School of Economics

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Multidimensional Poverty Dynamics in Indonesia (1993 - 2007)

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Abstract

Most of the remaining unresolved issues in poverty analysis are related directly or indirectly to the multidimensional nature and dynamics of poverty (Thorbecke, 2005). Analysis on multidimensional poverty has occupied much attention of economists and policymakers, particularly since the writing of (Sen, 1976) and the rising of data availability for relevant research purpose. A significant development for research has been the improvement in constructing a coherent framework for measuring poverty in multidimensional environment analogously to the set of techniques developed in one-dimension space. Multidimensional measures provide another insight into particular elements of poverty that is useful and relevant to poverty interventions.

The advances in poverty research also embrace the dynamic perspective in assessing living conditions. The distinction of poverty condition between chronic and transient is not only important from the perspective of measurement accuracy, but also for policy implication purposes as well. Chronic versus transient poverty would call for different policy alleviation strategies (Hulme and Shepherd, 2003).

This paper provides microeconometric analysis of the socio economic variables using Indonesian panel household surveys. The first topic is the determinants of multidimensional poverty for household, with special attention given to operationalise conceptual thinking of multidimensional poverty. The second topic adopts multiple correspondence analyses (MCA) in order to construct an index which better reflects poverty measurement. By adopting such an approach we are able not only to establish the key determinants of poverty but also to provide a microeconometric perspective on defining factors and setting optimal weights. The third topic looks at how multidimensional poverty index can play a major role in observing whether people are trapped in poverty over long periods to establish the extent of chronic and transient poverty in Indonesia.

This paper estimates the incidence of multidimensional poverty to reach higher level compared to monetary poverty. However, the two types of poverty are quite positively correlated and have similar trend. It is also found that chronic poverty has characterised the pattern for the long run.

Keywords: Multidimensional poverty, chronic poverty, transient poverty, multiple correspondence analyses.

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Last but surely not least, for the poor people that have been the focus of my dissertation. I hope this small work will be a dedication to them.

Courtesy image from: ryansan

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CHAPTER 1
INTRODUCTION

1.1. Introductory Remarks

What makes an individual poor? If a person owns money what determines whether they prosper in their lives? Is money the only determinant of well being? What other important determinants to decide whether people are poor? These are some of the research questions that this dissertation aims to explain.

Several definitions of poverty have prior conception of welfare, the choice of a “poverty line” divides the population into those who have an adequate level of welfare and those who do not. Measuring the welfare level of an individual or a household can be considered as challenging task, but it can be made simpler if one limits the concept to material welfare. In doing this, one omits away a variety of immaterial factors that influence happiness and satisfaction. In welfare economics, the starting point for the measurement of welfare is the utility function, which can be observed as an index of well-being and has positive correlation with goods and services that are consumed.

Furthermore, measures of living conditions at one point in time will not necessarily reflect a good indicator of their stability over time. This matters more for some dimensions of living conditions. A child may currently be attending school, but that does not guarantee her not to drop out before completing studies, or even still attend school next year. Similar points also apply to other dimensions on living conditions.

Traditionally, poverty has been defined as a discrete characteristic. Given a particular indicator of welfare, a certain line or standard is drawn, and an individual or household falls on one side or the other so that it will make analysis of poverty takes place at two extremely different levels. To define poverty means classifying the population into two groups i.e. the poor and the non-poor. Measuring poverty seeks to aggregate the “amount” of poverty into a simplified statistics.

This dissertation uses household surveys to capture the development of social characteristics and dynamics of welfare attributes. First of all, we will establish the main socio economic determinants as an alternative for conventional methodology. The second part will provide an empirical analysis of the main determinants in describing multidimensional poverty over periods. The third main area will elaborate poverty dynamics.

This chapter briefly provides introduction to these aforementioned issues, and establishes the concept. The second section of this chapter will provide details of the data set used in the analysis. Finally, the last section of the chapter then outlines thesis organisation and gives an overview of the analysis contained within.

1.2. General Issues

Evaluation of well being has been considered as a multi-attribute exercise. Several indicators are built on composite basis such as Human Development Index and Human Poverty Index but less consensus can be found on such matters as which attributes are relevant to overall well being, and what criteria to employ for complete ranking of well-being situations.

Traditional poverty measurement has been receiving criticism in defining welfare attributes. Critics argue it hardly reflect the actual condition of well being and simplifying. Recently there has been an increase in poverty awareness and interest on its existence, much of which was generated by Sen (1976) and Townsend (1979), that later has altered the perception of how poverty is conceptualised and defined. This had an impact on how poverty is measured, resulting in the alternatives to the traditionally accepted poverty measures (Tsui, 2002) The general move has been away from the view of income as the only measure of poverty in search of other indicators that provide a more well rounded and more accurate picture.

The rationale behind the use of income as a measure was based on the idea that income as a source of cash, which can be spend to satisfy and fulfil basic human needs (Scott, 2002). However, the assumption of money market existence, which supplies all these basic needs, has been severely criticised (Tsui, 2002). Another criticism of this measure is the assumption that each member of the household has access to a fair and proportional share of the income at the household level (DFID, 2001).As a result of the flaws in the use of income as the only poverty measure, researchers have attempted to build various, diverse indices that add to, or substitute for, income and consumption data.

The multidimensional approach to poverty has been discussed by several authors such as Atkinson and Bourguignon (1982), Waglé (2008) and Duclos et al. (2006). In many researches, income remains important instrumentally, because to some extent it can afford these capabilities, but it should be noted that poverty can also be measured in other dimensions more directly. Practical research that attempts to apply the new approach include the UNDP's Human Development Index (1994) as well as more general research that considers multiple dimensions of poverty simultaneously Sahn (1999) and Duclos et al., 2006). Such measures that aim to assess the fulfilment of basic needs and access to services are driven by development economists who see a decrease in poverty as sustained improvements in basic needs such as health and education and not simply income (Tsui, 2002).

Supporting evidence for the multidimensional measurement of poverty is abundant. The justification behind the measurement of more than one dimension of poverty is based on the idea that income indicator is incomplete and its shortfalls lead to inaccurate estimations of poverty (Diaz, 2003). Having said that, alternative dimensions such as health, educational attainment, social exclusion, and insecurity are often weakly correlated with income or expenditure Appleton and Song (1999) and Sahn (1999). These poor correlations highlight the fact that measuring these additional dimensions enriches and provides additional information to the poverty picture (Calvo and Dercon, 2005).

When choosing the measure, it is important to ensure a fit between the properties of a poverty index and policy objectives. This suggests that different indices lead to different images and thus the poverty picture can be highly dependent on the indicators chosen. In order to better capture full picture of multidimensional poverty an argument is made to keep the measurement approach as broad as possible (Ruggeri-Laderchi, 2003). Consequently the poverty measurement field is littered with various measures each assessing a particular dimension of poverty.

Each theory or definition of poverty differs slightly as to what it sees as contributing to poverty and hence utilises a unique combination of indicators in its measures. However, the strength of measurement lies in the construction of indices that capture the relative importance of each indicators in the total poverty picture. The weighting of each indicator is meant to reflect the strength of the relationship with 'wealth factor' as proposed by Sahn and Stifel (2000) for asset-based measurement.

While the most important component in poverty measures is identification, there are two main approaches in identifying the poor in a multidimensional setting (Alkire and Foster, 2008) i.e. "union" and "intersection" approach. The former regards someone who is deprived in a single dimension as poor in the multidimensional sense while the latter requires a person to be deprived in all dimensions being identified as poor. Empirical assessments of multidimensional poverty need a satisfactory solution to the identification problem.

This research proposes exploration of multidimensional poverty measurement in Indonesia which aims to examine empirically the significance of identification and attempts to throw light on the construction of multidimensional poverty indicator. In addition, analysing dynamic patterns of poverty will produce major benefits for being able to formulate efficient policy toward specific areas which are likely to benefit poor people.

Why choose Indonesia as object of study? First, Indonesian economy has been experiencing "boom" and "bust" period yet economic reforms over recent years aim to increase capacity of human development mainly through three policies: pro-growth, pro-job, and pro-poor. Concern for poverty is therefore of fundamental importance. Second, Indonesia is considered as good examples in reducing poverty incidence, although there has been no in depth analysis on establishing to what extent poverty persists over time and characteristics associated with multidimensional poverty. Third, for a microeconometric focus of the type undertaken in this study, the recent household data sets for Indonesia are known to be relatively accurate. Finally, the author has an interest in exploring the concept of multidimensional poverty and its application which stems back from previous research and methodologies. This work is a reflection of the author's occupation as planner and social researcher.

1.3. Data

Indonesia has rich publication on statistics, however only few are available for household analysis. Data sets mainly produced through routine surveys conducted by National Statistics Agency (*Badan Pusat Statistik*). From microeconometric perspective, there have been four household panel data surveys released by RAND Corporation known as Indonesian Family Life Survey (IFLS).

The IFLS surveys were undertaken in four waves i.e. 1993, 1997, 2000, and 2007 equipped with tracking method to anticipate attrition and missing variables. These are representative of 83% of the population living in 13 provinces. Using the four waves, we built panels from 1993 to 2007 comprising roughly 32,000 individuals living in 7,000 households.

In addition to the IFLS, the surveys also enable re-contact with households and split-off households where individuals who have moved are tracked to their new location (see Strauss et al., 2004). IFLS is acknowledged as reliable panel data set among statistician due to its high re-contact rate. It is a comprehensive multipurpose survey that collects data at the community, household and individual levels. The survey includes household and individual-level information. One or two household members were asked to provide information at the household level. The interviewers attempted to conduct an interview with every individual age 11 and over, and to interview a parent or caretaker for children less than 11.

The advantages of using this data set is that we can analyse poverty and welfare issue from unique point of view. It is reasonable not only because the methodology for IFLS is different than other survey data set, but also due to the fact that these data sets are bearing different stress on touching the household issue and reached the community level. It should clearly be taken into account that the research does not meant to compare directly the result of official statistics and IFLS since both are different in methodologies and periods of survey conducted.

1.4. Organisation and Overview

The study empirically examines the relevant determinants of multidimensional poverty in Indonesia. Specifically related to poverty dynamics, this analyses how dimensions or variables can be associated with multidimensional poverty indicator.

Detailed outline of each chapter can be found in the following paragraphs and commences with an overview of Chapter Two, which provides some general details and stylised facts about Indonesia.

Chapter Two provides background for Indonesia so that its current economic and political context can be presented. The chapter starts by providing information primarily focussing on the major political and economic changes that occurred in Indonesia's post-independence history. This is then complemented by a review of Indonesia's effort in alleviating poverty.

Chapter Three provides a detailed overview of the current theory that underlies the determinants of multidimensional poverty. An outline of the theory relating to analysis is provided before articulating the function which can be used as a basis for the empirical analysis in the following chapters.

Chapter Three also presents an overview of the recent literature that has examined the key determinants of multidimensional poverty. The critique highlights that there tends to be limited consensus regarding many of the key determinants of poverty although an important message from this review is that there tends to be consistency in the approach used for analysing.

Chapter Four provides an analysis of the determinants of poverty for individuals according to social and economic categories. Also, we are able to identify some of the key characteristics associated with poverty. This will discuss the choice of determinants and models for explaining multidimensional poverty in Indonesia. Using specific methodology we can test the main determinants and attributes best reflect social and economic condition. This test also concerns the issue of inequality and poverty dynamics.

In Chapter Five, a summary of the results from the study is provided and some overall conclusions. We also discuss the shortcoming of the results and methods. Finally, we provide some suggestions for future research and practical policies.

CHAPTER 2
INDONESIA – BACKGROUND

2.1. Introduction

From a macroeconomic perspective, Indonesia is perceived to be an example of successful economic development. Over last ten years, since free democracy and rapid reform took place in 1998, a combination of policy packages and the creation of able economic environment has resulted in sustainable economic growth. However, Indonesia's history is more complicated than the prevailing economic success story. In the periods following transition between old into new regime in 1966, Indonesia underwent political moderation, economic liberalisation, and social change. Over a period of 20 years, from 1970s, real GDP per capita rose by more than 5%. This situation was supported by world oil price increase which give positive impact on Indonesia's economy. Situation abruptly changes during mid 1990s when Asian financial crisis struck the country and put economy into chaos and caused social turmoil. Given such a dramatic history it is therefore important that current economic and social environment are put into context.

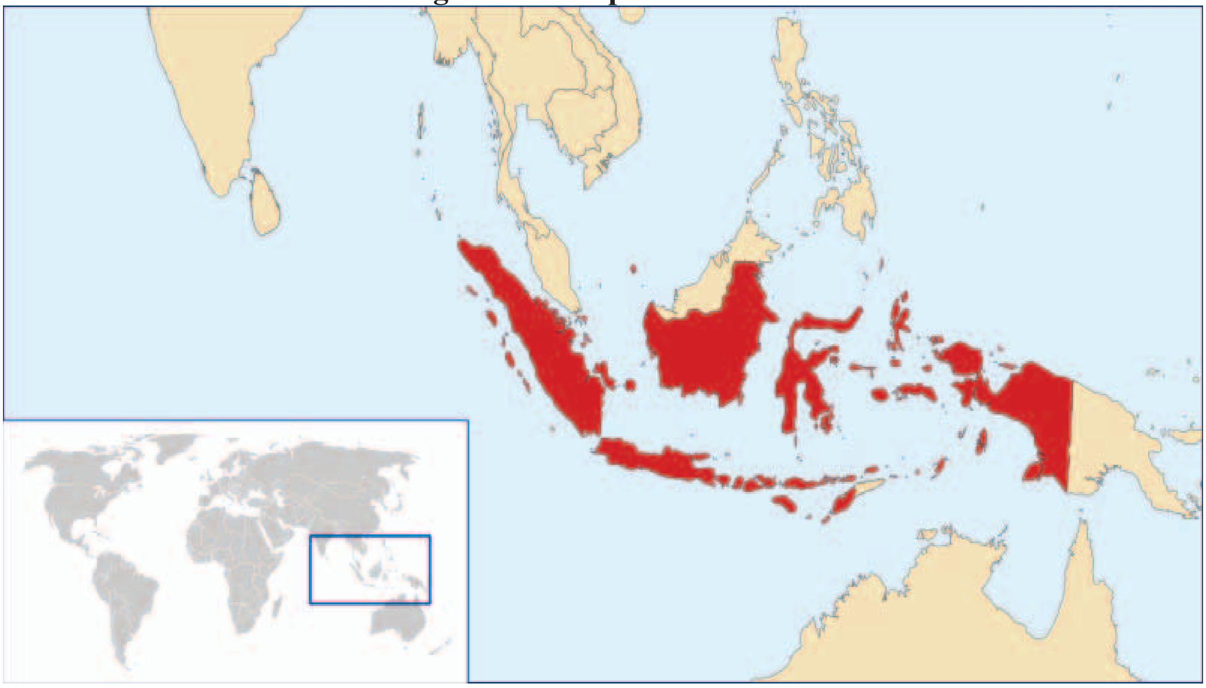
This chapter starts by providing some general background on Indonesia before section 2.3 gives an historical perspective with a specific focus on the economic and political history of Indonesia. Next sections then sets the scene by providing specific background on multidimensional poverty in Indonesia, combined with its policy measures.

2.2. General Background

The Republic of Indonesia is an archipelagic country consists of 17,000 islands located at the junctions of two continents: Asia and Australia. It shares border (sea and land) with Malaysia, Singapore, The Philippines, East Timor, Papua New Guinea, and Australia. Indonesia has a surface area of near 2 million sq. km and a population of 230 million people with growing rate 1.18% per annum (World Bank, 2009) puts Indonesia into fourth most populated country in the world.

Geographically, most islands lie above labile tectonic plate with series of volcanoes make Indonesia unto being very prone to natural disasters. Located surrounding equator line, the climate is mainly tropical with high precipitation throughout the year. As a consequence, Indonesia's agricultural potential is good with reasonable climate and fertile soils spanned most of the country which enable self sufficiency for food and production of cash crops such as rubber, palm oil, and spices.

Figure 2.1: Map of Indonesia



2.3. Historical Perspective – Political and Economic

There is no reliable statistics record during the colonial era (1400s-1945) and revolution era (1945-1965) yet it is believed that Indonesia struggled with high-rise inflation and large budget deficit which caused by financing war and debt inherited from colonial era.

In 1965, intense political turmoil and worsened economic situation made President Soekarno being overthrown in the following year. This started the "New Order" era of President Soeharto for the following 32 years with more open and freer economy. Soeharto's new government were offered a series of stabilisation packages from international donors and world community. Although new government inherited inflation-ridden and debt-burdened economy, they managed to win support from international donor community. By adopting new economic policies and rescheduling debt repayment there was soon a sharp turn in economic performance. During 1970s, revulsion of world oil price gave windfall profit to the country and by 1980s while series of deregulation policy brought financial and banking sectors into booming period. Not only did government concern with economic issues but also they managed to stabilise political situation using autocratic-style regime and control demographic rate through family planning program (*Keluarga Berencana*).

In 1997, the country was struck with Asian financial crisis which initially ignited in currency crisis and ended into political turmoil and social upheavals which then forced Suharto left his long term presidency. After series of dramatic events, Indonesia has started to regain its footing. The country has largely recovered from the economic crisis that flung millions of its citizens back into poverty and saw Indonesia regress to low-income status. Recently, it has once again become one of the world's emergent middle-income countries (Table 1.1).

Table 1.1: Selected Macroeconomic Variables for Indonesia

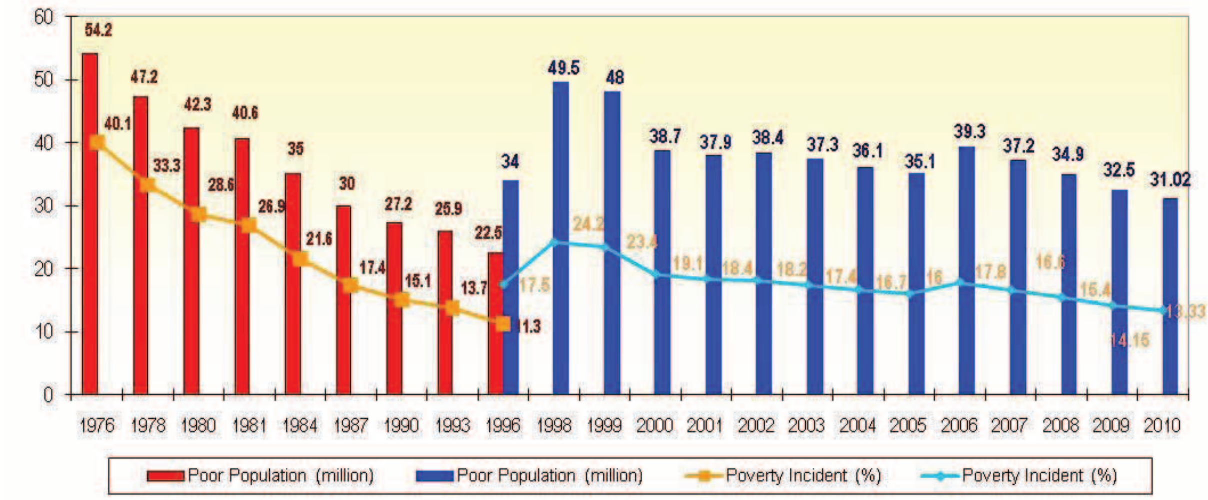
%	1980	1991	2000	2008
GDP Growth (y-o-y)	8.7	8.9	3.6	6.1
Inflation (y-o-y)	18.4	9.4	3.8	2.78
Exports to GDP	34.2	25.8	41	29.8
Imports to GDP	20.2	24.1	30.5	28.6
Exchange rates (Rp/USD)	799	1,950	8,292	9,400
Investment to GDP	24.1	31.6	22.2	27.8

Source: World Bank (2009)

2.4. Social Development in Indonesia

One of the key achievements in reducing poverty rate is its success in enabling self sufficiency and food security in agriculture sector (*swasembada pangan*). Indonesia has a potential for rapidly reducing poverty. First, given the nature of poverty in Indonesia, focussing attention on a few priority areas could deliver significant impact in the fight against poverty and low human development outcomes. Second, as an oil and gas producing country, Indonesia chances to benefit in the next few years from increased fiscal resources thanks to higher oil prices and better fiscal management. Third, Indonesia can harness further benefits from its ongoing processes of democratisation and decentralisation process. Meanwhile, Indonesia has undergone some major social and political transformations, emerging as a vibrant democracy with decentralised government and far greater social openness and debate. Poverty levels that had increased by over one-third during the crisis are now back to pre-crisis levels (Figure 2.2).

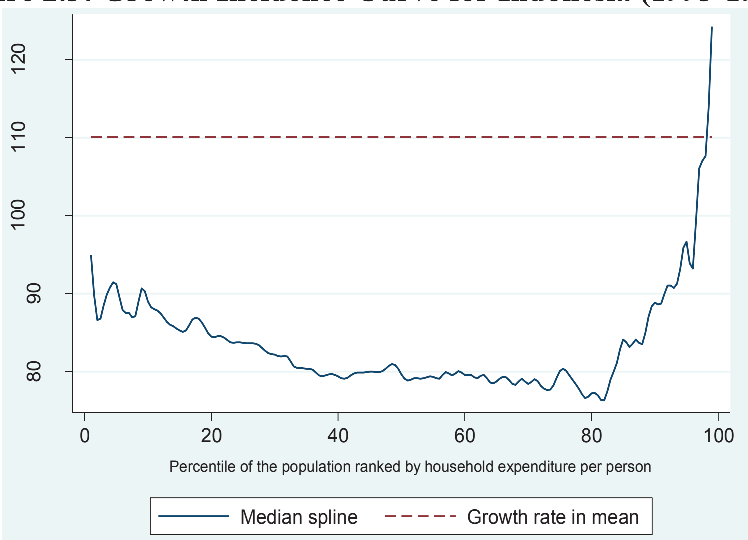
Figure 2.2: Poverty Incidence in Indonesia (1976-2010)



Source: Statistics Indonesia (www.bps.go.id)

Indonesia has had remarkable success in reducing poverty since the 1970s. The period from the late 1970s to the mid-1990s is considered one of the most "pro-poor growth" episodes in the economic history of any country, with poverty declining by half. After series of spike during the economic crisis, poverty has generally returned to its pre-crisis levels. The poverty rate fell back to about 16 percent in 2005 following a peak of over 23 percent in 1999 in the immediate wake of the economic crisis. However, Figure 2.3 shows that in 1993-1997 economy takes side with non-poor groups with highest growth per capita was benefited disproportionately to highest percentile of population.

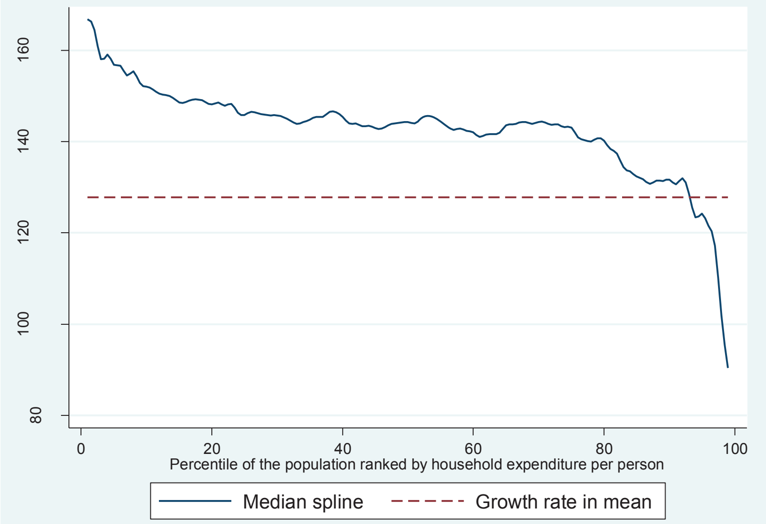
Figure 2.3: Growth Incidence Curve for Indonesia (1993-1997)



Source: Author's calculation based on IFLS

Nevertheless, Indonesia successfully reverse this trend into more pro-poor situation during 2000-2007 as graphed in Figure 2.4. Several measures were undertaken such as direct subsidy, cash transfer, and social programmes toward poorest groups. Macroeconomic stabilisation from mid-2001 onwards also underpinned, bringing down the price of goods, such as rice, that are important to the poor. Despite steady progress in reducing poverty recently there has been an unforeseen upturn in the poverty rate. This reversal appears to have been caused primarily by a sharp increase in the price of rice, an estimated 33 percent for rice consumed by the poor between February 2005 and March 2006, which largely accounted for the increase in the poverty headcount rate to 17.75 percent.

Figure 2.4: Growth Incidence Curve for Indonesia (2000-2007)



Source: Author's calculation based on IFLS

2.5. Dimensions of Poverty in Indonesia

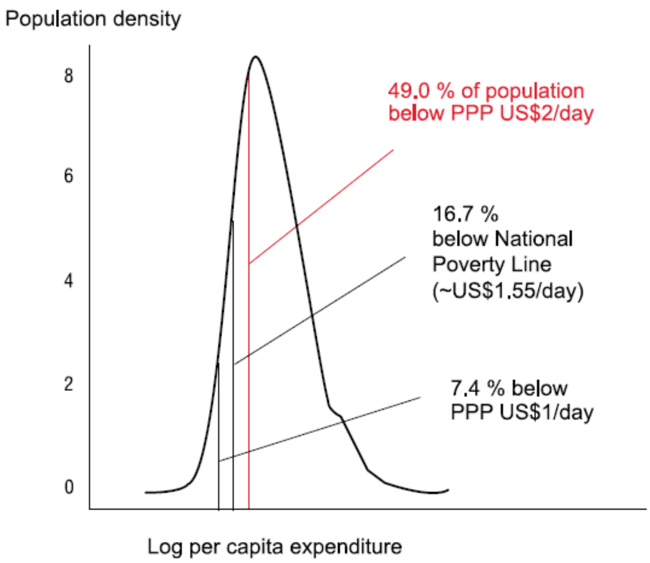
Poverty in Indonesia has three features. First, many households are clustered around the national income poverty line of about PPP[1] US$1.55-a-day, making even many of the non-poor vulnerable to poverty. Second, the income poverty measure does not capture the true extent of poverty in Indonesia; many who may not be "income poor" could be classified as poor on the basis of their lack of access to basic services and poor human development outcomes. Third, given the vast size of and varying conditions in the Indonesian archipelago, regional disparities are a fundamental feature of poverty in the country.

A large number of Indonesians are vulnerable to poverty. The national poverty rate masks the large number of people who live just above the national poverty line. A remarkable and

[1] Purchasing power parity:

defining aspect of poverty in Indonesia is shown in Figure 2.5 says that almost 42 percent of population live between the US$1 and US$2 a day. indicates that there is little that distinguishes the two groups, suggesting that poverty reduction strategies should focus on the lowest groups.

Figure 2.5: Density Curve for Per Capita Expenditure (2006)

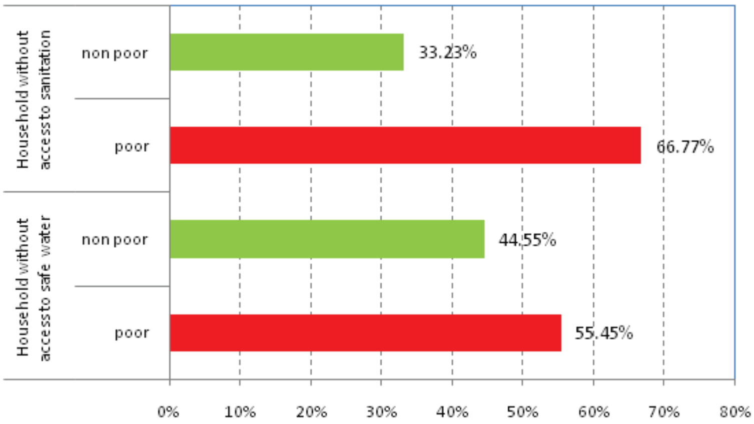


Source: Susenas 2006 in World Bank (2006)

The most striking fact is that non-income poverty is considered more serious than income poverty (Figure 2.6). When one acknowledges all dimensions of human well-being-adequate consumption, reduced vulnerability, education, health and access to basic infrastructure-then almost half of all Indonesians would be considered to have experienced at least one type of poverty. Nevertheless, Indonesia has made significant progress in past years on improving some human capital outcomes. There have been notable improvements in educational attainment at the primary school level, basic healthcare coverage, and dramatic reductions in child mortality. Indeed, specific areas that require concern are:

- Malnutrition rates are quite high and have even increased in recent years.
- Maternal health is worse than neighbouring comparable countries.
- Education outcomes are still weak.
- Access to safe water is low, especially among the poor.
- Access to sanitation is a crucial problem.

Figure 2.6: Non-Income Poverty



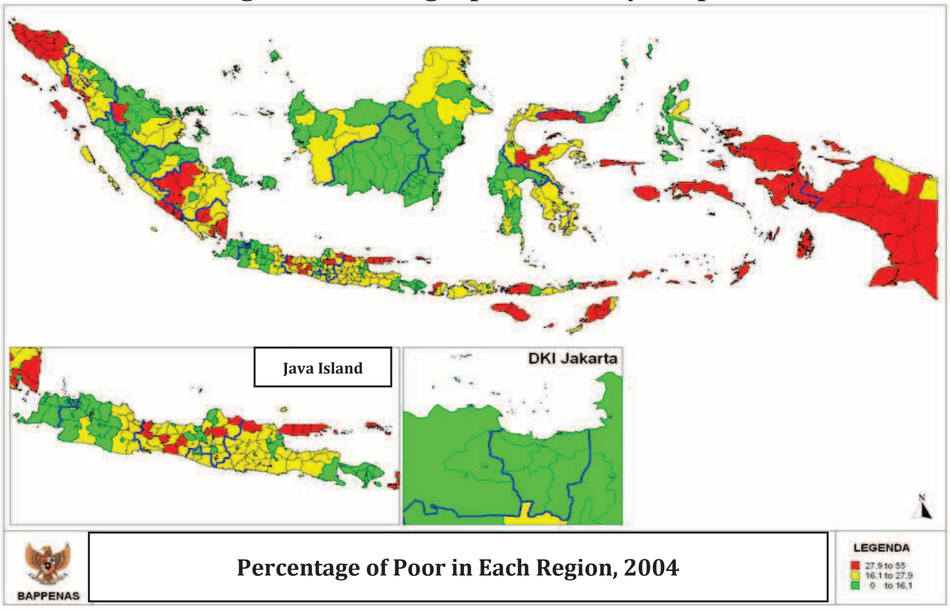
Source: Author's calculation based on Susenas 2008

Wide regional differences characterise Indonesia, some of which are reflected in disparities between rural and urban areas. Rural households account for around 57 percent of the poor in Indonesia and also frequently lack access to basic infrastructure services. But importantly, across the vast archipelago, it is also reflected in broad swathes of regional poverty. In addition to smaller pockets of poverty within regions, for example, the poverty rate is 15.7 percent in Java and Bali and 38.7 percent in remote Papua.

Public services are also unequally distributed across regions, with an undersupply of facilities in remote areas. A challenge is that although poverty incidence is far higher in eastern Indonesia and in more remote areas, most of Indonesia's poor are situated in the densely populated western regions of the archipelago. For example, while the poverty incidence in Java is relatively lower, the island is actually home to 57 percent of Indonesia's total poor, than Papua, which only has three percent of the poor (see Figure 2.7).

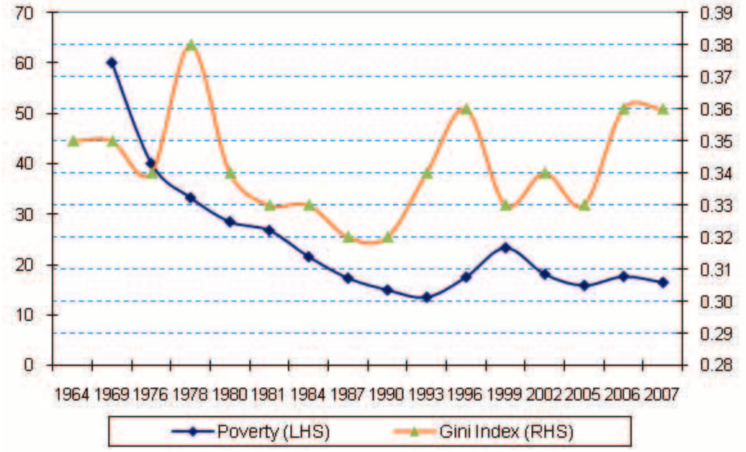
Considered as the side effect of poverty, inequality problem also entangles Indonesia with Gini index recently always remains in the medium inequality position with fluctuating range despite significant progress improvements in poverty alleviation (Figure 2.8). Along with poverty and social problem, this situation will seriously affect social livelihood and have potential to impoverish people even deeper.

Figure 2.7: Geographic Poverty Map



Source: Ministry of Planning

Figure 2.8: Poverty Rate and Gini Coefficient (1964-2007)



Source: Statistics Indonesia

2.6. Summary of Background

Over the last 10 years, since "*reformasi*" era begun, Indonesia has experienced fastest economic recovery in South East Asia region. This is a remarkable achievement considering the scale of Asian economic crisis that devastated almost entire economic structure and productivity sectors. High levels of economic growth and realignment of economic policy has not only enabled Indonesia to overcome many social and political problems but also managed to reduce poverty rate significantly.

However, the aforementioned gains have not been apparent in all geographic areas and all sectors of economy. With Eastern region still lag and poverty alleviation program still require substantial improvement and planning in order that sustainable development be attained. Furthermore, given the relatively low base from which Indonesia has achieved it substantial rates of growth and poverty reduction over the last decade, future development at such levels is likely to be difficult to attain. As such the success is likely depend upon more efficient government policies and targeting. The analysis within this thesis is expected to have contribution in giving assistance and guidance.

CHAPTER 3
THEORY AND LITERATURE

3.1. Introduction

Understanding multidimensional poverty is important because there is no clear non-arbitrary level to set the poverty line. In the case of money-metric assessment, poverty lines are often derived from the food consumption level required to meet caloric intakes, based on prevailing consumption patterns, or from the costs of a basket of basic needs. As an alternative, international poverty lines might be used, such as the PPP US$1 one day per capita consumption level often used by World Bank (2001). For multidimensional poverty indices, however, there is no comparable indication of what would be an appropriate poverty line.

Traditional approaches to the measurement are dominated by a single indicator such as income, consumption, or expenditure per capita, to show the level of deprivation. This measures separate the population between poor and non-poor on the basis of poverty lines which can be absolute or relative. According to the absolute approach, thresholds are defined on the basis of the amount of money needed to secure a minimum standard of living (Nolan and Whelan, 1996). On the other hand, relative income is determined by single threshold at a certain percentage of median or mean income (usually at 50 or 60%), assuming that those falling below such threshold are unlikely to be able to fully participate in the life of the society. Although money-metric measures have some advantages, in terms of easiness for computation and comparability across countries, they also present some drawbacks (Sahn and Stifel, 2003).

For instance, access to water or sanitation is not a reflection of the money-metric poverty or lack of a community, but possibly of their geography. Although access to these services is certainly an important dimension of experienced deprivation, measuring differences in household welfare in terms of differences in access to public services alone conceals important differences in poverty within a community. However, difficulty may occur which makes the multidimensional index a poor tool for distinguishing between segments of the population who may be almost equally poorly served by public services. This holds important implications for the poverty indicators and conclusions that one draws from these analyses. Hence, this multidimensional index is perhaps best employed as a crude indicator of the relative social welfare ranking of the population within relatively broad categories.

3.2. Approaches to Multidimensional Poverty

In recent years, a consensus related to well-being has prevailed: poverty is best understood as a multidimensional phenomenon. However, different views occur among analysts toward the relevance and relative importance in dimensions. Welfarists stress the importance and existence of market imperfections or incompleteness and the lack of perfect correlation between relevant dimensions of well-being (Atkinson (2003); Bourguignon and Chakravarty (2002); and Duclos et al. (2006)), which makes the focus on a sole indicator such as income somewhat unsatisfactory. While non-welfarists urge the need to move away from the space of utilities to a different space, where multiple dimensions are both instrumentally and intrinsically important. Among non-welfarists, there are two main strands: the basic needs approach and the capability approach (Duclos et al., 2006). The first approach, based on Rawls' Theory of Justice, focuses on a set of primary goods that are elements of well-being and considered necessary to live a good life (Streeten, 1981). The second approach argues that the relevant space of well-being should be the set of functionings that the individual is able to achieve. This set is referred to as the capability set "reflecting the person's freedom to lead one type of life or another" (Sen, 1992).

Originated from different theoretical understandings of what constitutes a good life, all three approaches share the same problem: if well-being and deprivation are multidimensional, how should we make comparisons between two distributions and assess whether one distribution exhibits higher poverty levels than the other? To solve this problem one needs to make decisions about the domains relevant to well-being, their respective indicators, threshold levels, and the aggregation function. While these choices might differ substantially across approaches. In this paper, choice of dimensions, indicators and thresholds is considered instead on the different aggregation forms.

3.3. Multidimensional Poverty Indices

In constructing poverty measurement, it involves two steps: the identification and the aggregation of the poor (Sen, 1976). In the one-dimension income approach, the identification step defines an income poverty line based on the amount of income that is necessary to purchase a basket of basic goods and services. Next, individuals and households are identified as poor if their income (per capita or adjusted by the demographic composition of the household) falls short of the poverty line. The individual poverty level is generally measured by the normalised gap defined as:

$$\begin{cases} g_i = [(z - x_i)/z] \; for \; x_i < z \\ g_i = 0 \qquad\qquad\quad for \;\; x_i > z \end{cases} \tag{3.1}$$

Information contained on every individual is most commonly aggregated in the second step using the function proposed by (Foster et al., 1984) known as the FGT measures, defined as:

$$FGT_\alpha = \frac{1}{n}\sum_{i=1}^{n} g_i^\alpha \tag{3.2}$$

The coefficient α is a measure of poverty aversion. Values of α refer to the emphasis for poorest among the poor. When α=0, FGT is the headcount measure, all poor individuals are counted equally. When the measure is the poverty gap (α=1), individuals' contribution to total poverty depends on how far away they are from the poverty line and if the measure is the squared poverty gap (α=2) individuals receive higher weight the larger their poverty gaps are. For α>0 it satisfies monotonicity (sensitive to the depth of poverty) while if α<0 it satisfies transfer (sensitive to the distribution among the poor).

In multidimensional context, distributional data are presented in a matrix size $n \times d$, in which every typical element x_{ij} corresponds to the achievement of individual i in dimension j. Following Sen (1976), it is required to identify the poor. The most common approach in the analysis is to define first a threshold level for each dimension j, under which a person is considered to be deprived. The aggregation of these thresholds can be expressed in a vector of poverty lines $z = (z_i, \dots, z_d)$. In this way, whether a person is considered in deprived situation or not in every dimension could be defined. This research computes poverty line using two-step FGT method as follows:

The non-normalised FGT index is estimated as:

$$\hat{P}(z;\alpha) = \frac{\sum_{i=1}^{n} w_i (z - y_i)_+^\alpha}{\sum_{i=1}^{n} w_i} \tag{3.3}$$

where z is the poverty line and $x_+ = \max(x,0)$. The usual normalised FGT index is estimated as

$$\hat{\bar{\hat{P}}}(z;\alpha) = \hat{P}(z;\alpha)/(z)^\alpha \tag{3.4}$$

Unlike traditional measurement, a second decision is important to be made in the multidimensional context: among those who deprive in some dimension, who is to be considered as multidimensionally poor? A common starting point is to consider all those deprived in at least one dimension, also called *union approach*. However, stricter criteria can be used, even to the extreme of requiring deprivation in all considered dimensions, the so called *intersection approach*. According to Alkire and Foster (2008), this constructs a second cut-off: the number of dimensions in which someone is required to be deprived so as to be identified as multidimensionally poor. This cut-off is named after k. If c_i is the amount of deprivations suffered by individual i, then he will be considered multidimensionally poor if $c_i \geq k$.

Multidimensional poverty indicators are possibly heterogenous in the nature of quantitative indicators (income, number of assets) or qualitative or categorical indicators (ordinal, e.g. level of education and non-ordinal, e.g. occupation, geographical region). This paper assumes variables are either quantitative or qualitative. A variable which has no meaningful ordinal structure cannot be used as poverty or welfare indicator. The first step consists in defining a unique numerical indicator C as a composite of the K primary indicators I_k, computable for each population unit U_i, and significant as generating a complete ordering of the population U. A composite poverty indicator C takes the value $Ci(I_{ik},\ k=1,K)$ for a given set of elementary population unit U_i.

Any composite indicator is basically a reductive variable since it tries to summarise K variables into single variable. Statistical methods known as "factorial" techniques are efficient data reduction techniques as potentially appropriate for solving the problem at first sight. The basic optimal data reduction process originates from Principal Component Analysis (PCA) which essentially consists of building a sequence of uncorrelated (orthogonal) and normalised linear combinations of input variables (K primary indicators), exhausting the whole variability of the set of input variables, named "total variance" and defined as the trace of their covariance matrix, thus the sum of the K variances. These uncorrelated linear combinations are latent variable called "components". The optimality in the process comes from the fact that the 1st component has a maximal variance λ_1^2, the basic idea to visualise the whole set of data in reduced spaces capturing most of the relevant information. PCA is an attempt that explains the variance-covariance structure of a set of variables through a few linear combinations of these variables (Krishnakumar and Nagar, 2007).

However, PCA has two basic limitations i.e. it is applicable only to quantitative or continuous variables and the relationships between variables are assumed to be linear (Gifi (1990) and

Kamanou (2005)) and in the case of ordinal variables with skewed distributions, standard PCA will attribute large undue weights to variables that are most skewed. Standardisation adds some ambiguity in a dynamic analysis where the base-year weights are kept constant.

Since concepts of multidimensional poverty are frequently measured with qualitative ordinal indicators, for which PCA is not a priori an optimal approach, looking for more appropriate factorial technique is justified. Here comes an alternative into the picture of Multiple Correspondence Analysis (MCA), designed during 1960s-1970s to improve previous approach and to provide more powerful description tools of the inner structure of qualitative variables. It analyse the pattern of relationships between several ordinal/categorical variables, whose modalities are coded as 0 or 1 that eliminates arbitrariness as much as possible in the calculation of a composite indicator. Unlike PCA that was originally designed for continuous variables, MCA makes fewer assumptions about the underlying distributions of indicator variables and is more suited to discrete or categorical variables. Hence, we opted to employ MCA in constructing the multidimensional poverty index.

3.4. Multiple Correspondence Analysis (MCA)

In multivariate statistics, MCA is based on the statistical principle of multivariate statistics to perform trade studies across multiple dimensions while taking into account the effects of all variables on the responses of interest, which involves observation and analysis of more than one statistical variable at a time. It is basically a data analysis technique for nominal or categorical data, used to detect and represent underlying structures in a data set. It works by representing data as points in a low-dimensional Euclidean space (Asselin and Anh, 2008). The procedure thus appears to be the counterpart of PCA for categorical data (Le Roux and Rouanet, 2004). It is an extension of simple correspondence analysis (CA) which is applicable to a large set of variables. Instead of analysing the contingency table or cross-tabulation, as PCA does, MCA analyses an indicator matrix consists of an *Individuals* × *Variables* matrix, where the rows represent individuals and the columns represent categories of the variables (Le Roux and Rouanet, 2004). By analysing the indicator matrix, it enables the representation of individuals as points in geometric space.

Relationships between variables in the matrix are discovered by calculating the chi-square distance between different categories of the variables and between respondents. These relationships can be represented visually as "maps", which eases the interpretation of the structures in the data. Opposed values between rows and columns are then maximized, in order to uncover the underlying dimensions best able to describe the central oppositions in the data. As in factor analysis or principal component analysis, the first axis is the most important dimension, the second axis the second most important, and so on. The number of axes to be retained for analysis, is determined by calculating modified eigenvalues.

MCA allows to analyse the pattern of relationships of several categorical dependent variables (Asselin, 2002). Each nominal variable comprises several levels, and each of these levels is coded as a binary variable. MCA can also include quantitative variables by transforming them as nominal observations. Studies based on MCA to generate composite poverty indices include the works of Asselin and Anh (2004) in Vietnam; Ki et al. (2005) in Senegal; Ndjanyou (2006) and Njong (2007) both for the Cameroon case. Technically MCA is resulted from a standard correspondence analysis on an indicator matrix (*i.e.,* a matrix whose entries are 0 or 1). The principle of the MCA is to extract a first factor which retains maximum information contained in this matrix. The ultimate aim of MCA (in addition to data reduction) is to generate a composite indicator for each household.

For the construction of K categorical indicators, the monotonicity axiom must be respected (Asselin, 2002). The axiom means that if a household i improves its situation for a given variable, then its composite index of poverty (CIPi) increases: its poverty level decreases (larger values mean less poverty or equivalently, welfare improvement). The monotonicity axiom must be translated into the First Axis Ordering Consistency (FAOC) principle (Asselin, 2002). This means that the first axis must have growing factorial scores indicating a movement from poor to non-poor situation. For each of the ordinal variables, the MCA calculates a discrimination measure on each of the factorial axes. It is the variance of the factorial scores of all the modalities of the variable on the axis and measures the intensity with which the variable explains the axis.

The weights given by MCA correspond to the standardised scores on the first factorial axis. When all the variable modalities have been transformed into a dichotomous nature with binary-coded 0/1, giving a total of P binary indicators, the CIP for a given household i can be written as (see Asselin, 2002):

$$\mathrm{CIP_i} = \frac{1}{\mathrm{K}}\left(\mathrm{W_1 I_{i1}} + \mathrm{W_2 I_{i2}} \dots + \mathrm{W_p I_p}\right) \tag{3.5}$$

Where Wp = the weight (score of the first standardised axis) of category p. Ip = binary indicator 0/1, in which values 1 when the household has the modality and 0 otherwise. The CIP value reflects the average global welfare level of a household.

Constructed using MCA, CIP tends to have negative values in its lowest part. This would make interpretation becoming difficult. However, it can be made positive by a translation using the absolute value of the average C_{min} of the minimal categorical weight W^{k}_{min} of each indicator. Asselin (2002) expresses this average minimal weight as:

$$C_{min} = \frac{\sum_{k=1}^{K} W_{min}^{k}}{K} \quad (3.6)$$

The absolute value of C_{min} can then be added to the CIP calculation of each household to obtain the new positive CIP scores.

3.5. Inequality

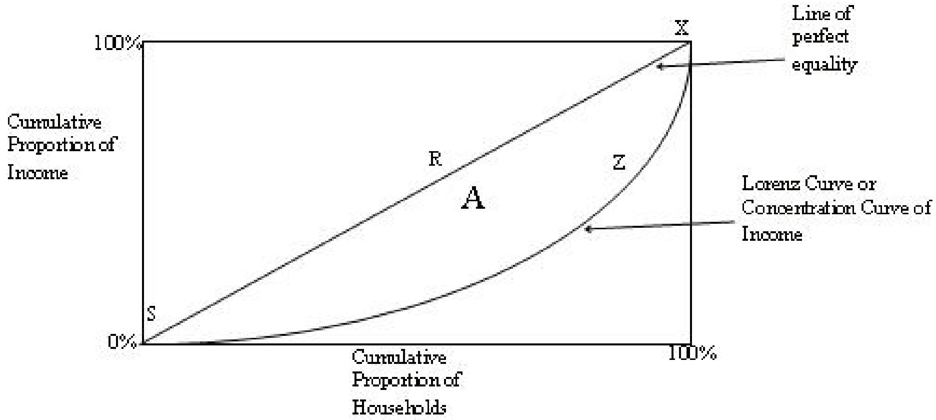
Economists always discuss inequality problem for three major reasons; (i) extreme income inequality leads to economic inefficiency; (ii) extreme disparities undermine social stability and solidarity; (iii) philosophically viewed as unfair condition to humanity since it gives no equal probability to everyone in their lives (Todaro and Smith, 2009).

Analysis on inequality often involves estimation on percentile distribution. In this paper, we employ Gini coefficient as an aggregate numerical measure of relative inequality to observe percentile distribution on MCA scores. It ranges from a value of *0* to express total equality and a value of *1* for extreme unequal condition.

Graphically measured by dividing the area between perfect equality line and the Lorenz curve by the total area lying to the right of the equality line as this can be displayed Figure 3.1. If the Lorenz curve is represented by the function *Y = t-Lorenz(t)*, the value can be found with integration and:

$$G = 1 - 2\int_0^1 \big(t - Lorenz(t)\big)\, dt \quad (3.7)$$

Figure 3.1: Gini Coefficient and Lorenz Curve



It is mathematically equivalent to think of the Gini coefficient as a half proportion of the relative mean difference. The mean difference is the average absolute difference between two numbers selected randomly from a population, and the relative mean difference is the mean difference divided by the average, to normalise for scale.

For a population has uniform values y_i, $i=1$ to n, indexed in non-decreasing order ($y_i \leq y_{i+1}$):

$$G = \frac{1}{n}\left(n + 1 - 2\left(\frac{\sum_{i=1}^{n}(n+1-i)y_i}{\sum_{i=1}^{n} y_i}\right)\right) \tag{3.8}$$

For a cumulative distribution function $F(y)$ that is has characteristic: piecewise differentiable, has a mean μ, and is zero for all negative values of y:

$$G = 1 - \frac{1}{\mu}\int_0^{\infty}\left(1 - F(y)\right)^2 dy = \frac{1}{\mu}\int_0^{\infty} F(y)\left(1 - F(y)\right)dy \tag{3.9}$$

Since the Gini coefficient is half the relative mean difference, it can also be calculated using formulas for the relative mean difference. For a random sample S consisting of values y_i, $i = 1$ to n, that are indexed in non-decreasing order ($y_i \leq y_{i+1}$), the statistic:

$$G(S) = \frac{1}{n-1}\left(n + 1 - 2\left(\frac{\sum_{i=1}^{n}(n+1-i)y_i}{\sum_{i=1}^{n} y_i}\right)\right) \tag{3.10}$$

is a consistent estimator of the population Gini coefficient, but is not unbiased. $G(S)$ has a simpler form:

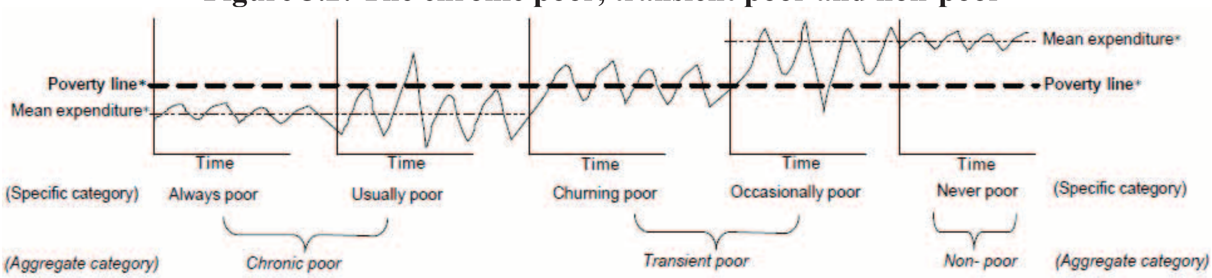
$$G(S) = 1 - \frac{2}{n-1}\left(n - \frac{\sum_{i=1}^{n} i y_i}{\sum_{i=1}^{n} y_i}\right) \tag{3.11}$$

3.6. Poverty Dynamics

The fundamental of dynamic analysis is to estimate and to classify poverty incidence regarding to its components. The analysis will revisit the extent of transient and chronic poverty using two main approaches i.e. spells and component approaches. The former identifies the poor based on length of experienced poverty periods with various *a priori* standards while the latter distinguishes permanent and transitory components of household income variations through specific method.

Spells approach criteria vary on data availability and choice of method. Problems surround this approach are truncated data and noise-creating intervals. Of component approach, it is perceived that poor have permanent component below the poverty line. It is defined that 'transient poverty' as the component of time-mean consumption poverty at household level that is directly attributable to variability in consumption (Jalan and Ravallion, 1998).

Figure 3.2: The chronic poor, transient poor and non-poor



Notes: Categorisation from (Hulme et al., 2001)

Jalan and Ravallion (1998) have explored expenditure data on six-year panel of rural households in China in which they utilise a four-tiered categorisation of poverty. Building on their work, they propose a five-tier category system (Figure 3.2). This categorises into following:

- *Always poor:* expenditure or incomes or consumption levels in each period below a poverty line.
- *Usually poor:* mean expenditures over all periods less than the poverty line but not poor in every period
- *Churning poor:* mean expenditures over all periods near to the poverty line but sometimes experience poor and sometimes non-poor in different periods
- *Occasionally poor:* mean expenditures over all periods above the poverty line but at least one period below the poverty line

- *Never poor:* mean expenditure in all periods above the poverty line

These categories can be aggregated into the *chronic poor* (always poor and usually poor), the *transient poor* (churning poor and occasionally poor) and the *non-poor* (the never poor, continuing through to the always wealthy condition).

Figure 3.3: Categorising the poor in terms of duration and severity of poverty

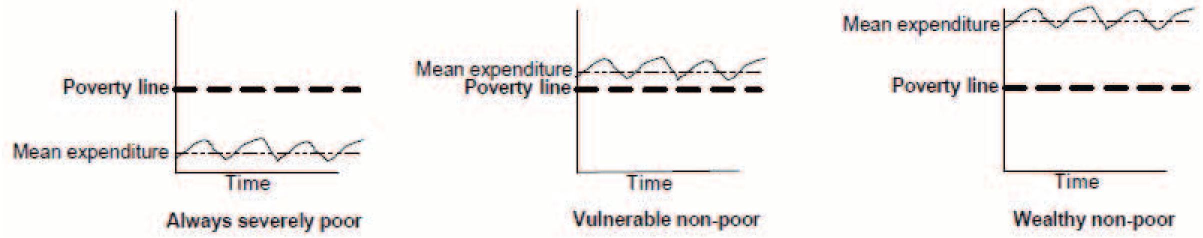


Figure 3.3 illustrates detailed categories as this is an important factor for understanding chronic poverty and poverty dynamics. We can incorporate this, at least partly, by specifying the distance of the poverty line below or above household mean expenditure (or income or consumption). Alternatively, permanent component can be obtained through alternative method which uses regression of income on household characteristics to purge effect of transitory shocks (Gaiha and Deolalikar, 1993). Regressed income method is preferable in principle yet its reliability depends on how well household characteristics can explain income variations.

This paper uses spell approach from Jalan and Ravallion (1998) in decomposing transient and chronic poverty which focuses directly on the contribution of inter-temporal variability in living standards to poverty. To do this, let (y_{i1}, y_{i2},...,y_{iD}) be household i's (positive) consumption stream over D dates. We assume normalised consumptions, such that y_{it} is an agreed metric of welfare. Let $P(y_{i1}, y_{i2},...,y_{iD})$ be an aggregate inter-temporal poverty measure for household i. We define the transient component (T_i) of $P(.)$ as the portion that is attributable to inter-temporal variability (Ravallion, 1992). Total poverty is then decomposed as:

$$T_i = P(y_{i1}, y_{i2}, \dots, y_{iD}) - P(\bar{y}_i, \bar{y}_i, \dots, \bar{y}_i) \qquad (3.12)$$

in which $\bar{y}_i$ is the expected value of consumption over time for household i. Using the term "chronic poverty" for the non-transient component, so the measure of chronic poverty (C_i) is simply poverty at time mean consumption for all dates:

$$C_i = P(\bar{y}_i, \bar{y}_i, \dots, \bar{y}_i) \qquad (3.13)$$

Thus total poverty at household level is divided into transient and non-transient (chronic) components. These formulae can be derived into econometric methods by regressing the measures of transient and chronic poverty on the same set of household as follows:

$$T_i = T_i^* \; if \; T_i^* > 0 \; where \; T_i^* = x_i' \beta^T + u_i^T \qquad (3.14)$$
$$T_i = 0 \; otherwise$$

where T_i^* is a latent variable, T_i is the observed transient poverty, β^T is a $k \times 1$ vector of unknown parameters, x' is a $k \times 1$ vector of explanatory variables, and $u^T$are the residuals. The analogous model for chronic poverty is given by:

$$C_i = C_i^* \; if \; C_i^* > 0 \; where \; C_i^* = x_i' \beta^C + u_i^C \qquad (3.15)$$
$$T_i = 0 \; otherwise$$

These methods are robust with the only assumptions required for consistency of the non intercept coefficients are that the errors be independently and identically distributed, and continuously differentiable with positive density at the chosen quintile. Multidimensional poverty index can be classified according to its length of poverty period so it enables to identify transient and chronic poverty. Let y_i^t be the income of individual *I* in period *t* and μ_i be average income over the *T* periods for that same individual$i, i = 1, \dots, N$. Total poverty is defined as

$$TP(\alpha, z) = \frac{\sum_{t=1}^{T} \sum_{i=1}^{N} w_i (z - y_i^t)_+^\alpha}{T \sum_{i=1}^{N} w_i} \qquad (3.16)$$

The chronic poverty component is then defined as:

$$CPC(\alpha, z) = \frac{\sum_{i=1}^{N} w_i (z - \mu_i^t)_+^\alpha}{\sum_{i=1}^{N} w_i} \qquad (3.17)$$

and transient poverty equals:

$$TPC(\alpha, z) = TP(\alpha, z) - CPC(\alpha, z) \qquad (3.18)$$

CHAPTER 4
ANALYSIS OF THE DETERMINANTS

4.1. Introduction

The cornerstone of multidimensional poverty measurement is the identification and the selection of relevant indicators because these determine the true concept of poverty as expressed by any aggregate of all of them. The aggregation of variables can be achieved in many ways. Statistical approaches provide alternative solutions to select and to aggregate variables in index form without *a priori* assumptions in the weighting scheme. This section presents only those features of each approach that are relevant to our context, namely the construction of a composite poverty index.

4.2. Composite Indexing

When poverty is conceptualised as a multidimensional construct, it should be taken into account through the aggregation of different deprivation variables experienced by individuals. Accordingly, measuring multidimensional poverty usually involves the incorporation of information with several variables into a composite index. The general procedure in the estimation of composite indices involves: (i) choice of the variables, (ii) definition of a weighting scheme, (iii) aggregation of the variables and, (iv) identification of a threshold which separates poor and non-poor individuals. All of these issues should be carefully addressed.

The first step in the building of a summary measure concerns the selection of appropriate indicators. The choice not only depends on the availability of data, but also on the variables that affect the formation of the index. The selection of elementary variables relies on researcher's arbitrary choices with a trade-off between possible redundancies caused by overlapping information and the risk of losing information (Pérez-Mayo, 2005). A partial solution to such arbitrariness is to use multivariate statistics which allows researchers to reveal the underlying correlation between basic items and to retain only the subset that best summarises the available information.

After selecting a preliminary set of variables, their aggregation into a composite index implies an appropriate weighting structure. A number of different weighting techniques have been used in the literature. First, some studies apply equal weighting for each variable (Townsend, 1979; UNDP, 1997; and Nolan & Whelan, 1996), thereby avoiding the need for attaching different importance to the various dimensions. Second, in an attempt to move away from purely arbitrary weights variables have been combined using weights determined by a consultative process among poverty experts and policy analysts. Although this approach is an improvement on the first solution, it still involves subjective acts when choosing the welfare value of each component. Third, weights may be applied to reflect the underlying data quality of the variables, thus putting less weight on those variables where data problems exist or with large amounts of missing values (Rowena et al., 2004).

The reliability of a composite index can be improved only if it gives more weight to good quality data. However, this tends to give more emphasis to variables which are easier to measure and readily available rather than on the more important welfare issues which may be more problematic to identify with good data. Fourth, variables have been weighted using the judgment of individuals based on survey methods to elicit their preferences (Smith, 2002). The difficulty encountered here relates to whose preferences will be used in the application of the weights, whether it be the preferences of policymakers, households, or the public. Fifth, a more objective approach is to impose a set of weights using the prices of various items. However, this is only possible if prices are available for all goods and services. Unfortunately, most of respondents were unable to reveal the values of their goods realistically and responses are therefore likely to contain a large number of errors. This is further compounded in situations with significant fluctuation, regional price differences, and high inflation.

Other studies developed composite indices by aggregating the variables on the basis of relative frequencies or by relying on multivariate statistical methods to generate weights (Pérez-Mayo, 2005). This approach, will be discussed in greater detail in the next sections. Finally, the process of identifying the poor or deprived households/individuals requires the definition of a threshold, an issue that raises several theoretical and empirical problems. Independently of the particular choice about the threshold or cut-off, the identification of households/individuals to be considered poor always implies some degree of arbitrariness.

4.3. Construction of the Composite Index of Poverty

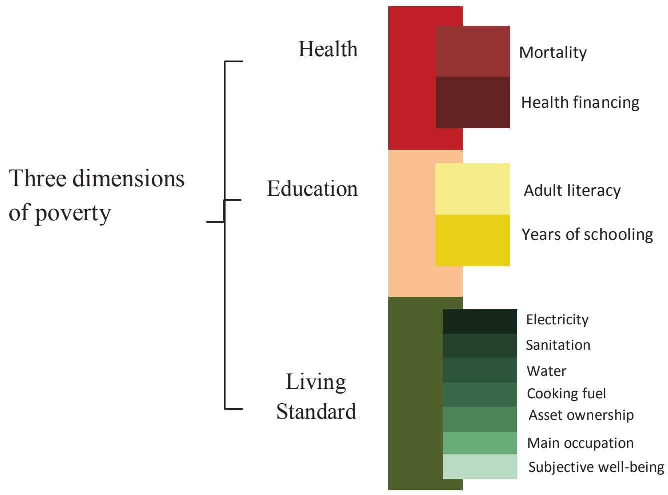
The Composite Index of Poverty (CIP) has several indicators that consist of variables representing health, education, and living standards. To ensure comparability across time, only variables that appear in all waves of IFLS were utilised. Figure 12 lists selected variables, with the categories for each variable noted in the second column. The index construction is based on binary and categorical indicators. The fact that only a relatively small number of variables is included in the analysis is the result of earlier surveys including fewer questions and allowing fewer responses than subsequent surveys. Understandably this reflects the development of surveys rather than particular trends in human development or access to public services *per se*.

The index reflects deprivations in rudimentary services and core human functionings for households. This shows various patterns for poverty rather than for income poverty, as the index reflects a different set of deprivations. It consists of three dimensions: health, education, and standard of living (measured using 12 main indicators).

Sen (1976) has argued that the choice of relevant functionings and capabilities for any poverty measure is a value judgment rather than a technical exercise. The potential dimensions that a measure of poverty might reflect are broad. In choosing capabilities that have a moral weight akin to human rights, Sen has suggested focusing on the following dimensions:

a) *Special importance* to the society or people in question
b) *Socially influenceable*, which means they are an appropriate focus for public policy, rather than a private good or a capability.

Figure 4.9: Dimensions and Indicators of Poverty Index



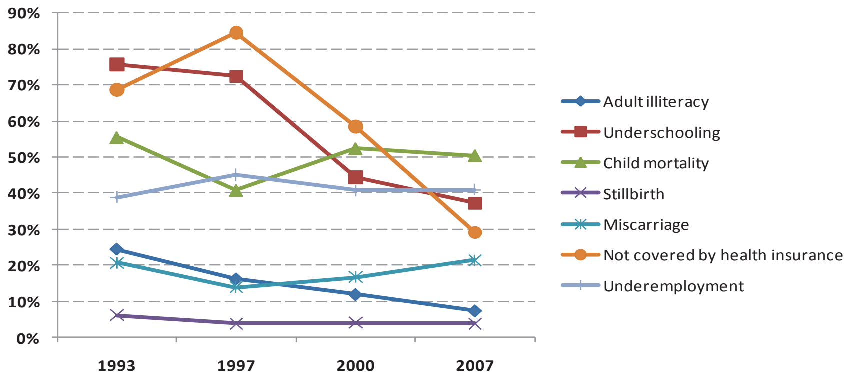
However there are several arguments in favour of the chosen dimensions.

1) Parsimony or simplification: limiting the dimensions to three simplifies poverty measures.
2) Consensus: While there could be some disagreement about the appropriateness including other indicators, the value of health, education, and standard of living variables are still widely recognised.

3) Interpretability: Substantial literatures and fields of expertise on each topic make analyses easier.
4) Data: While some data are poor, the validity, strengths, and limitations of various indicators are well documented.
5) Inclusivity: Human development includes intrinsic and instrumental values. These dimensions are emphasised in human capital approaches that seek to clarify how each dimension is instrumental to welfare.

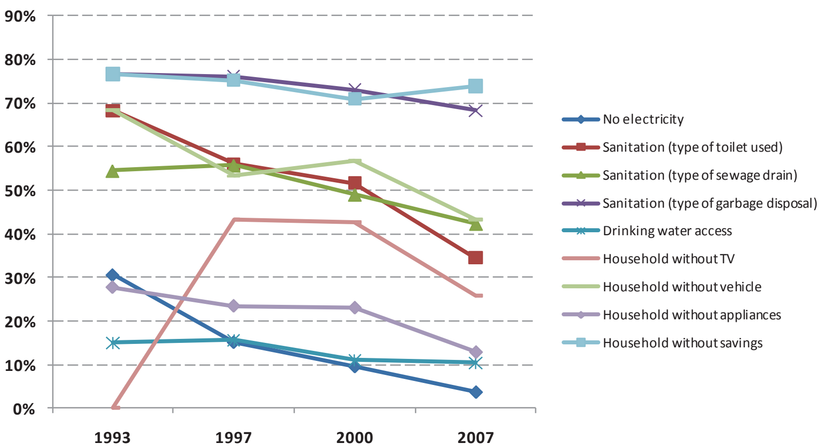
Figure 4.2 displays poverty incidence according to seven indicators. We may assess how these various indicators have performed between periods. This graph implies that poverty was likely higher in 1993 compared with 2007 and shows that these indicators tend to converge. Generally speaking, this graph indicates that these variables have improved in most categories.

Figure 4.2: Poverty Incidence: Human Assets (1993-2007)



Source: Author's calculation from IFLS

Figure 4.3: Poverty Incidence: Physical Assets (1993-2007)



Source: Author's calculation from IFLS.

From the perspective of physical assets, 12 indicators are plotted in Figure 4.3. Unlike previous findings, this graph shows no stylised pattern. In addition, some indicators deteriorate over periods.

Looking at both graphs, poverty seems to have been reduced more significantly in human-assets than in physical assets. Nonetheless, this result is only considered as a preliminary finding and treated as the basis for further analysis. At this juncture, it is natural to ask whether the importance of every variable differs significantly across periods. In order to address this, we estimate the weights to observe some indicators which have more effect in determining poverty or welfare.

Before weighting the variables, the indicators were scrutinised based on data availability and characteristics. These resulting 20 variables explain deprivation on three dimensions. These variables are considered feasible to be weighted as part of poverty index. Table 4.1 provides detailed indicators for multidimensional poverty. The cut-offs or thresholds for deprivation are taken based on the survey result.

The first survey actually involved around 7,000 households in the first survey and then expanded to around 10,000 households due to split-off households. The surveys include responses from all household members. The following equation is used to calculate a composite index score for each population unit (household):

$$^{\mathrm{MCA}}P_i = R_{i1}\mathrm{W}_1 + R_{i2}\mathrm{W}_2 + \cdots + R_{ij}\mathrm{W}_\mathrm{j} + \cdots + R_{iJ}\mathrm{W}_\mathrm{J} \tag{4.1}$$

Where $^{\mathrm{MCA}}P_i$ is the i^{th} household's composite poverty indicator score, R_{ij} is the response of household i to category j, and W_j is the MCA weight for dimension one applied to category j. MCA was employed to calculate these weights, using the *mca* command in Stata 11.

This command estimates an adjusted simple correspondence analysis on the Burt matrix constructed with the selected variables. Analysis applied to this matrix usually results in maps. Command *mca* adjusts the obtained principal inertias (*eigenvalues*) by following a method suggested by Benzécri (1979) and presented in Greenacre (1984). According to van Kerm (1998), the reported inertia explained by the first dimension is relatively high due to the fitting of these diagonal sub-matrices.

Table 4.1: Preliminary Indicators Extracted from Surveys

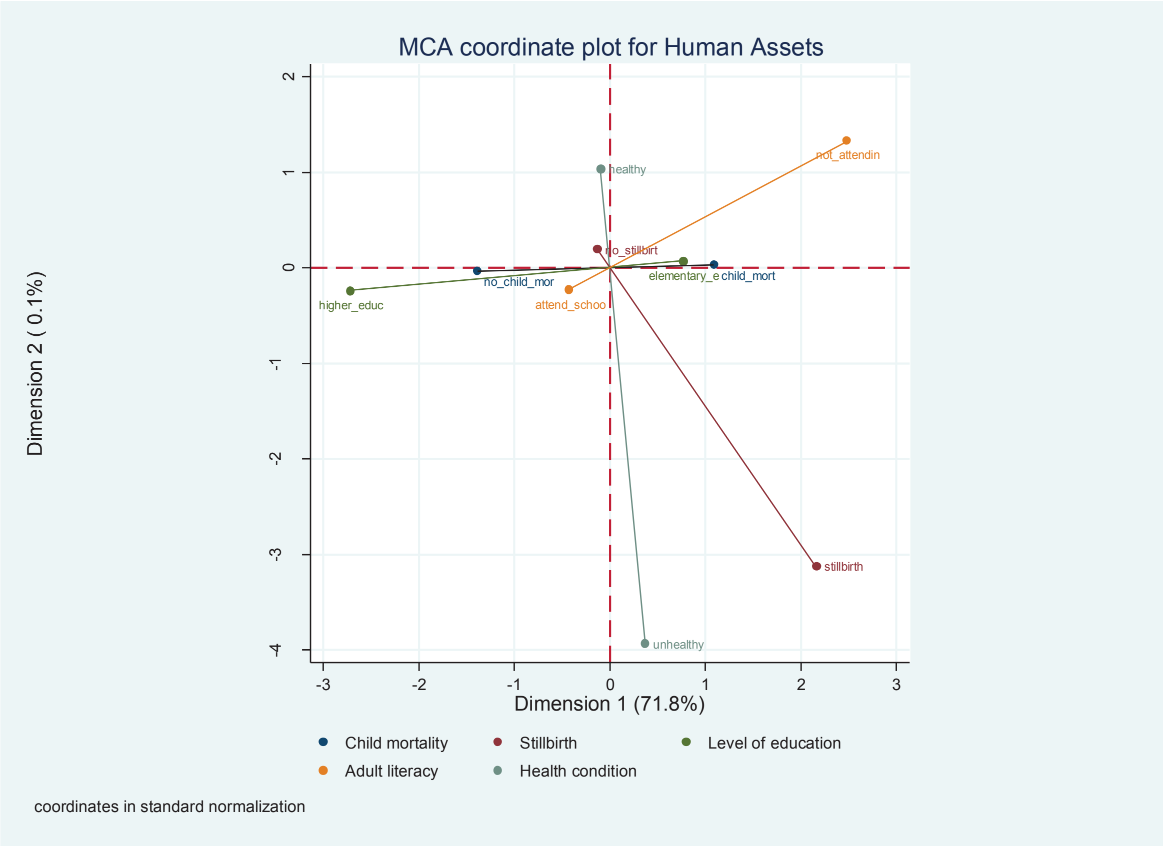
Dimension		Indicator	Deprived if
Human Assets	*Education*	*Adult Literacy*	No household member completed any schooling level
		Years of schooling	Only primary school completed
	Health	*Mortality*	Any child has died in the family
			Stillbirth case
			Miscarriage case
		Financial ability to health services during sickness	Is not covered by health insurance
		Health condition	Is not being healthy
Physical Assets	*Standard of Living*	*Electricity*	Household has no electricity
		Sanitation	Household has no toilet with septic tank
			Household use pit latrine
			Household shares public toilet
		Sewage	Household drain its sewage not in flowing ditch
		Garbage	Household dispose of its garbage not in trash can (not collected by sanitation service)
		Water	Household does not use piped water
			Household use surface water
			Household use other source of water
		Assets ownership	Household does not own one of: radio, TV, telephone, bike
		Vehicle ownership	Household does not own one of motorbike, a car or tractor
		Savings ownership	Household does not own any savings account
		Main occupation of breadwinner	Unemployed/job searching or sick/disabled

Source: Compiled from IFLS

In using the poverty index to consider the evolution of poverty over time, it is also necessary to construct asset indices that are comparable over time. Two possibilities would enable this comparison. One, is a multidimensional index that can be constructed using ‘pooled’ weights obtained from the application of MCA to all available data, in our case for all four periods. The second index can be based on ‘baseline’ weights obtained from an analysis of the data from the first period survey. On practical grounds we opted for ‘baseline’ weights, because one can apply these weights to data from subsequent surveys without having to recalculate the MCA weights and resulting index (Njong and Ningaye, 2008).

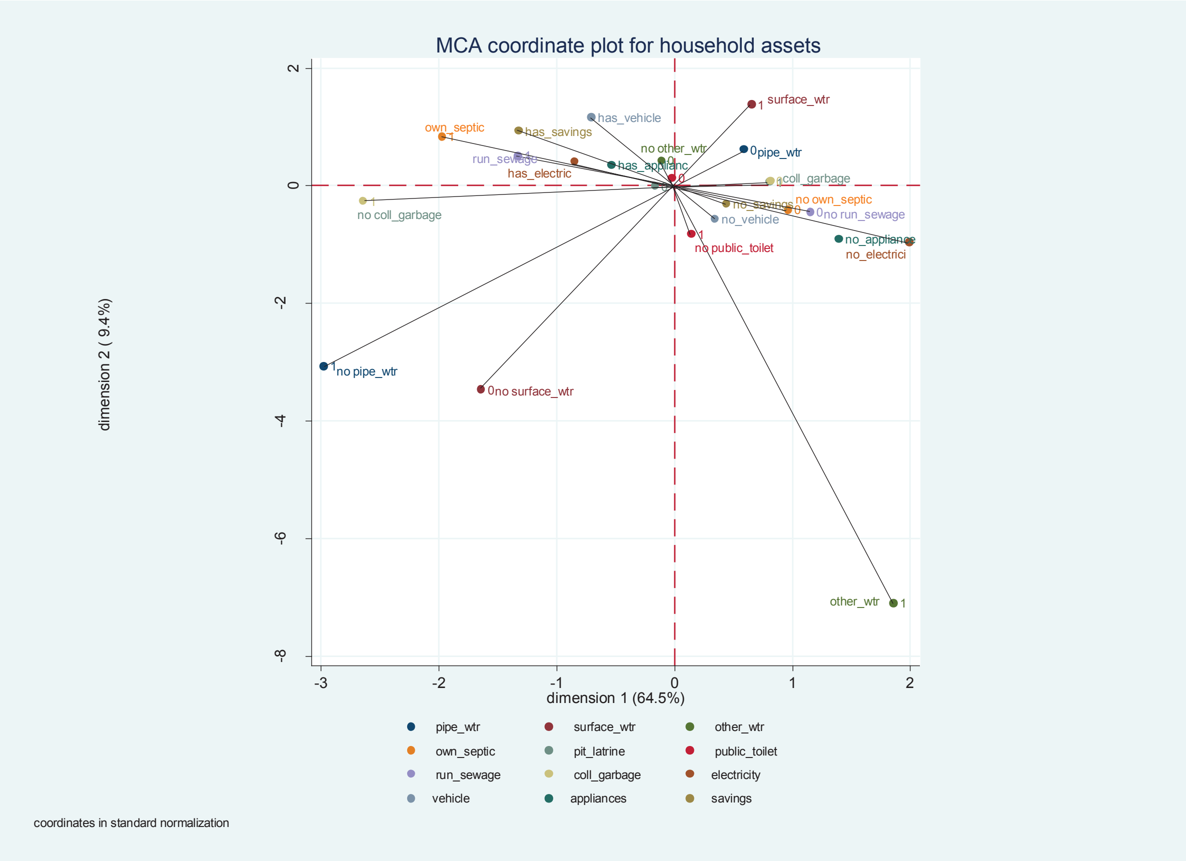
Figure 4.4 shows the map of indicators and category scores for physical assets on first two dimensions for 1993. There is a significant dispersion from the central coordinate on certain indicators. Based on the depiction of human assets-based indicators, it can be inferred that the welfare level is associated with illiterate adults, education level, underemployment, and illness. The distribution of indicators is scattered along the origin with a few outliers tossed away. However, a dominant pattern cannot be determined from this map. It is important to check the output (Appendix A1). A similar map describing human assets is in Appendix A2.

Figure 4.4: Indicators and Category Maps on Human Assets (1993, Baseline)



In the construction of our index, equal weight is given to each period, i.e. the experience of one period is given the same weight as that of another. For human assets, the result gives categorical scores (quantifications) for the first factorial axes, which account for 71.86% of the total inertia given by the formula $I_{total} = \frac{J}{K} - 1$ with most indicators are positioned in the centre of the axis. For physical assets (Figure 4.5), categorical scores account for 75.26% with more dispersed indicator positions.

Figure 4.5: Indicators and Category Maps on Physical Assets (1993, Baseline)



MCA were undertaken that combined human and physical assets in order to get the overall weight for each indicator. In so doing, both human and physical assets are jointly calculated to obtain a general multidimensional poverty index to be applied to different data sets. MCA has been run for the base year 1993 on all indicators for which the detailed results cannot be provided on a single x-y axis; instead, it will be presented in individual plots for each indicator (Appendix A3).

Total MCA scores[2] based on 20 modalities, demonstrate the first factorial axis which explains 79.57% of the observed inertia (the eigenvalue). To construct the CIP for each household, the functional form of CIP is expressed in equation (4.1). The weights attributed to all modalities are presented in Table 4.2. The second part of analysis uses CIP intensively for a detailed comparative analysis of multidimensional versus consumption poverty, for the base year 1993.

[2] Constructed using Stata, Version 11.

Table 4.2: Variables and Weights from MCA

Indicators	Categories	Weights	Squared correlation	Contribution
Source of Drinking Water	Pipe water	2.500	0.576	0.080
	No pipe water	-0.753	0.576	0.024
	Surface water	-0.728	0.358	0.020
	No surface water	1.481	0.358	0.040
	Other sources of water	-2.404	0.327	0.018
	No other sources of water	0.139	0.327	0.001
Sanitation:	Own toilet with septic tank	1.888	0.762	0.084
	No toilet with septic tank	-1.383	0.762	0.061
	Pit latrine	-0.853	0.246	0.007
	No pit latrine	0.189	0.246	0.002
	Public toilet	-0.944	0.238	0.005
	No public toilet	0.101	0.238	0.001
Sewage system:	Running sewage	1.352	0.880	0.053
	No running sewage	-1.502	0.880	0.059
Garbage disposal	Collected garbage	2.544	0.861	0.109
	No collected garbage	-1.102	0.861	0.047
Electricity	Has electricity	0.736	0.877	0.023
	No electricity	-2.460	0.877	0.077
Health insurance	Covered by insurance	2.196	0.871	0.053
	Not covered by insurance	-0.538	0.871	0.013
Vehicle	Own vehicle	0.959	0.817	0.017
	No vehicle	-0.464	0.817	0.008
Household appliances	Has appliances	0.562	0.897	0.013
	No appliances	-1.697	0.897	0.011
Savings	Has savings	0.562	0.919	0.033
	No savings	-1.534	0.919	0.011
Child mortality	No child mortality	0.502	0.743	0.006
	Has child mortality	-0.394	0.743	0.005
Stillbirth	No stillbirth	0.028	0.435	0.000
	Has stillbirth	-0.477	0.435	0.001
Level of education	Higher education	-0.580	0.919	0.015
	Elementary education	2.073	0.919	0.052
Adult literacy	Ever attending school	0.224	0.897	0.002
	Never attending school	-1.295	0.897	0.014
Health condition	Healthy	0.162	0.646	0.001
	Unhealthy	-0.622	0.646	0.004

In order to avoid an arbitrary assignment of weights on each variables, factor results are used in which weights shows that smaller number refers to lower welfare, while a larger one indicates higher welfare. To use these weights, the monotonicity axiom must be fulfilled, meaning that the CIP must be monotonically increasing for each primary indicator (Asselin, 2002). The axiom means that if a household improves its situation for a given primary variable, then its CIP value increases so that its poverty level decreases (larger values mean less poverty or equivalently, welfare improvement).

Logically, the first axis (which has the largest eigenvalue and is considered the poverty axis) must have growing factorial scores indicating a movement from a poor to a non-poor situation. Therefore, such variables which show peculiar relationships (signs) will be adjusted to follow the FAOC axiom. Analytically, the factorial scores on the first axis represent the weights attached to the variable modalities. However, detailed information (Appendix A4) shows the detailed weight for each indicators.

Following the construction of CIP, we employed this index to estimate poverty measures for each period using the appropriate methods. Negative and missing values, however, create problems for poverty analysis using higher orders (e.g., FGT measures for P_α where α=1 or higher). To obtain the positive values required for the further analysis, a value equal to the greatest negative value is added to each of the asset index values, so that the lowest observed values become zero. Moreover, Asselin (2002) and Sahn and Stifel (2003) encourage similar transformations. A small further magnitude is added to normalise the lowest value non-zero, as some poverty decomposition programmes in Stata ignore zero values. Although this normalisation has been discussed in a lot of literature, it does not affect the distribution of the poor and non-poor in the sample.

This transformation consequently implies that the values of the poverty measures other than the headcount ratio do not have any meaning on their own, but only obtain meaning in the context of the research. The absolute values of these poverty indices have been changed, but the distribution is the same as before the translation and thus the poverty measures still have meaning in a relative sense, enabling comparisons of the resulting estimates of the index across space or time (Sahn and Stifel, 2003).

CHAPTER 5
POVERTY ANALYSIS - RESULTS

5.1. Introduction

The discussion starts with the determination of poverty line on baseline period and followed by analysis on inequality and poverty dynamics using relevant methods. Calculation on CIP from previous section is used to analyse poverty. How these change on indices influence welfare is taken up in the end of this chapter. Important findings will be presented alongside with graphs and outputs with detailed results are placed on Appendix section.

5.2. Empirical Specification - Baseline

The choice of poverty line is crucial to the extent that it determines the conclusions for poverty comparisons. There is no apparent non-arbitrary level to set the poverty line. In a money-metric case, poverty lines are often derived from the food price required to meet caloric intake or from the costs of basic goods. Alternatively, international poverty lines often referred to the World Bank standard could be used. For multidimensional poverty indices such as these, there is no comparable indication of what would be an appropriate poverty line.

Sahn and Stifel (2003) set poverty lines at relatively high levels, where the discrimination ability of indices is somewhat better. We somewhat arbitrarily choose one out of two relative poverty lines. The first captures the bottom 40% of the population (often mentioned as the relatively poor who deserve policy attention); the second is at the bottom 60% of the population. Using the 40th percentile as a poverty line is quite acceptable as is often suggested by the World Bank for poverty analysis. Nonetheless, 60th percentile poverty line is computed as comparison.

In contrast to consumption expenditure or income, this paper uses CIP constructed from MCA scores as an instrument to determine whether an individual or a household belong to poor category. This will enable to track the welfare characteristics of 30,000 to 40,000 households over all four periods of sample. What matters most in this analysis is how much each accumulates CIP relatively to particular standard.

Before analysing poverty index, it is useful to start exploring percentile distribution of MCA scores for all periods of analysis. The statistics are presented in Table 5.1 showing number of observations and MCA scores range from 1% lowest to 99% highest percentile. This table gives a first approximation of the welfare magnitude for four periods. Looking at full sample columns, the mean values dramatically increase yet in group of highest MCA scores (75%-99%) eventually moves in declining pattern for the first three periods. The created 1993 data set has 29,931 observations, while in 2007 data set expands into 40,403 observations.

Table 5.1: Distribution of MCA scores

	Year							
	1993		1997		2000		2007	
	Values	Smallest/Largest	Values	Smallest/Largest	Values	Smallest/Largest	Values	Smallest/Largest
1%	1.745	0.000	1.538	0.000	2.478	0.000	5.388	0.000
5%	3.380	0.334	4.271	0.000	5.578	0.337	8.424	0.000
10%	4.683	0.334	5.697	0.162	7.094	0.337	10.196	0.000
25%	7.678	0.334	8.519	0.162	10.064	0.337	13.712	0.366
50%	12.107	12.107	13.206	13.206	14.468	14.468	17.506	17.506
75%	17.843	33.556	18.636	32.035	19.892	30.995	21.551	32.689
90%	23.026	33.556	23.745	32.035	24.317	31.117	24.910	32.689
95%	25.775	33.556	25.709	32.035	26.576	31.237	26.983	32.689
99%	29.423	33.556	28.539	32.035	29.803	31.876	29.845	32.689
	Obs	29,931	**Obs**	31,148	**Obs**	37,008	**Obs**	40,403
	Mean	13.106	**Mean**	13.877	**Mean**	15.142	**Mean**	17.583
	Std Dev	6.869	**Std Dev**	6.635	**Std Dev**	6.461	**Std Dev**	5.593
	Variances	47.193	**Variances**	44.025	**Variances**	41.747	**Variances**	31.291

Using FGT methods, poverty incidence can be presented as in Table 5.2. The question whether poverty has increased or diminished over the estimated periods will first be examined by comparing poverty incidence. Based on the computation results for poverty incidence or P_α ($\alpha=0$) using 1993 as baseline year, poverty line is defined on the value of 10.19 for the lowest 40 percentile or 14.30 for lowest 60 percentile. Wide margin between two type of poverty lines might give a hint on how distribution pattern can explain the rigidity in welfare improvement. This paper will employ lowest 40 percentiles standard to be poverty line into analysis as suggested by international literatures. According to this approach, poverty standard increased slightly between 1993 and 2000 (from 10.19 to 12.61) with dramatic increase in the year 2007 (15.92).

Table 5.2: Poverty Lines (Set on 40 and 60 Lowest Percentiles)

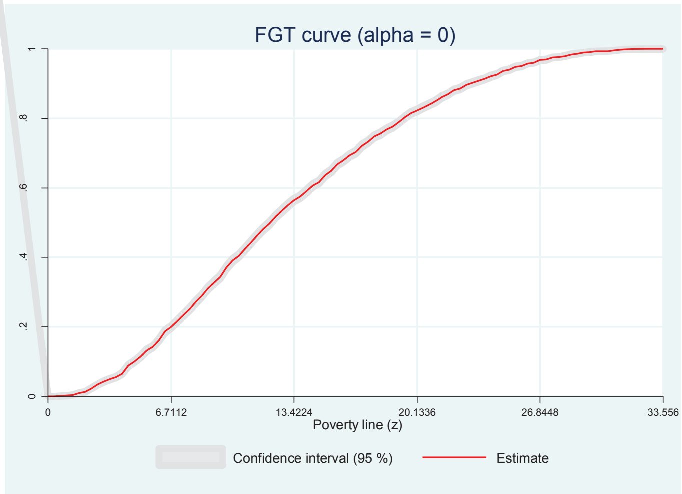
Year	Poverty Lines	
	Lowest 40	Lowest 60
1993	10.19*	14.30*
1997	11.37*	15.17*
2000	12.61*	16.49*
2007	15.92*	18.79*

t statistics in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

There are at least three main purposes following FGT curve: (i) show how the level of poverty varies with different poverty lines; (ii) test for poverty dominance between two distributions; (iii) test pro-poor growth conditions.

A contrasted picture of FGT poverty lines (also called primal dominance curves) appears when poverty lines are depicted in Figure 5.1. It shows an FGT curve in form of probabilistic scaling model exhibits positive relationship between the degree of poverty lines and probability on percentage poor population using 5% standard error. FGT curve in red line represents the relationship between estimated populations who live under various poverty lines (in percentage). The graph also conveys interpretation on sensitivity and holds the hypothesis of normal distribution. It must be noted that in all the following results and especially on poverty dynamics, one point in time has been fixed *a priori*: 1993 multidimensional poverty rate as parameter value as having anchored once and for all poverty lines and letting all factors influence the poverty difference across time.

Figure 5.10: FGT Curve on MCA (1993, Baseline)



Having analysed poverty line, it is interesting to compare characteristics among various poverty lines. As reported in Table 5.3, various poverty lines in Indonesia differ regarding its methods, standards, and sample sets. Higher poverty rate can be found using higher standard as World Bank suggest, while different size on sample sets also affect the outcome. Using MCA scores to construct poverty line for lower 40 percentiles also create different pattern on poverty figures (Appendix A4).

Table 5.3: Difference of Poverty Lines

Poverty Line	Thresholds	Methodology and Data Source	Periods	Results
Official (Statistics Indonesia)	~PPP USD1.55/capita/day	National method using data set from National Survey of Social and Economic Status (*Susenas*) data sets	1993	13.7%
			1998	24.2%
			2000	19.1%
			2007	16.6%

Poverty Line	Thresholds	Methodology and Data Source	Periods	Results
Simulated[3]	~PPP USD1.55/capita/day	Replicated official method using IFLS Consumption Expenditure Modules	1993	23.1%
			1997	14.6%
			2000	15.0%
			2007	n.a.
World Bank	PPP USD2/capita/day	International method using *Susenas* data sets	1990	71.1%
			1996	50.5%
			2000	59.5%
			2007	49.7%
Simulated	Lowest 40th percentiles (baseline = 1993)	Multidimensional poverty index using MCA scores	1993	40.0%
			1997	34.2%
			2000	25.7%
			2007	10.1%

5.3. Inequality

While economic growth has contributed to an increased level of welfare, it also has the potential to ignore fair redistribution of output and complicate poverty measurement. Moreover, problems with opportunity gap and unequal access for the poor can make them stay miserable for prolonged periods. As in most social relationships, it is difficult to separate the economic from the noneconomic manifestations of inequality since it reinforces each other in a complex and interrelated process.

This paper observes inequality on CIP instead of income or expenditure. Table 5.4 compares Gini index over four periods shows that inequality barely change during 1993-2000 (ranges from 0.29 to 0.24), only a little equality despite significant improvement in economic growth or poverty reduction. Surprisingly, Gini index drops to 0.18 in period 2007 implying that MCA tend to converge among percentile groups and suggests that society are more likely to achieve equality in multidimensional aspects. These fluctuations may reflect a delayed response to policy or situation, apparent in the households' characteristics as the surveys in 1997 and 2000 took place during the time of economic crisis. Moreover, Figure 5.2 shows small measure Lorenz curve which supports previous findings.

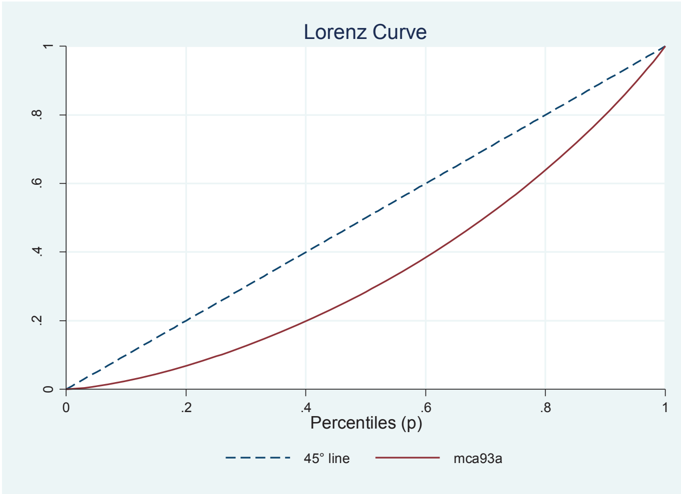
One hypothesis explored in this study is that Gini index from 1993-2007 obtained from MCA has different pattern with ordinary index from income distribution. However, this study reveals that Indonesian households are relatively more equal in terms of multidimensional livelihood rather than in money-metric terms particularly in the most recent period. Extensive output can be found in Appendix A5

[3] Widyanti et. al (2009)

Table 5.4: Gini Index on MCA

Year	Gini Index	Lower 95% CI	Upper 95% CI	S.E.
1993	0.297	0.296	0.299	0.001050
1997	0.273	0.271	0.275	0.000977
2000	0.244	0.242	0.245	0.000812
2007	0.181	0.180	0.183	0.000646

Figure 5.2: Lorenz Curve for MCA (1993, Baseline)

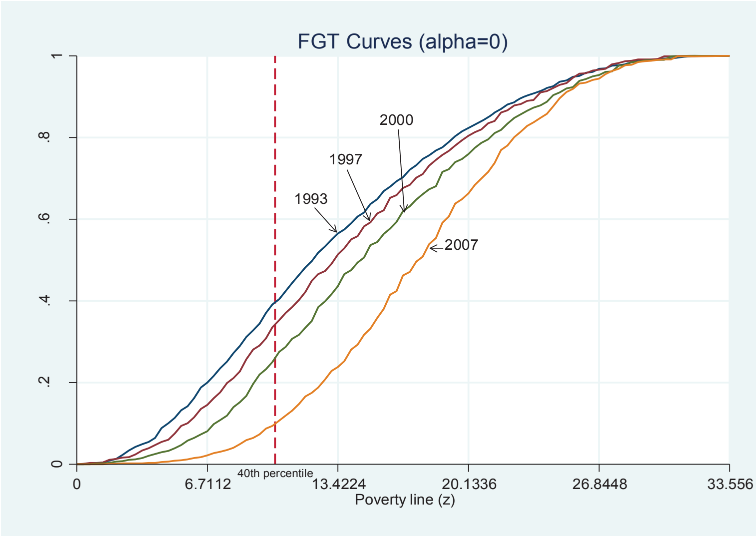


5.4. Poverty Dynamics

Results obtained from baseline calculation can be employed to analyse dynamic poverty setting. The analysis is undertaken to estimate the degree of changes over subsequent periods. This part also checks whether poverty rate fluctuates across periods.

At first sight, looking at Figure 5.3 we can compare FGT curves which shift over four periods. We can infer that poverty line had increased during 1993-2007 and 1993 poverty line is the lowest. The graph also shows that distribution in 2007 clearly dominates the other distributions. The crossings of the line occurs either at the lower or at the upper segments of the distribution, outside the interval containing all range of plausible poverty lines. However, using 40th lowest percentile standard, number of population live below poverty line can be found higher in the past periods. In other words, this result conveys the improvement on standard of welfare.

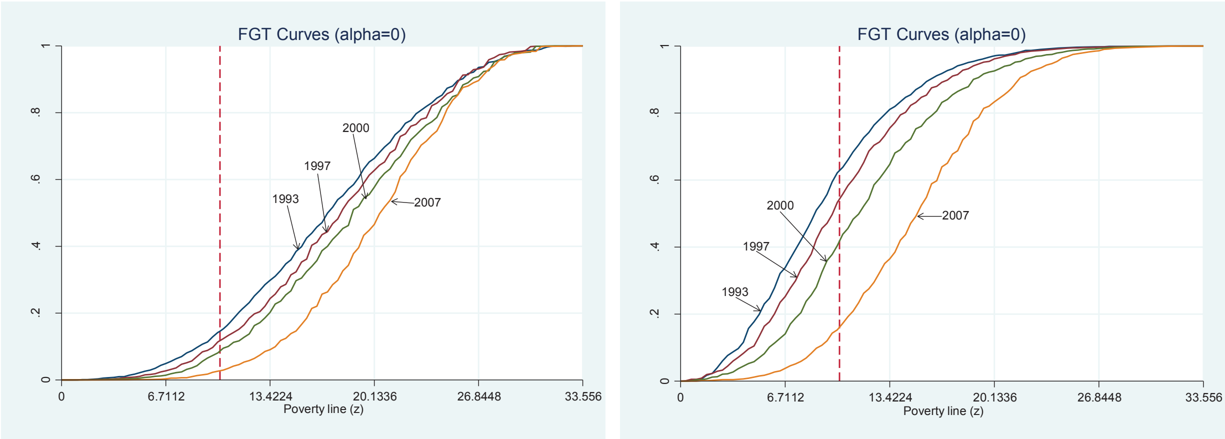
Figure 5.3: FGT Curves on MCA (1993-2007)



After painting a broad picture on CIP distribution and poverty problem, it is argued that the magnitude of welfare results not only from possession of assets or human capital factor but also from the place and environment where they live. As stated in Todaro and Smith (2009) that perhaps the most valid generalisations about the poor are that they are disproportionately located in rural areas and that they primarily engaged in agricultural activities.

Rural-urban difference can be analysed considering the different setting of poverty between the two regions. With respect to urban households, the first three poverty lines were almost the same trend. Over this amount the 1993 distribution was clearly dominated by distributions from three other periods with converging pattern. Using 40th lowest percentile standard, poverty in urban areas undoubtedly has smaller proportion and declined steadily in especially in 2007. Figure 5.4 below shows significant increase of poverty line in 2007. This finding reinforces the hypothesis that the occurrence of poverty is still emphasised in rural areas. The impact of development has reached rural region but it is outweighed by the rate of poverty incidence. This requires intensive concern mainly on agriculture sector in villages and rural areas through support and infrastructure provision which are expected to improve local economy and contributes to welfare improvement.

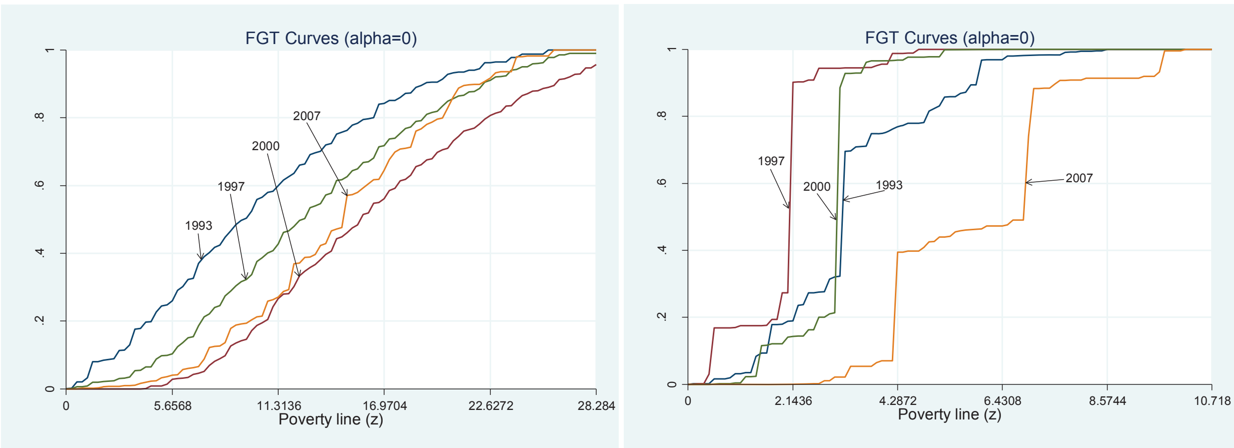
Figure 5.4: Rural-Urban Differences of FGT Curves (1993-2007)



(a) Urban Poverty Lines (b) Rural Poverty Lines

Figure 5.5 plots disaggregated poverty lines into two main components of CIP. The plot on the left includes physical assets while the right plot displays human assets. These graphs point out different pattern than previous ones. In physical asset, it is surprising when looking at 2000 poverty line dominates the other three lines and it is also worth noting that 2007 poverty crosses with 1997 poverty line in higher percentiles. This implicitly conveys that welfare improvement mainly occurs in human asset e.g. education and health but not necessarily followed with increase in asset entitlement.

Figure 5.5: Component Differences of FGT Curves (1993-2007)



(a) MCA by physical asset (b) MCA by human asset

Further test to analyse whether multidimensional poverty in Indonesia decreased between 1993 and 2007 can be undertaken by estimating difference between FGT indices. This test attempts to provide evidence if the difference is significantly different from zero assuming that test statistics follows a normal distribution. Thus test:

$$H_0\colon \Delta P(z = 10.19, \alpha = 0) = 0 \text{ against } H_1\colon \Delta P(z = 10.19, \alpha = 0) \neq 0 \qquad (5.1)$$

Difference test proves highly significant difference on two sets of distribution i.e. 1993 and 2007 (see Appendix A6). Macroeconomic environment has been the background for significant changes at the household level. Figure 5.6 compares the density function of MCA in four surveys. It indicates a slight flattening and rightward shift of the density function over the first three periods (1993-2000), suggesting marginally increased welfare level.

A potentially important observation about density curve for multidimensional poverty indices in Figure 5.6 illustrates poverty incidence as a subject to change following the relative increase of population's welfare. This is illustrated more clearly by the density function shown, which for any given periods show increasing mean value and variance. The distributions of indices are very close to the normal distribution, where the shape of the distribution functions follow Gaussian kernel estimator of a density function $f(x)$ is defined by:

$$\hat{f}(x) = \frac{\sum_i w_i K_i(x)}{\sum_{i=1}^{n} w_i} \text{ and } K_i(x) = \frac{1}{h\sqrt{2\pi}} exp(-0.5\lambda(x)^2) \text{ and } \lambda_i(x) = \frac{x - x_i}{h} \qquad (5.2)$$

where h is a bandwidth that acts as a smoothing parameter.

The equation has two implications of interest here. First, estimates of the head-count index of poverty will be particularly sensitive to the exact time of the poverty line, as our comparison of the poverty lines difference (Figure 5.7) has suggested. Second, measured levels of poverty will be very responsive to horizontal shifts in the distribution of MCA index. If the poverty line is at the mode of per capita, the response of the head-count index to an additive gain or loss at all levels will be at its maximum. As a result, the response of poverty in Indonesia is shifted to neutral toward distributional changes in the average value that was also high in the recent periods. This is a factor in understanding how recent economic growth has delivered impact on poverty. What clearly emerges from this finding is that welfare level tends to improve over time and reaches highest level in 2007.

Figure 5.6: MCA Density Curves (1993-2007)

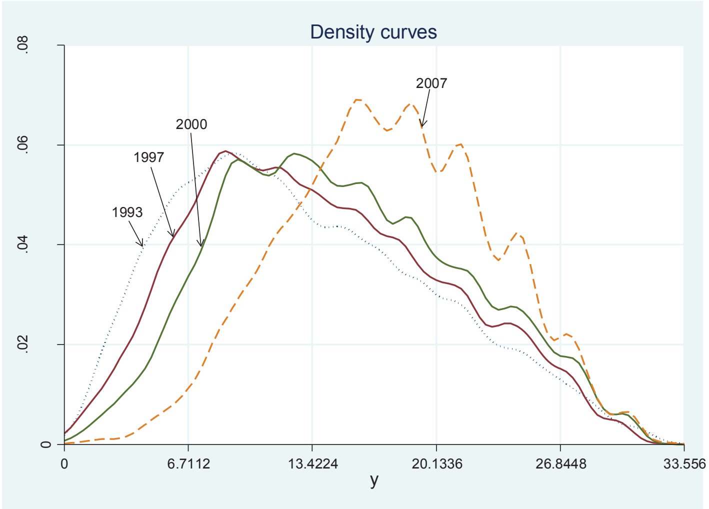
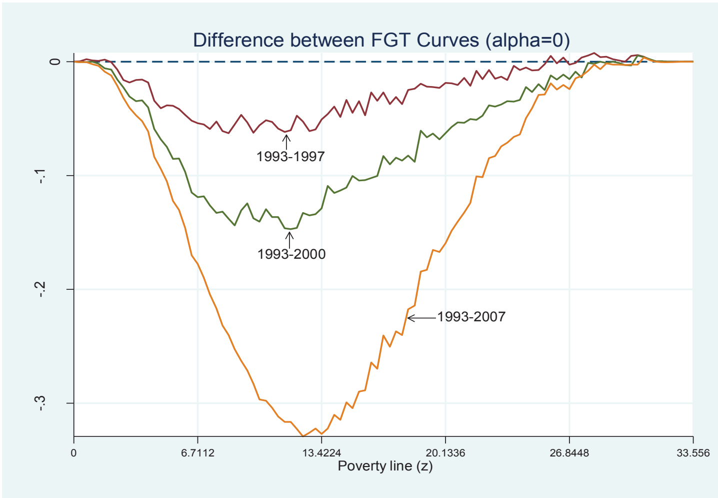


Figure 5.7: Difference between FGT Curves (1993-2007)



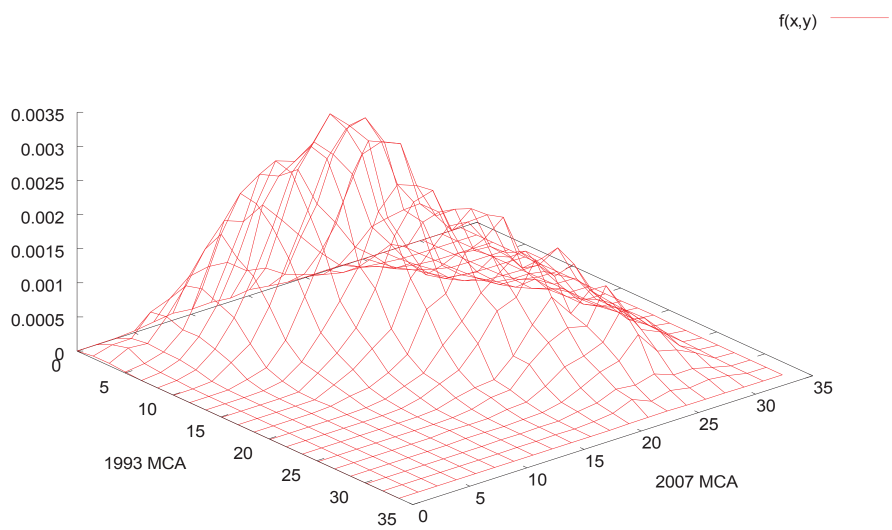
To show the partial correlation between the two periods of wellbeing and having MCA as latent variable, a positive correlation is portrayed by the direction which we observe for the pick mountain of the joint density function and the 45° diagonal line. Joint density estimation has been prominently used to measure poverty from grouped data by representing mean incomes of population percentiles.

Joint distribution is translated into distribution matrix $f(x, y) = P(X = x, Y = y)$ with properties: (1) $f(x, y) \geq 0$ (2) $\sum_{x,y} f(x, y) = 1$. Using modules in DASP software, joint density surface can be drawn with Gaussian kernel estimator of the joint density function $f(x, y)$ is defined as:

$$\hat{f}(\bar{x},\bar{y}) = \frac{1}{2\pi h_x h_y \sum_{i=1}^{n} w_i} \sum_{i=1}^{n} w_i \, exp\left(-\left(\frac{1}{2}\right)\left(\left(\frac{\bar{x}-x_i}{h_x}\right)^2 \left(\frac{\bar{y}-y_i}{h_y}\right)^2\right)\right) \quad (5.3)$$

Before using the formula, the two variables of interest or dimensions should be selected. The findings from joint density function (Figure 5.8) shows consistency with the generally higher levels of welfare in 2007 than 1993. This apparent convexity in MCA scores for 2007 is confirmed by the surface plot. In this plot, the x and y axes show the value of MCA scores in 2007 and in 1993, while the z axes shows the relative frequency of observations. The surface plots for these periods clearly has a single global maximum at around 15 worth of CIP, a local maximum can be seen the foreground of the surface plots for other combinations around 5 in 2007. Complete results for the other combination periods (compiled in Appendix A6) seem to be as asymmetric as the surface for the graph shown below.

Figure 5.8: Joint Density Plot for MCA scores (1993-2007)

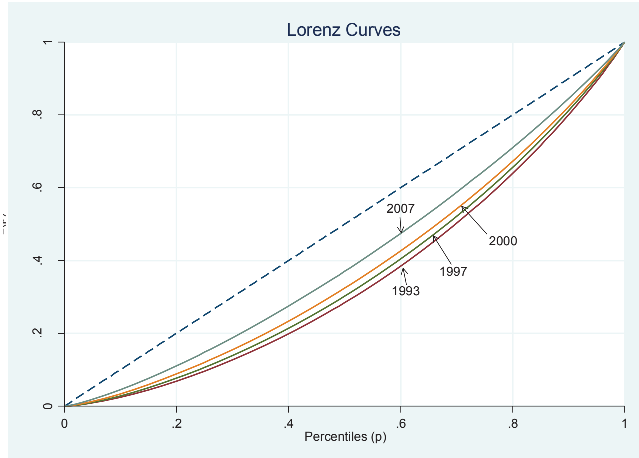


5.5. Inequality Dynamics

To estimate dynamic inequality, comparative analysis towards Lorenz curves is a good start. The ability of the grouped-data CIP to estimate the size of Lorenz curve is analysed. This is of intrinsic interest because it will shed further light on the performance of the technique in estimating degree of inequality. These are diagrams of the Lorenz curves for each period (generated through the different number of observation from each period). Using data from the MCA score distribution, Figure 5.9 shows an example of how Lorenz curve can be implemented to estimate the average welfare of the poorest against the richest population. It shows that all Lorenz curves shift slightly for the first three periods which implies hardly any changes on Gini indices during the research period. However, it shows no crossing between Lorenz curves and shifts upward toward equality line particularly in 2007 where significant distribution improvement occurs. To reinforce this finding, Lorenz curves differences between periods which notify the largest value occurs during 1993-2007 (Appendix A7).

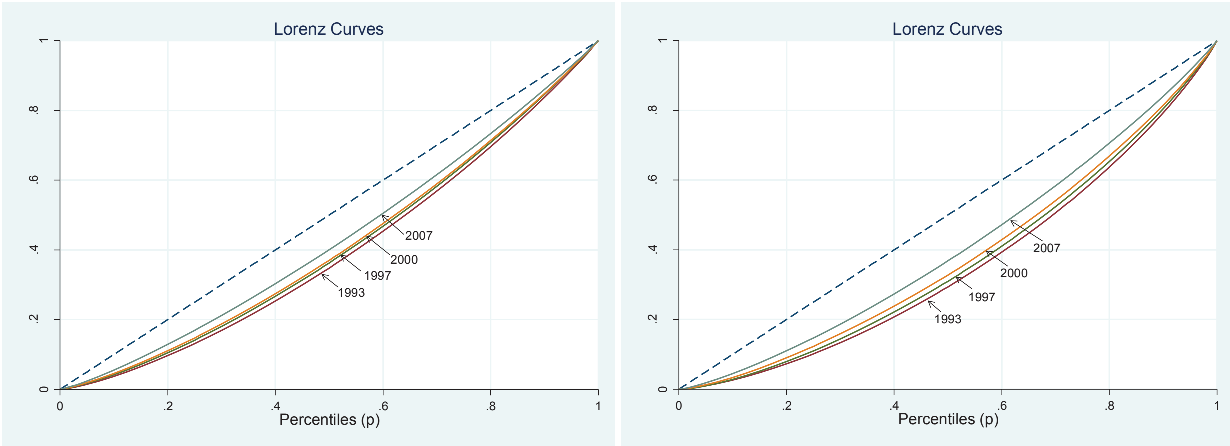
These findings are in line with income-based Gini index (see Figure 8). Since the beginning of economic reform began in 1970s, Indonesia's economy has gradually developed into new level, eliminating poverty rate significantly. While some of this reflects higher welfare, particularly for the money-metric analysis, at the same moment it confirms that problem of inequality has been very rigid to eradicate. This finding is worth to ponder whether poverty reduction and equality are complementary or not.

Figure 5.9: Lorenz Curve for MCA (1993-2007)



Turning to Figure 5.10, it repeats the exercise for the previous MCA score distributions. It shows two Lorenz curves representing different regional types i.e. urban and rural. Figure 5.10(a) depicts Lorenz curve in urban setting while Figure 5.10(b) represents inequality in rural area. Different size of Lorenz curves tells us the different inequality on welfare between these two regions. Urban population have their welfare unchanged, but people who stay in rural area experience significant improvement yet left wide curve area. It can be inferred that rural-urban differences can also create different trend and distinctive particular movement.

Figure 5.10: Urban-Rural Differences for Lorenz Curve (1993-2007)



(a) Urban Lorenz Curve (b) Rural Lorenz Curve

5.6. Chronic and Transitory Poverty

Todaro and Smith (2009) said that perhaps one-third of all families that are poor at any one time are always chronically poor, as indicated by evidence from (McKay et al., 2004) that an individual has been poor at least five years in the late 1990s. The rest two-thirds consists of families that are vulnerable to poverty and become extremely poor from time to time.

Results of poverty measurement in terms of overall incidence, transition into and out of poverty for three periods of analysis are described in this section. During observed periods, number of poor is estimated around 19.9%. Table 5.5 provides the result using method from Jalan and Ravallion (1998), calculation is operated using Stata and DASP software. Regarding the incidence of chronic and transient poverty in other periods, we compare the results from (Alisjahbana and Yusuf, 2003) who published their findings using multinomial logit model for household panel data (Table 5.6).

Table 5.5: Multidimensional Poverty Dynamics (1993-2007)

	Transient poor			Chronic Poor			Total Poor		
	Urban	Rural	Total	Urban	Rural	Total	Urban	Rural	Total
No. of Population	878	1,843	2,677	527	5,486	6,057	1,405	7,286	8,734
% total population	2.0***	4.2***	6.1***	1.2***	12.5**	13.8**	3.2***	16.6***	19.9***
% poor population	62.49	25.30	30.65	37.51	75.30	69.35	100	100	100

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.6: Poverty Dynamics (1993-1997) from Alisjahbana and Yusuf (2003)

	1-Period (Transient) Poor			2-Period (Chronic) Poor			Total Poor		
	Urban	Rural	Total	Urban	Rural	Total	Urban	Rural	Total
No. of Population	486	777	1,263	211	312	523	3,071	3,615	6,686
% poor population	15.8	21.5	18.9	6.9	8.6	7.8	100	100	100

However, their result demonstrates that during 1993-2000 poverty in Indonesia is more characterised by transient poverty rather than chronic poverty. Two contrasts are worth noting: (1) there is a significant difference on analysis subject to number of sample sets included. It employs only two waves of IFLS data sets which results in smaller number of observations and (2) their analysis in deciding transient and chronic poverty is mainly based on monthly consumption per capita. Intuitively, given the different situation put into context i.e. monetary crisis in 1997-1998 created temporary shocks to most households and increase vulnerability to poverty. Furthermore, a longer period for analysis is enabling to catch the aftermath effect of crisis. Post-crisis situation is left marked with severe poverty condition requires longer period for recovery and makes people fall into chronic poverty trap.

Figure 5.11 to 5.13 allow a better view of poverty dynamics. Classifications of poverty are set out on the horizontal scale. The population of the poor is given with reference to the vertical scale; the number of the poor is given the nominal value in the left-hand axis and percentage of the poor is expressed as a proportion of total population. Wherever a vertical line is drawn, there is a component of that chronic poverty in the mixture with transitory poverty indicated. Figure 5.11 shows decomposition of poverty in 1993-1997, total poor reached 24.9% population which was dominated by chronic poverty (23.2%) mostly happened in rural area (19.9%). Meanwhile, transient poverty only contributes 4.3% shared between urban (1.0%) and rural area (3.3%). In other words, the vulnerability to poverty among Indonesian households during crisis period has unambiguously high level. As in Figure 5.12, there is a slight decrease in poverty rate for period 1997-2000. Chronic poverty is still considered dominant in this period with overall rate 22.0% (19.1% rural and 2.9% urban). Transient poverty record decreasing pattern to 3.5% consists of 2.4% in rural and 1.1% in urban area.

Finally, poverty dynamics in 2000-2007 is presented in Figure 5.13, showing that transient poor have a lower percentage at both the start and end periods (5.2% and 9.5%) compared to the chronically poor of 22.5% and 16.6%. Both transient and chronic poverty have declining figures. In terms of regional pattern, the composition of poverty is still largely dominated by rural and chronic poverty incidence. This finding is somehow different from a study in Indonesia by (Suryahadi and Sumarto, 2003) as well as from other developing countries (McKay et al., 2004) which report dominant and increasing trend on transient poverty. However, this is not surprising because different result may occur due to difference in their estimation that limits only to consumption expenditure variable.

Figure 5.11: Decomposition of Change in Poverty (1993-1997)

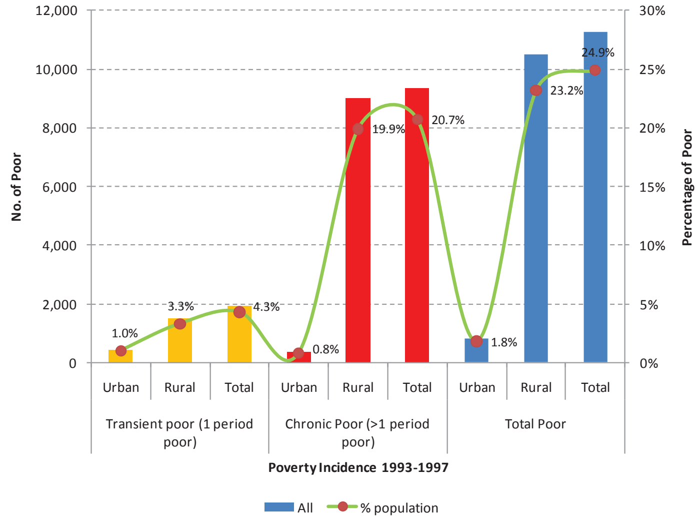


Figure 5.12: Decomposition of Change in Poverty (1997-2000)

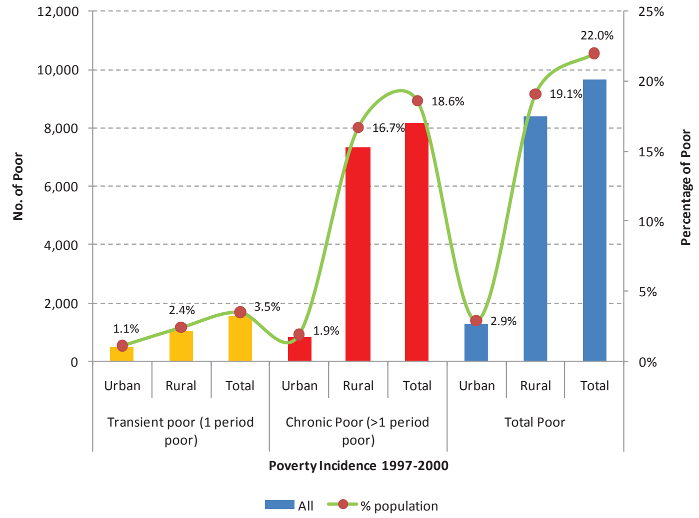
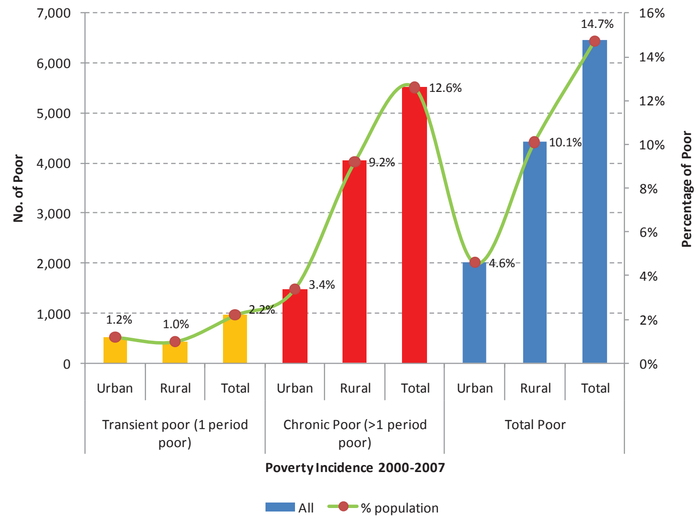


Figure 5.13: Decomposition of Change in Poverty (2000-2007)



CHAPTER 6
SUMMARY AND CONCLUSION

6.1. Introduction

This final chapter presents an overview of the dissertation and summary of the results obtained in previous parts. From these results, various conclusions concerning the determinants of multidimensional poverty and poverty analysis are drawn before concluding the chapter with some suggestions for relevant research in the future.

6.2. Overview

This paper performs multidimensional poverty analysis for households and individuals in Indonesia including three dimensions of wellbeing: education, health, and standard of living. Four rounds of Indonesia Family Life Survey (IFLS) data for the period 1993, 1997, 2000, and 2007 are utilised. An aggregative approach on multiple correspondence analysis (MCA) is used to compute composite index of poverty (CIP). The paper further tests for poverty analysis and setting particular standard to determine poverty lines and inequality so that it will enable comparison with ordinary measurement.

We extend the simulation using Foster-Greer-Thorbecke (FGT) approach to measure poverty lines while Lorenz curve and Gini coefficient are implemented to estimate the extent of inequality during research periods. Poverty dynamics is analysed through the length of experienced poverty applying method from Jalan and Ravallion (1998). Components of poverty are decomposed using poverty dominance. To reinforce the relationship hypothesis of wealth between periods, analysis is complemented with results from joint density function.

We find that the estimated multidimensional poverty indices depend on the number of factors or variables considered and that the poverty measures are surrounded by macroeconomic situation. Poverty dominance analysis suggests that the highest contribution to multidimensional poverty is from human assets relative to physical assets, disaggregated poverty profile shows that higher rates occur in rural areas than urban areas, and dynamic analysis show higher presence of poverty in the period of 1993 compared to 2007. We further find that poverty is more characterised as chronic rather than transitory. Poverty declined marginally between 1993 and 2000, but drops significantly between 2000 and 2007.

6.3. Implications

Most of our results conform to referenced literatures and justified by surrounding economic situation. Some aspects of the methodology can throw light on the potential for poverty measurement in Indonesia. We can use our results to enhance policymaking process especially related with poverty alleviation. For example, the distinction of poverty condition between chronic and transient is not only important from the point of view of accuracy, but for policy implication purposes as well. Chronic poverty *vis a vis* transient poverty would call for different policy alleviation strategies.

Most poverty reduction policies are aiming to promote economic growth as in (McCulloch and Baulch, 2000) as it assumes that improved endowments will allow households to increase their productivity. They often focus upon improving poor elements of human and physical assets that found to be most strongly associated with poverty. In a country where the poverty problem is characterised by the chronic poor, then the appropriate strategy for instance would be to redistribute assets, providing basic physical and human capital infrastructure (Hulme, 2003). Likewise if the predominant poverty problems relate to transient poverty, the strategy would be directed towards providing safety nets and coping mechanism to reduce their vulnerability and help them return to a non-poor situation.

The results imply that economic shock and location differences play a major part in shaping the extent of poverty measurement. The results of this study also indicate that the multidimensional poverty rate differ from the consumption-based poverty rate. In fact, the multidimensional poverty rate, in particular the incidence of chronic poverty tends to be higher than that of lower vulnerable groups.

It has been shown that economic growth *per se* has positive effect on poverty eradication. Economic growth translates into larger opportunities consequently increases capacity to add to total wealth. Policies that would facilitate empowerment and intervention to chronic poverty rate are to be prioritised and need to be encouraged.

6.4. Suggestion for Future Research

Results as presented in this paper are still in preliminary stage. Further refinement is needed in terms of disaggregation particularly relates to variables and locations. It should also be associated with variables that represent or proxy consumption expenditure and income. Disaggregation into local level (provincial) is also suggested once data made available.

While most of the factors affecting transient and chronic poverty are the same, some are different. Further analysis is needed to disentangle how each factor relates to the poverty transition. A more ideal approach, beyond the scope of this paper, is to combine the quantitative poverty dynamics study with panel data regression estimation to obtain more information on variables affecting poverty transition. Clear policy implication will emerge from results of such refined analysis.

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Appendix

Appendix A1: Detailed Percentile Distribution of MCA Scores (1993-2007)

mca93a

	Percentiles	Smallest		
1%	1.745	3.20e-07		
5%	3.38	.334		
10%	4.683	.334	Obs	29931
25%	7.678	.334	Sum of Wgt.	29931
50%	12.107		Mean	13.10589
		Largest	Std. Dev.	6.869756
75%	17.843	33.556		
90%	23.026	33.556	Variance	47.19355
95%	25.775	33.556	Skewness	.4513047
99%	29.423	33.556	Kurtosis	2.422985

mca97a

	Percentiles	Smallest		
1%	1.538	-4.58e-07		
5%	4.271	-4.58e-07		
10%	5.697	.1620002	Obs	31148
25%	8.519	.1620002	Sum of Wgt.	31148
50%	13.206		Mean	13.87729
		Largest	Std. Dev.	6.635209
75%	18.6365	32.035		
90%	23.745	32.035	Variance	44.02599
95%	25.709	32.565	Skewness	.3252795
99%	28.539	32.565	Kurtosis	2.32473

mca00a

	Percentiles	Smallest		
1%	2.478	-4.58e-07		
5%	5.578	.3370004		
10%	7.094	.3370004	Obs	37008
25%	10.064	.3370004	Sum of Wgt.	37008
50%	14.468		Mean	15.14254
		Largest	Std. Dev.	6.461239
75%	19.892	30.955		
90%	24.317	31.117	Variance	41.74761
95%	26.576	31.237	Skewness	.2574639
99%	29.803	31.876	Kurtosis	2.334301

mca07a

	Percentiles	Smallest		
1%	5.388	2.14e-07		
5%	8.424	2.14e-07		
10%	10.196	2.14e-07	Obs	40403
25%	13.712	.3660004	Sum of Wgt.	40403
50%	17.506		Mean	17.58342
		Largest	Std. Dev.	5.593892
75%	21.551	32.689		
90%	24.91	32.689	Variance	31.29163
95%	26.983	32.689	Skewness	-.0126836
99%	29.845	32.689	Kurtosis	2.527215

Appendix A2: FGT Indices for 40th Lowest Percentile MCA Scores (1993-2007)

Poverty index : FGT index
Parameter alpha : 0.00

Variable	Estimate	STE	LB	UB	Pov. line
mca93a	0.399987	0.000000	0.399987	0.399987	10.19
mca97a	0.398937	0.000000	0.398937	0.398937	11.37
mca00a	0.400146	0.000000	0.400146	0.400146	12.61
mca07a	0.394393	0.000000	0.394393	0.394393	15.92

Appendix A3: FGT Indices for 60th Lowest Percentile MCA Scores (1993-2007)

Poverty index : FGT index
Parameter alpha : 0.00

Variable	Estimate	STE	LB	UB	Pov. line
mca93a	0.600180	0.000000	0.600180	0.600180	14.30
mca97a	0.600364	0.000000	0.600364	0.600364	15.17
mca00a	0.600515	0.000000	0.600515	0.600515	16.49
mca07a	0.587527	0.000000	0.587527	0.587527	18.79

Appendix A4: Poverty Incidence using FGT Index (Baseline Year = 1993)

Poverty index : FGT index
Parameter alpha : 0.00

Variable	Estimate	STE	LB	UB	Pov. line
mca93a	0.400187	0.002832	0.394636	0.405738	10.19
mca97a	0.342485	0.002807	0.336985	0.347986	10.19
mca00a	0.257319	0.002579	0.252263	0.262374	10.19
mca07a	0.101197	0.001825	0.097621	0.104773	10.19

Appendix A5: Indicators and Category Scores for Physical Assets (1993)

```
Multiple/Joint correspondence analysis         Number of obs     =     17525
                                               Total inertia     =  .0379471
    Method: Burt/adjusted inertias             Number of axes    =         2
```

Dimension	principal inertia	percent	cumul percent
dim 1	.0244864	64.53	64.53
dim 2	.0035667	9.40	73.93
dim 3	.0003074	0.81	74.74
dim 4	.0001638	0.43	75.17
dim 5	.000033	0.09	75.26
Total	.0379471	100.00	

Statistics for column categories in standard normalization

Categories	mass	overall quality	%inert	dimension_1 coord	dimension_1 sqcorr	dimension_1 contrib	dimension_2 coord	dimension_2 sqcorr	dimension_2 contrib
pipe_wtr									
0	0.070	0.703	0.026	0.590	0.608	0.024	0.609	0.094	0.026
1	0.014	0.703	0.129	-2.975	0.608	0.122	-3.069	0.094	0.130
surface_wtr									
0	0.024	0.600	0.113	-1.639	0.363	0.064	-3.467	0.237	0.286
1	0.060	0.600	0.045	0.654	0.363	0.025	1.383	0.237	0.114
other_wtr									
0	0.079	0.585	0.003	-0.110	0.187	0.001	0.421	0.398	0.014
1	0.005	0.585	0.055	1.856	0.187	0.016	-7.099	0.398	0.235
own_septic									
0	0.056	0.746	0.046	0.965	0.727	0.052	-0.409	0.019	0.009
1	0.027	0.746	0.094	-1.971	0.727	0.106	0.836	0.019	0.019
pit_latrine									
0	0.069	0.252	0.005	-0.165	0.252	0.002	-0.013	0.000	0.000
1	0.014	0.252	0.024	0.807	0.252	0.009	0.062	0.000	0.000
public_toi~t									
0	0.072	0.042	0.003	-0.022	0.007	0.000	0.127	0.035	0.001
1	0.011	0.042	0.021	0.145	0.007	0.000	-0.827	0.035	0.008
run_sewage									
0	0.045	0.883	0.044	1.154	0.864	0.059	-0.442	0.019	0.009
1	0.039	0.883	0.051	-1.328	0.864	0.068	0.509	0.019	0.010
coll_garbage									
0	0.064	0.860	0.032	0.811	0.859	0.042	0.082	0.001	0.000
1	0.020	0.860	0.102	-2.637	0.859	0.136	-0.266	0.001	0.001
kr11									
has electr~y	0.058	0.899	0.031	-0.847	0.870	0.042	0.408	0.029	0.010
no electri~y	0.025	0.899	0.073	1.993	0.870	0.099	-0.960	0.029	0.023
hr01e									
has vehicle	0.027	0.884	0.014	-0.705	0.633	0.014	1.163	0.251	0.037
no vehicle	0.056	0.884	0.007	0.344	0.633	0.007	-0.567	0.251	0.018
hr01f									
has applia~s	0.060	0.921	0.013	-0.535	0.868	0.017	0.348	0.053	0.007
no applian~s	0.023	0.921	0.033	1.396	0.868	0.045	-0.907	0.053	0.019
hr01g									
has savings	0.021	0.986	0.026	-1.320	0.919	0.036	0.931	0.067	0.018
no savings	0.062	0.986	0.009	0.442	0.919	0.012	-0.312	0.067	0.006

Appendix A6: Indicators and Category Scores for Human Assets (1993)

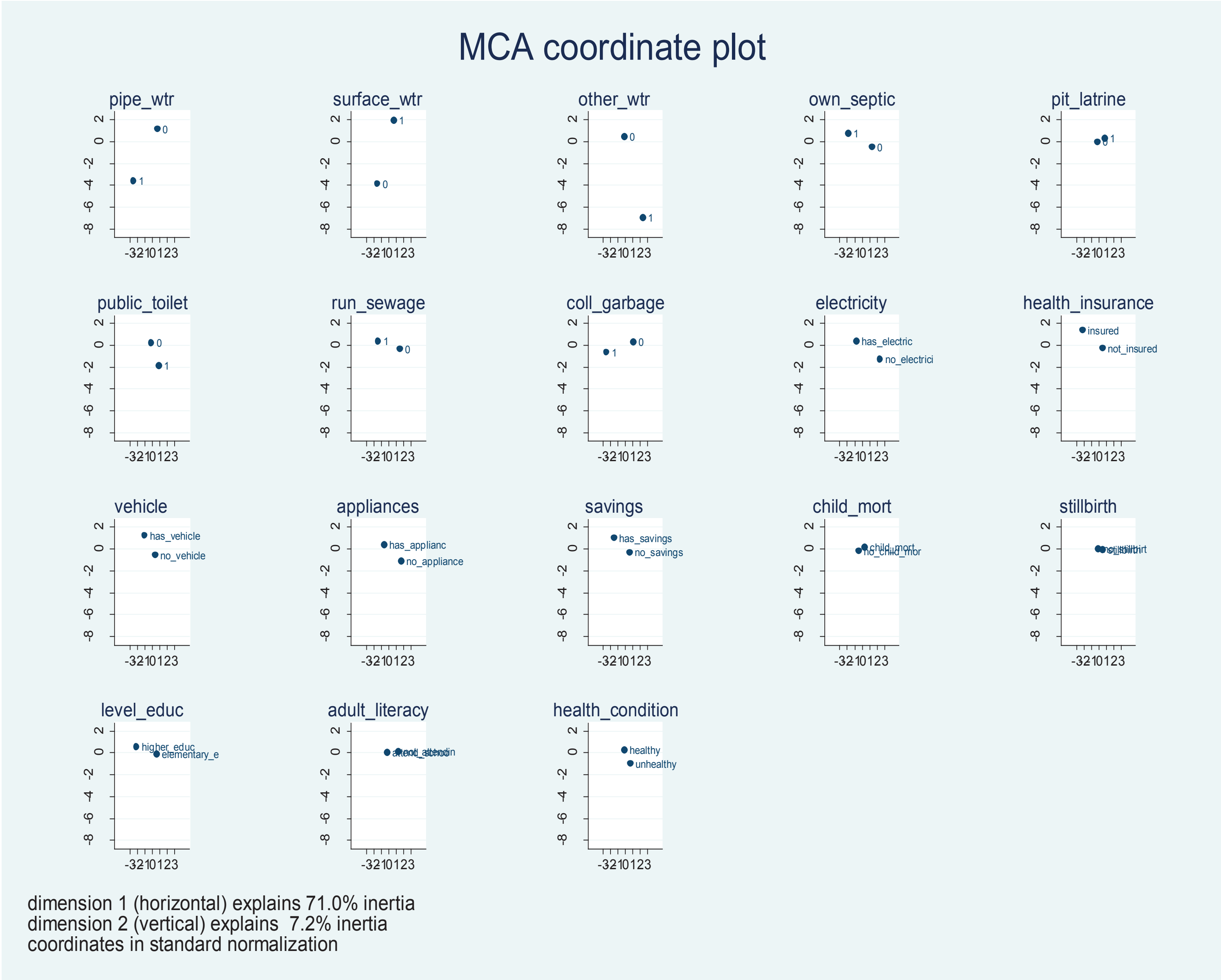
```
Multiple/Joint correspondence analysis          Number of obs     =      2280
                                                Total inertia     =  .0041091
    Method: Burt/adjusted inertias              Number of axes    =         2
```

Dimension	principal inertia	percent	cumul percent
dim 1	.0029488	71.76	71.76
dim 2	4.08e-06	0.10	71.86
Total	.0041091	100.00	

Statistics for column categories in standard normalization

Categories	mass	overall quality	%inert	dimension_1 coord	dimension_1 sqcorr	dimension_1 contrib	dimension_2 coord	dimension_2 sqcorr	dimension_2 contrib
br08									
child mort	0.112	0.729	0.132	1.096	0.729	0.134	0.030	0.000	0.000
no child m~t	0.088	0.729	0.167	-1.388	0.729	0.170	-0.038	0.000	0.000
br11									
stillbirth	0.011	0.845	0.046	2.163	0.843	0.054	-3.128	0.002	0.112
no stillbi~h	0.189	0.845	0.003	-0.132	0.843	0.003	0.191	0.002	0.007
dl06									
higher educ	0.044	0.681	0.343	-2.717	0.681	0.326	-0.240	0.000	0.003
elementary~c	0.156	0.681	0.097	0.769	0.681	0.092	0.068	0.000	0.001
dl04									
attend sch~l	0.171	0.780	0.029	-0.430	0.779	0.031	-0.230	0.000	0.009
not attend~g	0.029	0.780	0.168	2.486	0.779	0.182	1.331	0.000	0.052
kk01									
unhealthy	0.042	0.398	0.012	0.372	0.345	0.006	-3.938	0.053	0.646
healthy	0.158	0.398	0.003	-0.098	0.345	0.002	1.036	0.053	0.170

Appendix A7: Indicators and Category Maps for Physical and Human Assets (1993)



Appendix A8: Indicators and Category Scores for Physical and Human Assets (1993)

Multiple/Joint correspondence analysis — Number of obs = 2263; Total inertia = .0258462

Method: Burt/adjusted inertias — Number of axes = 2

Dimension	principal inertia	percent	cumul percent
dim 1	.018357	71.02	71.02
dim 2	.0018646	7.21	78.24
dim 3	.0001814	0.70	78.94
dim 4	.0001077	0.42	79.36
dim 5	.0000359	0.14	79.50
dim 6	.0000181	0.07	79.57
dim 7	2.32e-06	0.01	79.57
Total	.0258462	100.00	

Statistics for column categories in standard normalization

Categories		overall		dimension_1			dimension_2		
	mass	quality	%inert	coord	sqcorr	contrib	coord	sqcorr	contrib
pipe_wtr									
0	0.043	0.699	0.030	0.753	0.576	0.024	1.089	0.122	0.051
1	0.013	0.699	0.099	-2.500	0.576	0.080	-3.615	0.122	0.168
surface_wtr									
0	0.018	0.608	0.080	-1.481	0.358	0.040	-3.883	0.250	0.276
1	0.037	0.608	0.039	0.728	0.358	0.020	1.909	0.250	0.136
other_wtr									
0	0.053	0.605	0.002	-0.139	0.327	0.001	0.403	0.277	0.009
1	0.003	0.605	0.038	2.404	0.327	0.018	-6.943	0.277	0.147
own_septic									
0	0.032	0.773	0.057	1.383	0.762	0.061	-0.533	0.011	0.009
1	0.023	0.773	0.078	-1.888	0.762	0.084	0.727	0.011	0.012
pit_latrine									
0	0.045	0.249	0.005	-0.189	0.246	0.002	-0.060	0.003	0.000
1	0.010	0.249	0.021	0.853	0.246	0.007	0.270	0.003	0.001
public_toi~t									
0	0.050	0.334	0.002	-0.101	0.238	0.001	0.202	0.096	0.002
1	0.005	0.334	0.014	0.944	0.238	0.005	-1.883	0.096	0.019
run_sewage									
0	0.026	0.885	0.048	1.502	0.880	0.059	-0.369	0.005	0.004
1	0.029	0.885	0.043	-1.352	0.880	0.053	0.332	0.005	0.003
coll_garbage									
0	0.039	0.868	0.039	1.102	0.861	0.047	0.302	0.007	0.004
1	0.017	0.868	0.090	-2.544	0.861	0.109	-0.697	0.007	0.008
kr11									
has electr~y	0.043	0.902	0.019	-0.736	0.877	0.023	0.386	0.024	0.006
no electri~y	0.013	0.902	0.063	2.460	0.877	0.077	-1.289	0.024	0.021
ak01									
insured	0.011	0.903	0.043	-2.196	0.871	0.053	1.308	0.031	0.019
not insured	0.045	0.903	0.011	0.538	0.871	0.013	-0.320	0.031	0.005
hr01e									
has vehicle	0.018	0.951	0.014	-0.959	0.817	0.017	1.220	0.134	0.027
no vehicle	0.037	0.951	0.007	0.464	0.817	0.008	-0.590	0.134	0.013
hr01f									
has applia~s	0.042	0.934	0.010	-0.562	0.897	0.013	0.360	0.037	0.005
no applian~s	0.014	0.934	0.032	1.697	0.897	0.040	-1.086	0.037	0.016
hr01g									
has savings	0.014	0.955	0.026	-1.534	0.919	0.033	0.960	0.037	0.013
no savings	0.041	0.955	0.009	0.526	0.919	0.011	-0.329	0.037	0.004
br08									
child mort	0.031	0.755	0.005	0.394	0.743	0.005	0.156	0.012	0.001
no child m~t	0.024	0.755	0.006	-0.502	0.743	0.006	-0.198	0.012	0.001
br11									
stillbirth	0.003	0.436	0.001	0.477	0.435	0.001	-0.041	0.000	0.000
no stillbi~h	0.052	0.436	0.000	-0.028	0.435	0.000	0.002	0.000	0.000
dl06									
higher educ	0.012	0.925	0.040	-2.073	0.919	0.052	0.524	0.006	0.003
elementary~c	0.043	0.925	0.011	0.580	0.919	0.015	-0.147	0.006	0.001
dl04									
attend sch~l	0.047	0.897	0.002	-0.224	0.897	0.002	-0.016	0.000	0.000
not attend~g	0.008	0.897	0.011	1.295	0.897	0.014	0.093	0.000	0.000
kk01									
unhealthy	0.011	0.832	0.005	0.622	0.646	0.004	-1.048	0.186	0.013
healthy	0.044	0.832	0.001	-0.162	0.646	0.001	0.273	0.186	0.003

Appendix A9: Gini Coefficients for MCA Scores (1993-2007)

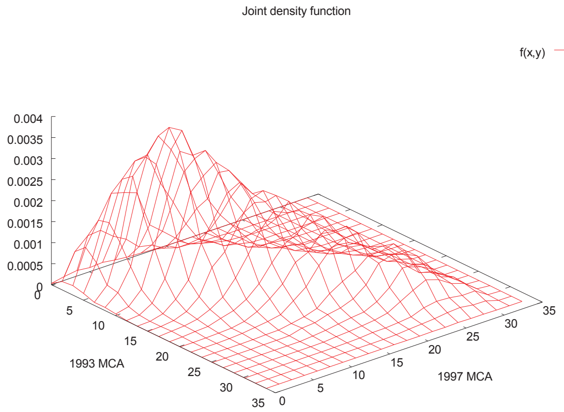
```
. igini mca93a mca97a mca00a mca07a

    Index           :  Gini index
```

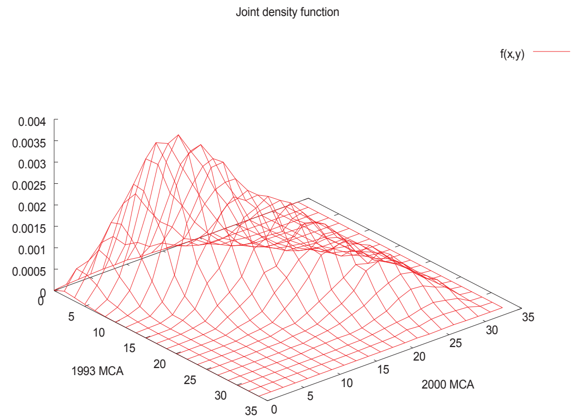
Variable	Estimate	STE	LB	UB
1: GINI_mca93a	0.297890	0.001050	0.295831	0.299948
2: GINI_mca97a	0.272878	0.000977	0.270964	0.274792
3: GINI_mca00a	0.243720	0.000812	0.242129	0.245312
4: GINI_mca07a	0.181360	0.000646	0.180094	0.182627

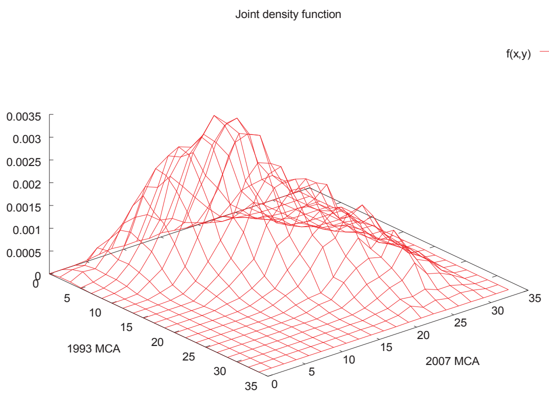
Appendix A10: Gini Coefficients for MCA Scores (1993-2007)

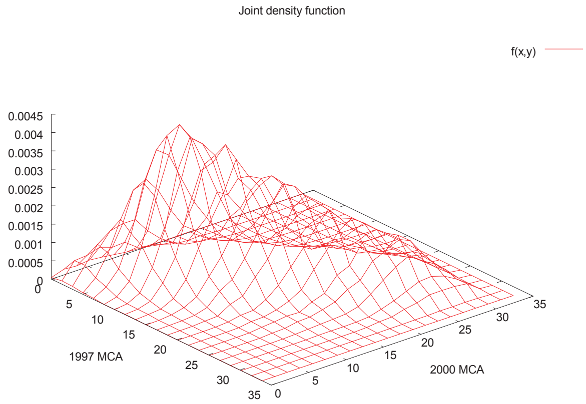
Variable	Estimate	Std. Err.	t	P>|t|	[95% Conf.	interval]	Pov. line
mca93a	.2651114	.0020766	127.666	0.0000	.2610412	.2691816	10.19
mca07a	.0875147	.0013295	65.8253	0.0000	.0849089	.0901205	10.19
diff.	-.1775968	.0021894	-81.1167	0.0000	-.1818881	-.1733055	---

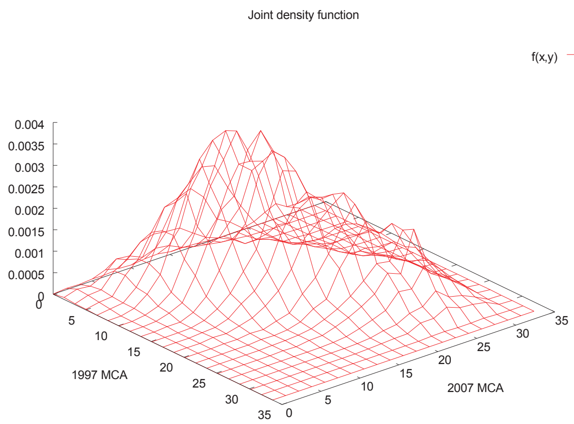
Appendix A11: Joint Density Functions for MCA Scores (1993-2007)

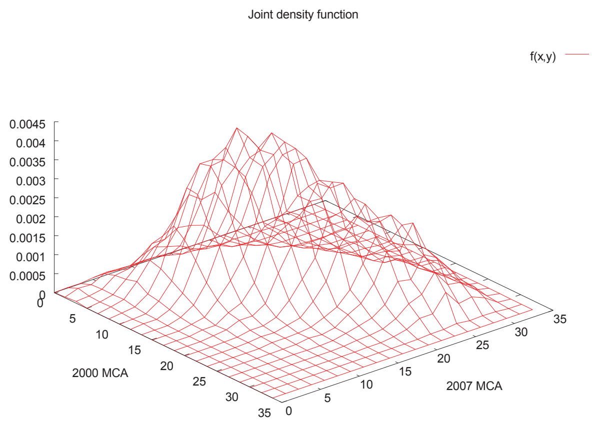




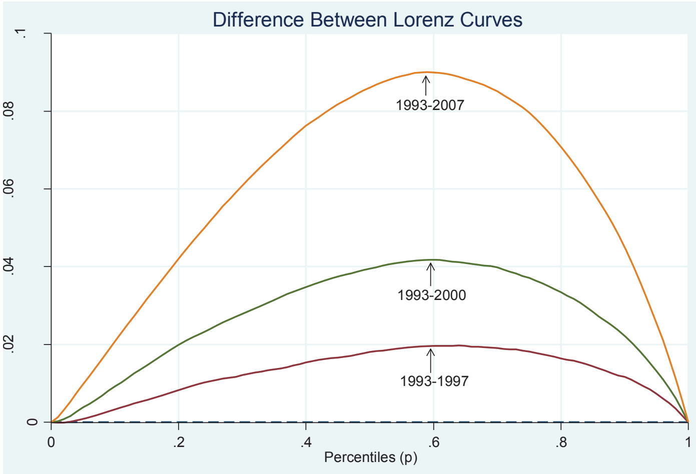








Appendix A12: Difference between Lorenz Curve (1993-2007)



Appendix A13: Decomposition of FGT by Components

1993-2007

```
. dtcpov  mca93a mca97a mca00a mca07a, alpha(0) pline(10.19)
     - Decomposition of total poverty into transient and chronic components.
     - Jalan and Ravallion approach (1998).
 Poverty line       :        10.19
 alpha              :         0.00
 # of observations  :        45070
 # of periods       :            4
```

Components	Estimate	STE
Transient	0.061	0.001
Chronic	0.138	0.002
Total	0.199	0.001

1993-1997

```
. dtcpov mca93a mca97a, alpha(0) pline(10.19)
     - Decomposition of total poverty into transient and chronic components.
     - Jalan and Ravallion approach (1998).
 Poverty line       :        10.19
 alpha              :         0.00
 # of observations  :        45070
 # of periods       :            2
```

Components	Estimate	STE
Transient	0.018	0.001
Chronic	0.232	0.002
Total	0.250	0.002

1997-2000

```
. dtcpov mca97a mca00a, alpha(0) pline(10.19)
     - Decomposition of total poverty into transient and chronic components.
     - Jalan and Ravallion approach (1998).
 Poverty line       :        10.19
 alpha              :         0.00
 # of observations  :        45070
 # of periods       :            2
```

Components	Estimate	STE
Transient	0.029	0.001
Chronic	0.192	0.002
Total	0.221	0.002

2000-2007

```
. dtcpov mca00a mca07a, alpha(0) pline(10.19)
     - Decomposition of total poverty into transient and chronic components.
     - Jalan and Ravallion approach (1998).
 Poverty line       :        10.19
 alpha              :         0.00
 # of observations  :        45070
 # of periods       :            2
```

Components	Estimate	STE
Transient	0.046	0.001
Chronic	0.102	0.001
Total	0.148	0.001