact that own consumption for 1991 was imputed using the method by Skinner (1987) so as to ensure the 1991 data was comparable with the other years.

Using the comparable consumption data, we came up with a robust profile of Zambia's poverty and inequality for 1991, 1996, 1998 and 2004. All the poverty and inequality estimates included bootstrapped standard errors. The resulting profile showed that between 1991 and 2004, poverty increased while inequality declined marginally. Since

poverty and inequality ranking might be sensitive to choice of index, we conducted poverty and inequality dominance tests. Inequality dominance was not established because Lorenz curves intersected. However using selected inequality indices including the Gini coefficient, the Theil index and the Mean Logarithmic Deviation (MLD), it was found that there was a decline in all three indices at national level. On the other hand, restricted poverty dominance results ranked poverty in 2004 to be higher than that in 1991. Therefore, for any poverty line between ZMK24,339 and ZMK100,000 in 1998 prices, one would end ranking poverty as being higher in 2004 than it was in 1991.

The effect of changes in education, employment and household attributes on inequality was investigated using a semi-parametric density re-weighting method. This method was preferred because it relies less on functional form. The method also shows visually exactly where and how the changes in education, employment or attributes impact the distribution of real equivalent consumption though this is possible with certain parametric formulations. It was found that education changes which involved an improvement in education endowments of those households in lower quintiles explained a significant part of the change in inequality. Another factor which accounted for changes in the distribution of wellbeing was changes in the 'economic returns' to education and employment. Since this effect could not be attributed to education alone or employment alone or attributes alone, it was not possible to tell how much changes in economic returns of each of these variables individually affected inequality.

A lognormal distribution was fitted to consumption and used to analyze how education, employment and household structure impact on poverty. In this analysis, goodness of fit involved plotting of quantile graphs which showed a good fit for consumption distribution lower than the poverty line. Using the fitted model, it was found that an increase in the number of children in the household unambiguously led to increased poverty risk for such households. On the other hand education was found to reduce the poverty risk of a household when such households have a head and spouse with secondary or higher level of education. This was true for both female and male headed households. A more surprising finding was that for households with head and spouse with primary education, being in self employment did not differ so much from being unemployed in terms of poverty risk faced by the household. Since data did not shed much light on why this is the case, we could only speculate that the effect of being unemployed and self employed with very low levels of education has no much difference in terms of poverty risk. If the data are captured accurately and these results are taken at face value, they might imply that people who are in self employment and have only primary education do not get good returns for their effort. Although

some, especially non-governmental development specialists, may argue that the these findings are common knowlegde, this research sheds more light by showing not only the impact on poverty of a particular but it also shows the magnitude of the impact. This then allows policy makers to have a better evidence-based understanding on what policy tools would have the greatest impact and targeted at what type of households.

The thesis further looked at whether the change in poverty over the period was due to the conditional poverty function or due to the change in the distribution of attributes. In this regard, the change in the conditional poverty function capture how returns to factors of production such as wages impact on poverty. Poverty decomposition between 1991 and 2004 found that the increase in poverty was due to changes in the conditional poverty function and not due to changes in the distribution of attributes. This finding suggests that to have poverty reduction the changes in wages and other transfers to the poor are more critical for poverty reduction.

It can be argued that the topic of this thesis has taken centre stage in the development discourse, especially with the global appeal for developing nations to meet the Millennium Development Goals. In Zambia, the goal of government is to reduce poverty and enhance growth particularly agricultural growth. Existing research fails to meet this goal because it has focused at either measurement of poverty and inequality trends or the aggregate level relationship between growth, poverty and inequality. Therefore, there is no empirical work focusing on the relationship between poverty and its covariates and factors that drive inequality to give more insight on what sort of poverty reduction policies should be targeted in order to be effective.

In terms of method application, very few studies in Africa have used the semi parametric re-weighting approach to study household welfare despite the fact that these methods are very informative and compare very favourably to competing models. Hopefully, therefore, this thesis has shown that using this method is useful in revealing subtle relationships that at times may not be achieved via using ordinary regressions. This is, therefore, a key methodological contribution of this thesis.

In Zambia, the results in this thesis can be a key input in the poverty reduction processes. However, there are areas that are not covered in this thesis due time and data limitations but are equally critical to Zambia's quest for poverty reduction and growth. For example, there is need to measure people that are chronically poor and those that face transitory or seasonal poverty. Factors that influence chronic poverty may be different so are the interventions required. However, such analysis requires the use of panel data that track people over time. Unfortunately, national panel data on living conditions in Zambia is not available. Another area for future research is multidimensional poverty because it is vital to understand other non-monetary measures

of poverty. In this line, the thesis would have been enriched if it included an analysis of the effect of changes in asset holding especially productive assets on poverty and inequality. This, however, was not possible due to data limitation where assets were captured differently in the four surveys.

This thesis results have shown that changes in education, employment and other household attributes are key determinants of household wellbeing either through levels or through returns to these factors. It is therefore important that government's objective to reduce poverty must enhance access to and utilization of education facilities in order to improve the wellbeing of households particularly those in the lower income quintiles. However, education alone can not bring about dramatic changes unless demand for labour is created to absorb the newly educated. This requires expanding formal sector employment and ensuring that those in the self employment sector are able to attain at least secondary education to reap the benefits of education. The sad reality is that creation of new job does not feature as one of the key goals of government policy in Zambia. This has to be done if poverty, particulary urban poverty, is to be reduced

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Appendix A

Appendix for Chapter 2

A.1 Proportions of Missing Values on key Household Variables

	1991	**1996**	**1998**	**2004**
Sample size (number)	9666	11712	16448	18994
Missing proportions				
Education of head of household	2.3%	2.1%	1.4%	1.6%
Age of Head of Household	0.1%	1.4%	0.03%	0%
Employment Status of Head of Household	0.3%	3.3%	1.7%	1.4%
Proportions of zero income/consumption				
Consumption	0.01%	0.05%	0.08%	0.01%
Income	1.0%	7.3%	2.3%	1.7%

A.2 Consumer Price Indices

Period	Metropolitan Low Income Group	Metropolitan High Income Group	Non-metropolitan Group
1990	4.2	4.5	4.3
1991	8.3	9.2	8.4
1992	23.1	23.0	22.6
1993	65.3	63.5	65.1
1994	100.0	100.0	100.0
1995	135.8	135.3	134.2
1996	192.8	188.3	196.3
1997	237.8	235.1	245.0
1998	295.9	292.3	305.1
1999	372.3	373.5	286.6
2000	462.7	482.5	483.3
2001	554.8	587.4	589.6
2002	690.3	697.7	727.0
2003	847.1	852.5	873.6
2004	988.8	1011.8	1032.7

Source: GRZ (2008)

A.3 Latham Adult Equivalent Scale

Age	Male Weight	Female Weight
0	0.33	0.33
1	0.46	0.46
2	0.54	0.54
3-4	0.62	0.62
5-6	0.74	070
7-9	0.84	0.72
10-11	0.88	0.78
12-13	0.96	0.84
14-15	1.06	0.86
16-17	1.14	0.86
18-29	1.04	0.80
30-59	1	0.82
60+	0.84	0.74

A.4 Computation of Own Consumption for 1991

Since the 1991 survey did not collect information on own consumption while own consumption was collected in the other years, in this paper the 1991 consumption includes an imputed own consumption aggregate. Estimation of this follows Skinner (1987) where a predicted consumption aggregate is estimated using cash consumption that is comparable from another survey. We estimate the model:

$$\log\left(totalconsumption\right)_{96} = \beta_0 + \beta_1 \log\left(marketconsumption\right)_{96} + \varepsilon \qquad \text{(A.1)}$$

where market consumption is defined as total consumption minus own-produce consumption. The results of this simple regression equation are presented in the table below.

	(1)
VARIABLES	lconseq22
lconseq23	0.655***
	(0.00317)
Constant	4.054***
	(0.0334)
Observations	11353
R-squared	0.790

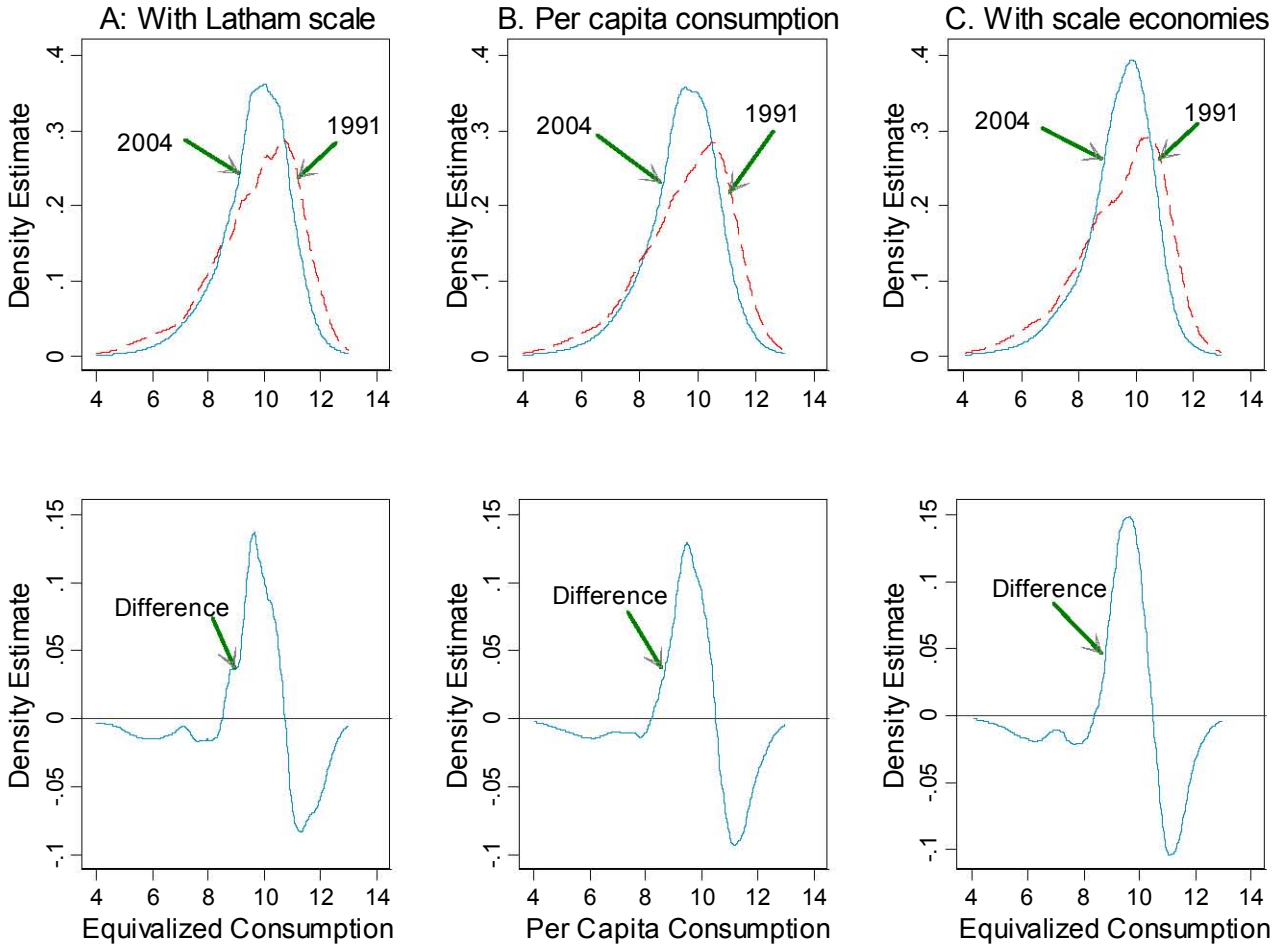
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

From this table we can see that the model has a high explanatory power where the r^2 is 79 percent. Skinner (1987) argues that this model can then be used to predict consumption in another year with the assumption that the regression parameters remain stable over the two years. We then use the predicted regression equation to predict log total consumption for 1991 and we take the antilog to obtain the total consumption. We make the assumption that total consumption must be an increasing function of market consumption and therefore replace predicted total consumption for 1991 by the market consumption if the predicted total consumption is less than the market consumption.

Assessing whether the regression estimates remain stable over the period 1991 and 1996 is tricky because it can not be tested directly. We however use a descriptive

approach to achieve this. Simply we look at the share of market consumption in total consumption in 1996 and compare that to the proportion in 1991. In 1996 market consumption accounted for 80 percent of total consumption while market consumption in 1991 accounted for 84 percent of our estimated total consumption for 1991. This is slightly higher that the share of 75 percent in 1998.

A.4.1 Consumption Distribution Using Different Equivalence Scales



A.5 Stochastic Dominance Tests

A.5.1 Second order poverty dominance tests 1991 and 2004

Poverty line	$\widehat{D}^2_{1991}(z)$	$\widehat{D}^2_{2004}(z)$	t	Poverty line	$\widehat{D}^2_{1991}(z)$	$\widehat{D}^2_{2004}(z)$	t
7,788	616	326	-3.2	55,076	22,639	26,928	1.6
10,152	1,027	670	-2.2	57,441	24,306	28,885	1.6
12,517	1,541	1,157	-1.5	59,805	26,014	30,877	1..7
14,881	2,148	1,778	-1.0	62,169	27,760	32,894	1.7
17,246	2,835	2,544	-0.6	64,534	29,543	34,932	1.7
19,610	3,606	3,447	-0.3	66,898	31,356	36,990	1.8
21,974	4,453	4,476	0.03	69,263	33,201	39,068	1.8
24,339	5,365	5,624	0.3	71,627	35,077	41,164	1..8
26,703	6,346	6,873	0.5	73,991	36,984	43,280	1.8
29,068	7,396	8,205	0.7	76,356	38,916	45,410	1.8
31,432	8,502	9,617	0.8	78,720	40,873	47,552	1.8
33,796	9,667	11,100	0.9	81,085	42,856	49,705	1.9
36,161	10,901	12,653	1.0	83,449	44,860	51,871	1.9
38,525	12,198	14,268	1.1	85813	46,885	54,046	1.9
40,890	13,546	15,941	1.2	88,178	48,930	56,230	1.8
43,254	14,945	17,6666	1.3	90,542	50,993	58,424	1.9
45,619	16,391	19,436	1.4	92,906	53,073	60,630	1.9
47,983	17,884	21,253	1.4	95,271	55,171	62,843	1.9
50,347	19,424	23,110	1.5	97,635	57,282	65,063	1.9
52,712	21,010	25,002	1.5	100,000	59,405	67,290	1.9

note: *** significant at 1 percent

Dominance achieved at order 1

Third order poverty dominance tests 1991 and 2004

Poverty line	$\widehat{D}^3_{1991}(z)$	$\widehat{D}^3_{2004}(z)$	t	Poverty line	$\widehat{D}^3_{1991}(z)$	$\widehat{D}^3_{2004}(z)$	t
7,788	1.6×10^6	6.8×10^5	-4.0	55,076	4.5×10^8	5.2×10^8	1.0
10,152	3.6×10^6	1.8×10^6	-3.3	57,441	5.1×10^8	5.8×10^8	1.0
12,517	6.6×10^6	4.0×10^6	-2.6	59,805	5.7×10^8	6.5×108	1.1
14,881	1.1×10^7	7.4×10^6	-2.0	62,169	6.3×10^8	7.3×10^8	1.2
17,246	1.7×10^7	1.2×10^7	-1.6	64,534	7.0×10^8	8.1×10^8	1.2
19,610	2.4×10^7	2.0×10^7	-1.2	66,898	7.7×10^8	8.9×10^8	1.2
21,974	3.4×10^7	2.9×10^7	-0.9	69,263	8.5×10^8	9.8×10^8	1.3
24,339	4.5×10^7	4.1×10^7	-0.6	71,627	9.3×10^8	1.1×10^9	1.3
26,703	5.9×10^7	5.6×10^7	-0.4	73,991	1.0×10^9	1.2×10^9	1.3
29,068	7.6×10^7	7.3×10^7	-0.2	76,356	1.1×10^9	1.3×10^9	1.4
31,432	9.4×10^7	9.4×10^7	0.01	78,720	1.2×10^9	1.4×10^9	1.4
33,796	1.2×10^8	1.2×10^8	0.2	81,085	1.3×10^9	1.5×10^9	1.4
36,161	1.4×10^8	1.5×10^8	0.3	83,449	1.4×10^9	1.6×10^9	1.5
38,525	1.7×10^8	1.8×10^8	0.4	85813	1.5×10^9	1.8×10^9	1.5
40,890	2.0×10^8	2.1×10^8	0.5	88,178	1.6×10^9	1.9×10^9	1.5
43,254	2.3×10^8	2.5×10^8	0.6	90,542	1.7×10^9	2.0×10^9	1.5
45,619	2.7×10^8	3.0×10^8	0.7	92,906	1.9×10^9	2.2×10^9	1.5
47,983	3.1×10^8	3.5×10^8	0.8	95,271	2.0×10^9	2.3×10^9	1.6
50,347	3.5×10^8	4.0×10^8	0.9	97,635	2.1×10^9	2.5×10^9	1.6
52,712	4.0×10^8	4.6×10^8	0.9	100,000	2.3×10^9	2.6×10^9	1.6

note: *** significant at 1 percent; Dominance achieved at order 1

Appendix B

Appendix for Chapter 3

B.1 Summary of Household Variables

B.1.1 Changes in Household Characteristics 1991-2004

	Actual Proportions			Differences		
	1991	1996	2004	1996-1991	2004-1996	2004-1991
Proportion of Households with average Education Endowments of:						
7 years and less of education	0.65***	0.61***	0.52***	-0.04***	-0.09***	-0.13***
	(0.0030)	(0.002)	(0.0027)	(0.004)	(0.003)	(0.004)
Between 8 and 12 years	0.34***	0.36***	0.43***	0.02***	0.07***	0.09***
	(0.0025)	(0.0016)	(0.0019)	(0.003)	(0.002)	(0.003)
Above 12 years	0.01***	0.03***	0.05***	0.02***	0.02***	0.04***
	(0.000007)	(0.00002)	(0.0002)	(0.00002)	(0.0002)	(0.0002)
Proportion of households with						
none employed in the formal sector	0.61***	0.69***	0.75***	0.08***	0.06***	0.14***
	(0.0050)	(0.002)	(0.002)	(0.005)	(0.003)	(0.005)
1 employed in the formal sector	0.31***	0.26***	0.16***	-0.05***	-0.1***	-0.15***
	(0.0030)	(0.001)	(0.0009)	(0.003)	(0.001)	(0.003)
2 employed in the formal sector	0.06***	0.05***	0.07***	-0.01***	0.02***	0.01***
	(0.00020)	(0.0001)	(0.0002)	(0.002)	(0.002)	(0.0003)
3 or more employed in the formal sector	0.02***	0.01***	0.02***	-0.01***	0.01***	0***

Note: standard errors in brackets

B.2 Sensitivity Analysis

B.2.1 Reverse Order Decomposition

To gauge whether the results of the primary decomposition are not sensitive to the changes in the order of decomposition, table B.2.2 shows the results in reverse order. What is noticeable from this table is that, with regard to inequality measures, the total effect of all factors in the last column is reduced though the signs remain the same. The same trend applies to individual factors. The effect of changes in education reduce inequality but the sign of effect remains the same. In this reverse order, education is found to contribute 8.7 percent of the changes in the Gini coefficient, 16.6 percent of Theil coefficient, 13.6 percent of the of the mean log deviation, 26.3 percent of the 90-10 percentile ratio and 38.4 of the 75-25 percentile ratio. In terms of the head count poverty, education still contributes significantly to the reduction in the number of people living below the national poverty line. A comparison of the effect of education on inequality and poverty in the two decomposition analyses leads to the conclusion that education did indeed contribute to the reduction in inequality on one hand and increase in poverty on the other. The contribution of changes in economic returns to inequality are significant but with reduced magnitudes. The signs of effect remain the same as in the primary order. However the effect of returns on poverty is slightly increased but again with the same signs. Like the other two factors, the effect of changes in employment states has a reduced magnitude but maintaining the same signs. Socio demographic factors is the set of variables whose magnitude of effect increased in the reverse decomposition while the sign remained the same. From this analysis, it is deduced that the signs of the effect do not change. Although changes in magnitude differ levels of significance in both the primary and reverse order decomposition remain the same.

Of concern though is the fact that the decomposition is sensitive to reverse order for poverty measures. The overall effect for the headcount, poverty gap and squared poverty gap measures are positive in the initial order but in the reverse case the effect changes to positive. That the simulation is not sensitive to order of decomposition for inequality measures but it is for poverty measures entails that largely the decomposition is not very good in observations particularly in the lower tail. This is compounded by the process of winsorizing observations to ensure that weights are not too large or too small.

B.2.2 Marginal Contribution: Reverse Order Decomposition 1991-2004

Statistic	Total	Effect of				All
	Change	Attributes	Education	Employment	Returns	Factors
Mean	-19272***	-48635***	21323***	28238***	-10000***	-9061***
	(2342)	(6546)	(2950)	(3800)	(1189)	(2133)
		[252]	[–110]	[-146]	[51]	[47]
Gini Coeff.	-0.08***	-0.10***	0.03**	-0.09***	-0.004**	-0.17***
	(0.021)	(0.030)	(0.010)	(0.014)	(0.014)	(0.017)
		[118]	[-33]	[115]	[5]	[206]
Theil's GE(1)	-0.30***	-0.27***	0.06	-0.21***	-0.055**	-0.47***
	(0.069)	(0.071)	(0.035)	(0.036)	(0.030)	(0.058)
		[89]	[-19]	[70]	[18]	[158]
MLD: GE(0)	-0.35***	-0.19***	0.05**	-0.31***	-0.019	-0.48***
	(0.051)	(0.057)	(0.024)	(0.044)	(0.028)	(0.040)
		[55]	[-14]	[90]	[6]	[135]
90-10	-31.6**	-2.88	0.00	-38.6***	-0.62	-42.1***
	(13.30)	(4.32)	(3.16)	(12.66)	(2.32)	(13.41)
		[9]	[00]	[122]	[2]	[133]
75-25	-3.0*	-0.73	0.20	-4.1**	0.17	-4.5**
	(1.60)	(0.74)	(0.53)	(2.04)	(0.49)	(1.84)
		[24]	[-7]	[137]	[-6]	[149]
Poverty: P0	0.12***	0.14***	-0.05***	-0.25***	0.12***	-0.04
	(0.014)	(0.025)	(0.008)	(0.021)	(0.009)	(0.027)
		[119]	[-45]	[–216]	[107]	[-34]
Poverty: P1	0.04***	0.07***	-0.03***	-0.21***	0.06***	-0.12***
	(0.010)	(0.013)	(0.004)	(0.019)	(0.007)	(0.017)
		[153]	[-61]	[-495]	[130]	[-273]
Poverty: P2	-0.01	0.04***	-0.02***	-0.17***	0.03***	-0.12***
	(0.009)	(0.009)	(0.003)	(0.017)	(0.005)	(0.015)
		[337]	[-141]	[-1480]	[253]	[1031]

Notes: in brackets are bootstrapped standard errors

B.2.3 Simulations using 2004 as base year

There is no guarantee that changing the base year of the simulations would lead to the same results as found under the primary order decomposition. Changing the base year means reversing the question of interest in the following manner: 'what would have been the distribution of equivalized consumption in 2004 if the education levels

remained as in 1991?' This would entail using the 2004 density function and finding an appropriate re-weighting function to derive the counterfactual density. To assess how different the results from such simulations would be, the study decomposed the consumption density change with 2004 as the base year[1]. As expected the results are not the same though the effect is similar with one major difference. With regard to inequality, the results show that changes in education and attributes explain a large proportion of the decline in the inequality measures while employment changes do not. The reversal of result is that there changes in economic returns countered the reduction in inequality. Similarly results on poverty show the opposite of what was obtained in the primary order decomposition. Changes in attributes, economic returns and employment contributed to reduction of all poverty indices. On the contrary, changes in education contributed to increasing poverty. Since this index number problem is a reality there is no way these results can be reconciled.

[1] These results not presented here but are available on request from the author.

B.2.4 Primary Order 1991-2004:Percentiles Inequality & Poverty Measures

Statistic	Actual	Change in 1991 Density Due to:				Actual
		With '04	With '04	With '04	With '04	
	1991	Attributes	Education	Employment	Returns	2004
Percentiles						
10^{th}	2,098	1,870	2,098	2,222	2,640	3,137
25^{th}	7,424	5,260	5,900	6,619	7,863	8,328
50^{th}	23,420	15,666	15,666	16,592	17,573	18,612
75^{th}	55,430	37,079	31,310	35,010	33,055	37,079
90^{th}	110,428	73,870	58,707	62,178	58,707	65,854
Inequality Indices						
Gini Coeff.	0.649***	0.662***	0.605***	0.591***	0.545***	0.567***
	(0.028)	(0.026)	(0.029)	(0.027)	(0.029)	(0.278)
Theil GE(1)	0.984***	1.085***	0.870***	0.838***	0.650***	0.682***
	(0.101)	(0.101)	(0.093)	(0.087)	(0.0722)	(0.071)
MLD:GE(0)	1.034***	1.016***	0.849***	0.829***	0.709***	0.688***
	(0.094)	(0.087)	(0.084)	(0.080)	(0.076)	(0.068)
90-10	52.62***	39.48***	27.98***	27.97***	22.23***	20.99***
	(15.89)	(11.49)	(9.52)	(11.43)	(8.67)	(5.40)
75-25	7.46***	7.04***	5.29***	5.29***	4.20***	4.45***
	(2.14)	(1.62)	(1.19)	(1.33)	(0.95)	(1.105)
Poverty Indices						
FGT:P0	0.585***	0.714***	0.752***	0.727***	0.747***	0.701***
	(0.052)	(0.045)	(0.044)	(0.048)	(0.049)	(0.053)
FGT:P1	0.374***	0.470***	0.472***	0.450***	0.439***	0.417***
	(0.036)	(0.036)	(0.034)	(0.035)	(0.035)	(0.038)
FGT:P2	0.287***	0.363***	0.352***	0.334***	0.316***	0.299***
	(0.030)	(0.032)	(0.032)	(0.031)	(0.030)	(0.032)

B.3 Employment Multinomial Logit Marginal Effects

	Ordered Logit Results for Sector of Employment							
	2004	2004	2004	2004	1991	1991	1991	1991
VARIABLES	0	1	2	3	0	1	2	3
ageyrs	-0.004*	0.003*	0.0007*	0.0001*	-0.01**	0.01**	0.001**	0.0002**
	(0.002)	(0.002)	(0.0003)	(0.00007)	(0.006)	(0.005)	(0.0005)	(0.0001)
ageyrs2	0.00006**	-0.00005**	-0.000010**	-0.000002**	0.0002**	-0.0001**	-0.00001*	-0.000003**
	(0.00002)	(0.00002)	(0.000004)	(7.42467e-07)	(0.00007)	(0.00006)	(0.000006)	(0.000001)
kids0_6	0.0009**	-0.0007**	-0.0002**	-0.00003**	0.001	-0.001	-0.00010	-0.00002
	(0.0005)	(0.0004)	(0.00008)	(0.00001)	(0.001)	(0.001)	(0.0001)	(0.00003)
kids7_17	0.0003	-0.0002*	-0.00005	-0.000009	0.0006	-0.0005	-0.00004	-0.00001
	(0.0002)	(0.0001)	(0.00003)	(0.000006)	(0.001)	(0.001)	(0.0001)	(0.00002)
adults65up	0.002**	-0.001**	-0.0003**	-0.00005**	0.006***	-0.006***	-0.0005***	-0.0001***
	(0.0006)	(0.0005)	(0.0001)	(0.00002)	(0.002)	(0.002)	(0.0002)	(0.00004)
m18up	-0.0006*	0.0005*	0.00010*	0.00002	-0.001	0.001	0.00008	0.00002
	(0.0003)	(0.0003)	(0.00006)	(0.00001)	(0.001)	(0.0009)	(0.00008)	(0.00002)
f18up	-0.0002	0.0001	0.00003	0.000005	0.001	-0.001	-0.00010	-0.00002
	(0.0003)	(0.0002)	(0.00005)	(0.000010)	(0.001)	(0.0009)	(0.00008)	(0.00002)
_Iarea_1	-0.07***	0.06***	0.01***	0.002***	-0.3***	0.3***	0.02***	0.006***
	(0.01)	(0.01)	(0.003)	(0.0005)	(0.03)	(0.03)	(0.004)	(0.0008)
_Ieduccat_2	-0.1***	0.1***	0.02***	0.005***	-0.2***	0.2***	0.02***	0.004***
	(0.02)	(0.01)	(0.003)	(0.0008)	(0.01)	(0.01)	(0.002)	(0.0004)
_Ieduccat_3	-0.4***	0.2***	0.09***	0.02***	-0.4***	0.3***	0.06***	0.02***
	(0.03)	(0.02)	(0.01)	(0.004)	(0.05)	(0.03)	(0.02)	(0.005)

Continued

	Ordered Logits for Sector of Employment							
	2004	2004	2004	2004	1991	1991	1991	1991
VARIABLES	0	1	2	3	0	1	2	3
area_f	-0.05**	0.04**	0.008**	0.002*	-0.01	0.01	0.001	0.0002
	(0.02)	(0.02)	(0.004)	(0.0008)	(0.05)	(0.04)	(0.004)	(0.0009)
_Iind_2	-0.7***	0.3***	0.3***	0.09***	-0.5***	0.3***	0.2***	0.04***
	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.009)
_Iind_3	-0.4***	0.2***	0.09***	0.02***	-0.4***	0.3***	0.08***	0.02***
	(0.04)	(0.02)	(0.01)	(0.004)	(0.04)	(0.02)	(0.02)	(0.005)
_Iind_4	-0.09***	0.07***	0.02***	0.003***	-0.3***	0.2***	0.03***	0.007***
	(0.02)	(0.02)	(0.005)	(0.001)	(0.05)	(0.04)	(0.007)	(0.002)
_Iind_5	-0.6***	0.3***	0.2***	0.05***	-0.6***	0.4***	0.1***	0.04***
	(0.04)	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)	(0.02)	(0.006)
_Iind_6	-0.5***	0.3***	0.1***	0.03***	-0.6***	0.4***	0.1***	0.04***
	(0.03)	(0.02)	(0.01)	(0.005)	(0.04)	(0.02)	(0.02)	(0.008)
_Ihhstr_2	-0.001	0.001	0.0002	0.00004	0.1**	-0.1**	-0.009**	-0.002**
	(0.03)	(0.02)	(0.004)	(0.0008)	(0.06)	(0.06)	(0.004)	(0.0008)
_Ihhstr_3	-0.09**	0.07**	0.02**	0.003*				
	(0.04)	(0.03)	(0.008)	(0.002)				
_Ihhstr_4	-0.1***	0.09***	0.02***	0.004***	-0.07*	0.06*	0.005*	0.001*
	(0.02)	(0.02)	(0.004)	(0.0008)	(0.04)	(0.03)	(0.003)	(0.0006)
female					-0.08	0.07	0.006	0.002
					(0.07)	(0.06)	(0.006)	(0.001)
Observations	16077	16077	16077	16077	8242	8242	8242	8242

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

B.4 Further Regression Results for Attributes, Education and Economic Returns

	Logit	Education Ordered Logits						Quantile Regressions	
VARIABLES		2004	2004	2004	1991	1991	1991	2004	1991
	Count	1	2	3	1	2	3	lconseq23	lconseq23
ageyrs	0.002	-0.01***	0.01***	0.001**	-0.00007	0.00007	0.000001	-0.03***	-0.01
	(0.003)	(0.004)	(0.004)	(0.0005)	(0.006)	(0.005)	(0.0001)	(0.005)	(0.009)
ageyrs2	-0.00002	0.0002***	-0.0002***	-0.00002***	0.00009	-0.00008	-0.000002	0.0002***	0.00003
	(0.00003)	(0.00004)	(0.00004)	(0.000005)	(0.00008)	(0.00008)	(0.000002)	(0.00006)	(0.0001)
kids0_6	0.01***	0.002***	-0.002***	-0.0002***	-0.0005	0.0004	0.000009	-0.005***	-0.02***
	(0.0007)	(0.0004)	(0.0003)	(0.00005)	(0.002)	(0.002)	(0.00003)	(0.0006)	(0.005)
kids7_17		0.0005	-0.0005	-0.00005	0.002	-0.002	-0.00003	-0.007***	-0.02***
		(0.0004)	(0.0004)	(0.00004)	(0.001)	(0.001)	(0.00002)	(0.0005)	(0.004)
adults65up	0.003***	0.002**	-0.001**	-0.0002**	-0.001	0.001	0.00002	0.004***	-0.002
	(0.0005)	(0.0007)	(0.0006)	(0.00007)	(0.002)	(0.002)	(0.00004)	(0.001)	(0.003)
m18up		-0.002***	0.002***	0.0002***	-0.003**	0.003**	0.00006**	0.003***	-0.01***
		(0.0003)	(0.0003)	(0.00004)	(0.001)	(0.001)	(0.00003)	(0.0005)	(0.004)
f18up		-0.002***	0.002***	0.0002***	-0.002	0.002	0.00003	0.005***	-0.009**
		(0.0006)	(0.0005)	(0.00006)	(0.001)	(0.001)	(0.00003)	(0.0006)	(0.004)
_Iarea_1		-0.3***	0.2***	0.03***	-0.3***	0.3***	0.006***	0.8***	1.1***
		(0.02)	(0.02)	(0.006)	(0.04)	(0.04)	(0.002)	(0.03)	(0.05)

Continued

	Logit	Education Ordered Logit Results						Quantile Regression	
Variables	Attributes	Primary 2004	Secondary 2004	Tertiary 2004	Primary 1991	Secondary 1991	Tertiary 1991	lconseq23 2004	lconseq23 1991
area_f		-0.1**	0.1**	0.01*	-0.1**	0.1***	0.003**		
		(0.05)	(0.04)	(0.007)	(0.05)	(0.04)	(0.001)		
_Iind_2		-0.3***	0.3***	0.08***	-0.2***	0.2***	0.006**		
		(0.02)	(0.02)	(0.02)	(0.06)	(0.05)	(0.002)		
_Iind_3		-0.2***	0.2***	0.02***	-0.1***	0.1***	0.003**		
		(0.03)	(0.02)	(0.007)	(0.04)	(0.04)	(0.001)		
_Iind_4		-0.2***	0.1***	0.02***	-0.2***	0.2***	0.004***		
		(0.02)	(0.02)	(0.003)	(0.04)	(0.04)	(0.001)		
_Iind_5		-0.4***	0.3***	0.1***	-0.3***	0.3***	0.009***		
		(0.02)	(0.02)	(0.03)	(0.05)	(0.04)	(0.003)		
_Iind_6		-0.2***	0.2***	0.04***	-0.2***	0.2***	0.006***		
		(0.03)	(0.02)	(0.01)	(0.04)	(0.04)	(0.002)		
_Ihhstr_2		-0.04	0.04	0.004	-0.04	0.04	0.0008		
		(0.05)	(0.04)	(0.005)	(0.04)	(0.04)	(0.0009)		
_Ihhstr_3		-0.03	0.03	0.003					
		(0.05)	(0.04)	(0.005)					
_Ihhstr_4		-0.2***	0.2***	0.01***	-0.1**	0.1**	0.002**		
		(0.04)	(0.04)	(0.004)	(0.04)	(0.04)	(0.0008)		
_Iland_1	0.4***								
	(0.04)								
_Iland_2	0.3***								
	(0.04)								
_Iland_3	0.2***								
	(0.05)								

Continued

	Logit	Education Ordered Logit Results						Quantile Regression	
Variables	Attributes	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary	lconseq23	lconseq23
		2004	2004	2004	1991	1991	1991	2004	1991
female	0.05***				-0.007	0.007	0.0001		
	(0.01)				(0.05)	(0.05)	(0.001)		
_Ieduccat_2								0.2***	0.5***
								(0.03)	(0.04)
_Ieduccat_3								0.7***	1.1***
								(0.04)	(0.2)
_Iempf_1								0.3***	0.4***
								(0.03)	(0.05)
_Iempf_2								0.3***	0.6***
								(0.04)	(0.07)
_Iempf_3								0.3***	0.4***
								(0.08)	(0.1)
Constant								10***	11***
								(0.1)	(0.5)
Observations	24319	16077	16077	16077	8242	8242	8242	15586	8242

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix C

Appendix for Chapter 4

C.1 Estimation of Parameters

We estimate the $\beta = \begin{bmatrix} \mu \\ \sigma^2 \end{bmatrix}$ vector of parameters using maximum likelihood method. We maximize the likelihood function:

$$\ln L = \sum_{i=1}^{n} \theta_i \ln x_i - \sum_{i=1}^{n} \theta_i \ln \sigma - \frac{1}{2} \sum_{i=1}^{n} \theta_i \ln (2\pi) - \frac{1}{2\sigma^2} \sum_{i=1}^{n} \theta_i (\ln x_i - \mu)^2 \tag{C.1}$$

where θ_i is the weight for individual i. To obtain an asymptotic covariance matrix of β that is robust to heteroscedasticity we use the Huber/White/sandwich estimator of variance-covariance matrix. this estimation takes into account sampling design by svy options in stata. The covariance matrix of $\widehat{\beta}$ was then used to estimate standard errors for the conditional poverty rate $p(t, w)$ and the poverty differential $d(t, w, w^*)$ via the delta-method Greene (2003) as follows:

$$\widehat{var}\left(\widehat{\beta}\right) = \left[\frac{\partial^2 \ln L\left(\widehat{\beta}\right)}{\partial\widehat{\beta}\partial\widehat{\beta}'}\right]^{-1} \widehat{var}\left(\ln L\left(\widehat{\beta}\right)\right) \left[\frac{\partial^2 \ln L\left(\widehat{\beta}\right)}{\partial\widehat{\beta}\partial\widehat{\beta}'}\right]^{-1} \tag{C.2}$$

with

$$\widehat{var}\left(\ln L\left(\widehat{\beta}\right)\right) = \frac{n_h}{n_h - 1} \sum_{j=1}^{n_h} (z_j - \overline{z})(z_j - \overline{z})' \tag{C.3}$$

and

$$z_j = \sum_{l \in H_j} \theta_l \frac{\partial \ln L\left(\widehat{\beta}\right)}{\partial\widehat{\beta}} \tag{C.4}$$

where $\overline{z} = n_h^{-1} \sum_{j=1}^{n_h} z_j$ and H_j denote households $j = 1...n_h$.

Variance estimates for the conditional poverty rate $p(t, w)$ and poverty differentials

$d(t, w, w^*)$ were calculated as follows:

$$\widehat{var}\left(p\left(t,w\right)\right) = \left[\frac{\partial p\left(t,w\right)}{\partial \widehat{\beta}}\right] \widehat{var}\left(\widehat{\beta}\right) \left[\frac{\partial p\left(t,w\right)}{\partial \widehat{\beta}'}\right] \tag{C.5}$$

and

$$\widehat{var}\left(p\left(t,w\right)\right) = \left[\frac{\partial d\left(t,w,w^*\right)}{\partial \widehat{\beta}}\right] \widehat{var}\left(\widehat{\beta}\right) \left[\frac{\partial d\left(t,w,w^*\right)}{\partial \widehat{\beta}'}\right] \tag{C.6}$$

C.2 Parameter Estimates

	1991		1996		2004	
VARIABLES	β_1	β_2	β_1	β_2	β_1	β_2
female	0.222***	0.00241	0.185***	0.0848**	0.104***	0.0249
	(0.0792)	(0.0777)	(0.0380)	(0.0333)	(0.0245)	(0.0162)
1 member employed	0.628***	-0.0759	0.332***	-0.0795**	0.258***	-0.164***
	(0.0670)	(0.0811)	(0.0253)	(0.0288)	(0.0493)	(0.0188)
2 members employed	0.862***	-0.121	0.444***	-0.105**	0.349***	-0.176***
	(0.0840)	(0.105)	(0.0394)	(0.0389)	(0.0528)	(0.0384)
at least 3 employed	0.759***	-0.0230	0.416***	-0.0629	0.412***	-0.184***
	(0.122)	(0.156)	(0.0806)	(0.0825)	(0.0688)	(0.0517)
Education of head	0.0917***	-0.00983	0.0837***	0.00445**	0.0710***	-0.00709***
	(0.00923)	(0.00827)	(0.00566)	(0.00199)	(0.00480)	(0.00246)
number of children	-0.0722***	0.00179	-0.204***	0.000513	-0.109***	-0.00339
	(0.00778)	(0.00759)	(0.0120)	(0.00649)	(0.00736)	(0.00389)
Constant	9.499***	1.157***	10.19***	0.773***	9.861***	0.949***
	(0.107)	(0.0804)	(0.0334)	(0.0240)	(0.0564)	(0.0176)
Observations	7689	7689	11385	11385	20806	20806

Note: Standard errors in parentheses

**** significant at 1 percent*

*** significant at 5 percent*

** significant at 10 percent*