Complete and partial ordering approaches in the context of poverty ordering and on the impacts of growth and inequality on poverty: A study on India

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I am the only person responsible for errors remaining in the thesis.

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Chapter 1

Introduction

1.1 Background and brief survey of poverty orderings and related aspects.

In a well-known article in Econometrica, Sen (1976) described the problems involved in developing a poverty index that summarizes the available information on the poor. Sen argued that any poverty measurement exercise must be based on two distinct steps namely identification of the poor and then aggregation of the available informations in the form of a poverty measure. Since after the publication of this ground-breaking research article, many researchers adopted Sen's axiomatic approach to form a new poverty measure. The literature of poverty measurement by now has been well reviewed and nicely documented (Sen, 1979; Chakravarty, 1990, 1983; Foster et al., 1984; Zheng, 1997).

The identification of the poor is based on a poverty line. Individuals with income below this line are considered to be poor and the rests are non poor. The choice of poverty line has always been one of the principal methodological issues in the analysis of poverty. Poverty line may be either absolute or relative in nature (see Hagenaars and Praag, 1985, for further details). Poverty line in developed economies are usually relative in nature, depending on the income distribution of the entire society. In developing economies poverty line is based on an absolute approach and considered to be the minimum amount of money required for existence and survival of a person with usual/normal physical efficiency. There are two widely used methods for the computation of absolute poverty line namely, Food Energy Intake method (FEI) (Dandekar and Rath, 1971a,b; Greer and Thorbecke, 1986; Paul, 1989) and Cost of Basic needs (CBN) (Ravallion and Bidani, 1994; Bidani and Ravallion, 1993; Wodon, 1997) methods. The basis of computing the poverty line for both these methodologies is the daily energy requirements. The proxy of the energy requirements is considered to be the average calorie norms of the society based on the age sex and activity status of all the individuals.

However, following the lines of Atkinson (1983) "There is no one line of food intake required for subsistence, but rather a broad range where physical efficiency with falling intakes of calories and proteins"(See Atkinson, 1983, page no 226). Clearly poverty ordering for two distributions may alter as a result of two different sets of poverty line or measures. In order to rule out these inconsistencies it is necessary to consider a ordering approach which relaxes the completeness axiom also known as partially ordering approach. Atkinson (1987) in his seminal contribution used a tool called stochastic dominance by which poverty scenarios of two income distributions may be evaluated without considering a poverty line and also for the choice of a large set of poverty measures. Furthermore, following the contributions of Foster and Shorrocks (1988a,b) stochastic dominance has also been related to welfare ordering. Thus income or any related measures of welfare for two distribution can not only be compared in terms of poverty reduction but also in terms of welfare increment. It should be noted in the context of partial ordering approach, since the relationship is not complete ordering results for two distributions may lead to inconclusive results. Several techniques has been proposed in the literature in this context. For example, instead of focusing on the entire distribution, focus may also be only on a particular range of distribution which may contain meaningful poverty lines (Atkinson, 1987). However, in such cases also situations may end inconclusively. For detailed survey on this regard see Zheng (1997).

So far our discussion has been limited only on different methodological aspects of poverty ordering. However, the fundamental objectives for most of the developing economies is reduction of poverty. There has been a longstanding debate on the role of growth and inequality on poverty reduction. In an interesting article Dollar and Kraay (2002) with data for 92 countries spanning mostly in the period of 1960-2000, found that average income of the poorest quantile moved almost one for one with average incomes overall. In the conclusion of the article it was pointed that standard growth enhancing policies should be at the center of any effective poverty reduction strategy. Ravallion (2001) criticized the study mainly on the ground that cross country study often have problems of data comparability. He further mentioned that in an absolute sense poorer may enjoy gains of growth, but the gains of the richer decile are much higher in most of the cases compared to that of poorest decile. This debates also raised an important question "*Is growth pro poor ?*" or equivalently *Whether growth is favorable to the poor ?* The above question might be answered by two different pro poor ordering senses viz, relative and absolute sense. In general growth is said to be pro poor in an absolute sense, if it raises income of the poor, or poverty declines (See Kraay, 2006) . Following Kakwani and Pernia (2000), growth is labeled as "pro-poor" in a relative sense, only if it raises the incomes of poor proportionately more than that of the non poor. Both absolute and relative pro poor growth can also be analyzed in a partial ordering sense following the contributions Ravallion and Chen (2003) and Son (2004). Following the contributions of Datt and Ravallion (1992); Kakwani (1993, 2000) change of poverty can be decomposed in growth and re distributive components. Usually such approaches are applied when data on the entire income distribution is available. In the context of studies based on a cross section of countries, several regression based methods has been applied to study responsiveness of growth and inequality on poverty reduction (Bourguignon, 2003; Epaulard, 2003; Kalwij and Verschoor, 2007; Fosu, 2009). However, these studies are based on cross sectional or panel observations of countries, they are criticized following weak comparability of primary survey rounds in most of the cases (for details see Ravallion and Datt, 2002). Furthermore, computation of poverty estimates are based on income in some countries and expenditure for some other, which creates problems in terms of comparability. For example, it is widely known that measuring inequalities (say gini) in terms of income is expected to be higher than that of expenditure (Datt and Ravallion, 1992).

1.2 Motivation and plan of the thesis

In the 1980's India lacked the confidence of international community on her economic viability, and the country found it increasingly difficult to borrow internationally. Since, after early 1990s, a structural change took place in policies, like loosening government regulations, especially in the area of foreign trade. Many restrictions on private companies were also lifted, and new areas were opened to private capital. There had been a strong opposition of these policies, especially among the trade unions belonging in the left wing. However, Indian GDP has been steadily increasing after these changes, (see Pedersen, 2000, for further details). Although poverty is declining steadily, but in the post reform period inequality has increased substantially (Dev and Ravi, 2007). Recently, Ravallion (2014) reviewed the aspects of income inequality of the developing economies and argued that

"It appears more likely today that high inequality will be seen as a threat to future development than as an inevitable and unimportant consequence of past progress. The long-standing idea of a substantial growth-equity trade-off has come to be seriously questioned." (Ravallion, 2014, page no 851).

Our primary objective in this thesis is to study on the impacts of growth and inequality in the context of the poverty ordering of India. We shall begin our analysis by introducing new sets of poverty line to check whether poverty has indeed declined or not. We shall then move to partial ordering approaches for robustness of the results. Our study on the impacts of growth and inequality on poverty begins with poverty decomposition methodology introduced by Kakwani (2000). Furthermore, we shall also introduce new growth curves to analyze different aspects of absolute and relative pro poor growth. Finally we shall extend our study in the context where poverty of a region may be spatially dependent to their neighbors. The summary of the and description of all the chapters are presented below.

1.3 Summary and description of chapters

The thesis has altogether five chapters excluding this introduction. The analysis of all the chapters are based on the quinquennial rounds of National Sample Survey Organization data. We have considered monthly per-capita expenditure data on a mixed recall period as the proxy of income in all cases. In each chapter the tables and figures are presented in the appendix.

Here we shall provide a brief summary of the remaining chapters

Chapter 2: Poverty line in India: A new methodology

In this chapter we propose a new methodology for the estimation of poverty line of India. We begin with a preliminary exercise on the computation of average calorie norm, as the average calorie requirement of the entire society based on age-sex and activity status. This calorie norm often has been considered as basis of estimation of an absolute poverty line (Dandekar and Rath, 1971a,b). Our analysis is based on an iterative *Costs of basic needs (CBN)* approach. In this approach the first step is to estimate the cost of calorie norm following a consumption bundle of a reference frame of households, we refer this cost as food poverty line. Instead of a single poverty line in the proposed methodology we estimate lower and upper bounds of poverty line following different non food allocations (Ravallion and Bidani, 1994; Wodon, 1997).

We specify a commodity basket, consisting of necessary food items. The consumption quantities of the basket are estimated following the average consumption of each items for a reference frame of households, who are expected to have the sufficient amount of money necessary to purchase the calorie norm and also lying closer to the poverty line. Initially we consider reference frame of households whose income lies in the range of food poverty line and an upper bound of poverty line following a food energy intake method. We compute the price of each item (per calorie) following the median level of prices. We obtain the food poverty line following the multiplication of the price vector for the entire society and average calorie consumption vector for the reference households. The upper bound of poverty line is also consequently obtained. Using the new food poverty line and upper bound of poverty line, the process is repeated until we have desired level of precision. Note that in each step we normalize the bundle such that the desired calorie norm is obtained. It should be noted that this chapter is based on the consumer expenditure data for two points: 2004-05 and 2009-10. We shall use the reference bundle of the year 2004-05 for both these time point.

We shall compare the poverty estimates to those proposed by the export committee headed by Tendulkar (Government of India, 2009). Furthermore, in order to study on the impacts of growth and inequality on poverty reduction we consider Kakwani (2000) decomposition methodology. We consider data for rural and urban India, respectively for the period of 2004-05 and 2009-10 to analyze poverty changes both at national level and also for some major states.

The chapter begins with a introduction. In section 2.2 we provide a detailed descriptions of concepts and estimation methodologies of absolute poverty line. In Section 2.3 we describe the details of the proposed methodology. In section 2.4 we provide the empirical illustrations with NSSO data, at the national level. In section 2.5 we interpret the results related to state level poverty line and estimates. In section 2.6 we discuss issues related to the choice of the poverty line. In section 2.7 we shall discuss the decomposition methodology and the results. Finally we conclude this chapter in section 2.8.

Chapter 3: Applications of Stochastic Dominance: A study on India

In this chapter we adopt stochastic dominance techniques in order to examine the performance of rural India, urban India, female headed households and backward caste households (scheduled caste and tribe) in terms of poverty reduction and welfare increment. We shall also use the same tools in order to compare the male and female headed households and backward and general caste households in terms of poverty reduction. We have used NSSO data on consumer expenditure 66th and 61st round for the reference period of 2009-2010 and 2004-2005 respectively. Further, for robustness of analysis we have used economies of scale in all the comparison exercises. We shall also use Kolmogrov Smirnov type of test statistics as proposed by Barrett and Donald (2003) for the validation of the results.

After an introduction, in section 3.2 we provide a brief preliminaries of the literature related to stochastic dominance. In section 3.3 we discuss very briefly on economies of scale. In section 3.4 we present a brief discussions of the NSSO data. The empirical illustration is provided in section 3.5. The concluding part of the chapter in section 3.7 highlights the main empirical results.

Chapter 4: Pro poor growth : A partial ordering approach

In this chapter we have generalized the concept of equally distributed equivalent growth rate (EDEGR) proposed by Nssah (2005), in a partial ordering sense. Originally EDEGR appeared to be the weighted average of points of the growth incidence curve (Ravallion and Chen, 2003) where the weights had been restricted to relative extended gini type (See, Yitzhaki, 1983). Instead of considering a specific class of the weight function, we restrict it on the basis of certain ethical properties. We have introduced a concept called EDEGR dominance, implying EDEGR being strictly positive for at least on one of the weights and negative for the none. The dominance ordering are based on inverse stochastic dominance on logarithmic income domain of one distribution over the other. The first order EDEGR dominance corresponds to the satisfaction of week monotonicity property of growth quantiles, i.e., if growth is positive in at least one of the quantiles, then it must not be anti poor. For satisfaction of this axiom we consider only non negative class of weights in the construction of EDEGR. For the second order EDEGR dominance, we have restricted EDEGR which satisfies transfer principle. It says that for any transfer of income from the richer quantile to the poorer one would lead growth to be pro poor. For satisfaction of this axiom we had to restrict the weights as differentiable and the corresponding first derivative being negative. Second order EDEGR dominance is obtained if EDEGR satisfies both monotonicity and transfer axiom. Additionally we need principle of positional version of transfer sensitivity for third order EDEGR dominance. It states that transfer is valued more if it takes place at the bottom quantile of the growth profile. EDEGR satisfies this property if second derivative of the weight function is non negative. The derived dominance conditions are nested i.e., lower order EDEGR dominance will always imply higher order, but the reverse is not necessarily true. In order to extend the results of third order EDEGR dominance for empirical applications, we have introduced a new growth curve based on the change of gini social welfare function with underlying domain being logarithmic income. Nssah (2005) also consider a relative version of EDEGR, known as Distributed adjusted factor(DAF) as the deviation of EDEGR from the growth rate of mean income. We have also extended the analysis in the context of relative pro poor comparison, i.e., for DAF dominance. However, it is necessary to change the domain by considering normalization of incomes by any pro poor standard e.g mean, median e.t.c (Duclos, 2009). For the sake of simplicity and especially make it comparable with DAF dominance we consider the pro poor standard as the mean income of the society. All the results derived in EDEGR are also applicable for DAF. Further, we have also shown that DAF dominance implies (implied by) EDEGR dominance when the average growth rate of the society is positive (negative).

So far in the current literature there has been evidence of two widely used pro poor growth curves by which growth might be analyzed pro poor or not in a partial ordering sense. The first one is Growth incidence curve (GIC) (Ravallion and Chen, 2003), as the rate of change of income quantiles. The second one is poverty growth curve (PGC) (Son, 2004) as the rate of change of the mean income of the all the quantiles. GIC(PGC) provides conclusive result if there is evidence of first(second) order stochastic dominance of one distribution over the other. We have established that in spite, of the fact that the domain of the growth curves being different, conclusive GIC/PGC appears to be a sufficient condition for the ordering of newly proposed growth curve. We have further shown that the newly proposed growth curve may provide conclusive results in many cases where GIC/PGC fails to do so. Furthermore, following the normalization approach suggested by Duclos (2009) it is also possible to relate the relative versions of GIC and/or PGC to that of the of the relative version of the newly proposed growth curve. The value added of the absolute and the versions of the proposed growth curve is justified in terms of pro-poor growth index EDEGR and DAF, respectively. In the empirical analysis we shall first evaluate the performance (in terms of conclusiveness) of the newly proposed growth curve. In an another empirical exercise, we shall evaluate whether the evidence of growth for the last two decades, is in favor of poor.

The chapter begins with a formal introduction in section 4.1. In section 4.2 a brief review of the concepts on stochastic dominance, inverse stochastic dominance, absolute and relative pro poor growth measures and many other related topics. In section 4.3 we formally introduce the new dominance result. An empirical analysis has been done in section 4.4. The first part of the empirical analysis deals with the performance of new growth curve in terms of conclusiveness. The second part is mainly to evaluate the pro poor scenarios of India for the last two decades. The chapter is concluded in section 4.5.

Chapter 5 : Impacts of growth and inequality on poverty of India: A spatial approach

The main objective of this chapter is to study on the heterogeneity on the impacts of growth and inequality on poverty reduction of India. In this chapter we shall compute the growth and inequality elasticity of poverty, which we have referred as GEP and IEP, respectively. Using the time series data on consumer expenditure and employment unemployment for the last six quinquennial rounds we consider a study on a state region basis. Furthermore, we have constructed a balanced panel data set with the state regions as the panel units. However, many new states has been formed over this period and NSSO has also reformulated many state regions. In order to maintain geographic identity we have to merge more than one state regions in many cases. Clearly, unlike most of the cross sectional studies, comparability is not an issue in this regard, since the units we consider are independent stratum and the survey design has remained unchanged over this period. We borrow the regression based approach suggested by Bourguignon (2003) for this analysis. Since, we have data on the entire distribution of income (MPCE as a proxy) poverty decomposition into growth and inequality components, seems to be more appropriate Datt and Ravallion (1992); Kakwani (1993, 2000). However, as pointed out by Zaman and Khilji (2013) these studies capture only short run relationships on growth poverty and inequality. The main reason for considering the regression based approach is to incorporate the fact that poverty of one region may be spatially dependent to their neighbors. We expect that poverty may be spatially dependent because of the fact constitution of India allows free migration of individuals from one part to another. Spatial dependence of prices of one region of the other may also be a factor for the spatial dependency of poverty rates. Furthermore, in many real life situations local level policy implementation are also affected spatially which also might have a role on poverty reduction. Poverty at the state region level also reflects the spatial dependency. For example, it has been observed that in one of the largest state of India, Uttar Pradesh, the percentage of poor in the western part is 34%, which on the eastern part is much higher (nearly 54%). Since, the western part shares a common boundary with Delhi, the development schemes of country's capital might have been trickled down to its neighbor. There are many such observations in this direction, which further motivates us to consider an econometric model with spatial dependencies. Ignoring these dependency, would lead to biased and inconsistent estimates of the parameters (See Anselin, 2009, for further details).

Incorporation of spatial dependencies for the estimation of GEP and IEP is new and has not been done in the literature so far we have surveyed. However, by forming the panel data at the state-region level we are losing many valuable informations contained in household surveys. We shall thus address the problem that has been posed in this chapter following the Poverty Equivalent Growth Rate (PEGR) that has been introduced by Kakwani and Son (2008). Following PEGR it is possible to decompose growth elasticity of poverty as sum of two components: (1) growth effect and distribution effect. We shall refer this as a non-spatial model. In fact we shall compare the findings of the spatial and the non-spatial model.

The chapter has been organized in the following fashion. In section 5.2 we discuss issues and results related to the estimation of PEGR. In section 5.3 we provide a brief description of a general Bourguignon type model and related issues. Section 5.4 provides a brief description of data and also on computation of poverty rates and inequality measures. In section 5.5 we discuss on incorporation of spatial dependencies. In Section 5.6 we discuss briefly on econometric models. A general model with further considering the problems of endogeneity has been discussed in section 5.7. The chapter has been concluded in section 5.8.

Chapter 6 : Conclusions and future research directions

This is the concluding chapter of the thesis. The major results and findings of the thesis has been summarized in Section 6.1. Possible limitations and future research directions are discussed in the next section.

Chapter 2

Poverty line in India: A new methodology

2.1 Introduction

The approach proposed by Dandekar and Rath (1971a,b) towards the estimation of India's poverty lines has been followed for the last four decades till the submission of the report by the expert committee headed by Tendulkar (Government of India, 2009). Prior to the publication of this report, the poverty lines, which were found in 1973 (Government of India, 1979), were projected using the consumer price index for agricultural labourers in rural India and the price index of industrial workers in Urban India. Given that the poverty scenarios changes over time, a modification for the change of the methodology is called for.[1] In the new approach the poverty line of the urban India, suggested by Dandekar and Rath (inflated in terms of the current price) has been considered to be appropriate. The poverty line for the rural India has been estimated considering the rural urban price differentials. There have been many

[1] On some further aspects of Indian poverty lines see Government of India (1993), Dev and Ravi (2007), Deaton and Drèze (2009), Patnaik (2010a), Manna (2007), Manna et al. (2009), Pal and Bharati (2009) Manna (2012), Vaidyanathan (2013).

debates among researchers on the acceptability of the newly proposed poverty lines. Firstly, on the fact that consideration of urban poverty line as appropriate and thus estimating the rural poverty line is completely arbitrary and has no scientific basis. Secondly it has been argued in the report that the new poverty line also provides for minimum nutritional, health, and educational outcomes. Swaminathan (2010) argued that these justifications do not stand up to scrutiny. In this chapter we shall introduce a new poverty line for India.

There are two widely used approaches for measuring poverty line, namely the absolute and the relative approach. The relative approach defines the poverty line in relation to average standard of living enjoyed by the society. This approach is more often used in developed countries. In the context of developing (under-developed) economies absolute approach is more widely used, since the concern usually is on the "*absolute standards of living*". Absolute poverty line is the minimum amount of money required for existence and survival of a person with physical efficiency. Any person earning less than the prescribed amount is termed as poor. In this entire thesis we shall focus the case of India. India being a developing nation, we shall thus restrict our attention throughout this thesis only on absolute poverty lines.

There are two widely used approaches for the specification of absolute poverty line, namely the Food Energy Intake (FEI) and Cost of Basic needs (CBN). In this chapter we shall suggest a modified CBN approach in order to obtain new sets of poverty line in the context of India. Before discussing the contributions of this chapter, we shall address the issue of preferring the CBN approach over the FEI method.

The basis of computing the poverty line following both these methodologies (FEI and CBN) is the daily energy requirements. The proxy to the energy requirements is considered to be the average calorie norms of the society based on the age sex and activity status of all the individuals. In the FEI method poverty line corresponds to the consumption expenditure or income level at which a person's typical food energy intake is just sufficient to meet a predetermined calorie norm, with physical efficiency.

A common practice is to compute the mean income and expenditures of a subsample of households whose estimated calorie requirements are close to calorie norm. CBN on the other hand considers poverty as a lack of command over basic consumption needs, and the poverty line is the cost of those needs. The first step for estimating poverty line using CBN approach is to specify a food basket containing the desired level of calorie norm. The bundle is then evaluated at local prices to get the food component of the overall poverty line. Since it is difficult to set such a norm for the analogous non food component one has to rely on the relationship between share of food and per capita expenditure.

Both FEI and CBN methods have some advantages and disadvantages. FEI method is simple and data on the price of the items are not necessary. Furthermore, it automatically includes an allowance for both food and non-food consumption - thus avoiding the tricky issue of determining exactly the basic needs of these goods - as long as one locates the total consumption expenditure at which a person typically attains the calorie requirement. On the contrary, following the logic of Ravallion (1992), there is nothing in the FEI methodology which reflects the poverty line differentials for two societies.[2] Ravallion and Bidani (1994) defined a poverty profile to be inconsistent if one of two households deemed to have exactly the same standard of living but located in different regions is classified as poor and the other as not poor. The FEI poverty line violates the property of consistency as defined above. Furthermore, in a survey article Kakwani (2003) argued that as a result of economic growth, consumption behavior of households may change and ultimately real poverty line shift

[2]Ravallion further pointed out that differences in poverty line across regions or sectors will simply arise because economies with higher mean income would tend to have lower share of food and consequently higher poverty line. On the other hand in the context of CBN approach assuming that taste remains same for two distributions and considering same basket of goods, one can explain the poverty line differentials in terms of prices. Similarly, different choices of commodity baskets allow incorporation of both price and taste differentials in the poverty line. For more on these issues, see Ravallion and Bidani (1994); Bidani and Ravallion (1993); Ravallion and Sen (1996); Wodon (1997).

upwards. Consequently, poverty may increase despite economic growth. Considering these issues, CBN is preferred over FEI and the former method has been adopted in the thesis.

The main difficulty in CBN approaches arises when prices of the items are unavailable. Furthermore, even if price data is available, the selection of commodity bundles often becomes questionable. Since, individuals food preferences tastes etc are often related to the culture and religious practices, an unique bundle for the entire society is always questionable. However, due to practical reasons there are very few options to incorporate these aspects in the estimation of poverty line. Bidani and Ravallion (1993) in their study on Indonesia, begin with an arbitrary basket of food item. For each item the calorie content corresponds to the mean consumption of the poorest 15% of the population. Further the consumption bundle is inflated such that the desired level of calorie norm is obtained.

It is widely known that the consumption bundle of the poor is mostly rich in coarse cereals and often lack essentials micro nutrients like vitamins and minerals and macro nutrients like protein. The poverty line in such a method may actually depend on the choice of the reference frame of the households. For example the commodity bundle for the bottom 10% population may produce a lower poverty line.

In this chapter we propose a modified CBN approach. We shall consider the reference bundle of the households actually having the purchasing power of the calorie norms and are expected to be in the poverty line interval. We shall begin with a two step FEI approach considering the reference frame as those households with income or expenditure lying in between FPL and upper bound of poverty line.[3] Once we get the commodity bundle, following a CBN approach we shall compute the FPL for these households and also the corresponding upper bound of poverty line. In the second stage we shall consider the average consumption bundle of the households lying in

[3]By two step FEI we mean estimation of FPL in the first step, and the non-food component in the second step. We shall discuss it on some appropriate part of this chapter.

between the new FPL and upper bound of poverty line. We shall repeat the process until a desired level of precision is obtained.

We shall apply this methodology on rural and urban sectors of India for the period 2004-05 and 2009-10. Further we shall also move to a micro level analysis to study the poverty dynamics of some of the major states of India. Note that our discussion is limited to the estimation of lower and upper bounds of poverty line. However, for policy prescription it is necessary to consider a single poverty line. We shall address this issue following the resource constraints of India, and chose lower bound as the final poverty line.

We shall also extend this study in a different direction. We shall use the lower and the upper bounds of poverty line to study on the decomposition of poverty rates in terms of growth and re distributive components following the contributions of Kakwani (2000). We shall also address this problem with different methodologies in Chapters 4 and 5.

The chapter has been organized in the following fashion. In section 2.2 we provide a detailed descriptions of concepts and estimation methodologies of absolute poverty line. In Section 2.3 we describe the details of the proposed methodology. In section 2.4 we provide the empirical illustrations with NSSO data, at the national level. In section 2.5 we interpret the results related to state level poverty line and estimates. In section 2.6 we shall discuss issues related to the choice of the poverty line. In section 2.7 we shall discuss the decomposition methodology and the results. Finally we conclude this chapter in section 2.8.

2.2 Existing methodologies for estimating absolute poverty line

In the context of developing economies like India, poverty is considered to be absolute in nature. It is the amount of money necessary to meet the energy requirements necessary for subsistence along with physical efficiency. Calorie is considered as a proxy to energy requirement. The first step towards estimating poverty line is the specification of calorie norm. Using the calorie norm one may consider either the Food Energy Intake (FEI) or Costs of Basic Needs (CBN) methods for the derivation of the poverty line.[4] It should be mentioned here we shall compute two different components of poverty line, namely, the food and the non food component. The poverty line is the sum of food and non food component components. In the remaining part of this section we shall have detailed discussions on these issues.

2.2.1 Calorie norms

The basis of estimating the poverty lines following FEI and CBN approach is the calorie norm. A calorie norm is defined as the average calorie requirement of a society. This requirements vary over individuals because of the differences in age, sex, activity status etc. Activity status refers to the type of work performed by an individual, usually divided in three categories: heavy, moderate and sedentary.[5]

Essentially, there are two steps of estimating the calorie norm. The first step corresponds to the division of the whole population in different age, sex and activity status categories. Let d be number of categories of such mutually exclusive classes. Let f_i denotes the relative frequency of the i th class. The second step is essentially an exercise for nutritionists, where the calorie requirement 'cr_i' for the i^{th} category is

[4]Note that in this chapter we shall adopt the CBN approach.

[5]Following recommendations of task force 1) heavy workers include persons engaged in cultivation, agricultural labor, mining and quarrying and construction; 2) moderate workers include persons engaged in livestock, forestry, hunting, plantations, orchards and allied activities, manufacturing, servicing and repairing; 3) sedentary workers include persons engaged in trade and commerce, transport, storage, communication and other allied services. Unemployed individuals are also assumed to be sedentary workers. Note that, calorie requirement also differs with the height and weight of an individual. Incorporating, such additional informations will give better estimates of the norm. However, such informations are rarely available.

fixed. The average calorie norm may be written as follows:

$$\bar{c} = \sum_{i=1}^{d} f_i.cr_i \tag{2.1}$$

In Table 2.1, we have presented the estimated calorie norms for the year 2004-05.[6] Classifications of the categories in this table and the calorie norm for each category are obtained from the Indian Council of Medical Research 1998 reports ICMR (1998). Relative frequency of different categories are computed from the 61 st round of National Sample Survey Office (NSSO) data on employment and unemployment conducted in the year 2004-05.[7] The classification of activity status of an individual is based on the *"National Classification of Occupation"* (NCO) 1968 codes.[8] Note that the empirical exercise of the paper is based on two time points 2004-05 and 2009-10. However, we shall use the same calorie norm for both the time points. The estimated calorie norms corresponds to 2365.2 and 2155.5. We approximate this figures as 2350 and 2150 for the sake of simplicity.[9] We have also computed the calorie norms for the fifteen major states of India. We have reported the state specific norms in Table 2.3.

[6] The entire analysis is almost similar to Manna (2007), who have estimated calorie norms for the year 1999-2000. Manna has also provided new classification considering all the managerial posts as sedentary.

[7] We shall have a detailed discussion on NSSO data later in this chapter. However, we shall consider the NSSO consumer-expenditure data in the remaining part of the analysis.

[8] For further details on the NCO codes see the website of the "*Directorate General of Employment & Training in Ministry of Labour.*"

[9] The calorie requirements were set as 2400 kcal an 2100 kcal by the Task force at 1979. There figures were rounded off to 1800 kcal by Tendulkar Committee (Government of India, 2009). However, this is based on the assumption that all persons are at sedentary level. Nonetheless, this is questionable. As argued by Swaminathan (2010) *"The proposal that the standard for light activity be taken as the requirement for an average person with expenditure around the poverty line is unacceptable. It is a fiction that will result in a gross under-estimation of the population of the poor."*

2.2.2 Food Poverty Line: FEI approach

In FEI approach the consumption expenditure or income level, at which a person's typical food energy intake is just sufficient to meet a predetermined calorie norm, with physical efficiency; is considered to be the poverty line. A common practice is to compute the mean income of a subsample of households whose estimated calorie consumption are close to calorie norm. The FEI methodology for estimation of poverty line has also been adopted by Dandekar and Rath (1971a,b) poverty line estimation.

Greer and Thorbecke (1986) proposed a methodology for estimating the food poverty line (FPL). They defined FPL as the minimum amount of food an individual must consume to stay healthy (see Greer and Thorbecke, 1986, pp 60). This is obtained following a regression equation on the costs of calorie:

$$zf_i = f(c_i) + u_i \tag{2.2}$$

where zf_i = Per-capita food expenditure, c_i = Per-capita calorie consumption and u_i is the error term with usual OLS assumptions, where i stands for the individual or household. For the sake of simplicity we consider the functional form as quadratic. A more general approach would have been consideration of a non parametric regression equation; where nothing has to be assumed regarding the functional form. Assuming $f(.)$ to be quadratic, we write the estimating regression equation as follows:

$$zf_i = \alpha_0 + \alpha_1 c_i + \alpha_2 c_i^2 + u_i \tag{2.3}$$

Let the calorie norm be $\bar{c}$, hence the FPL following Equation 2.3 may be written as $FPL = \hat{\alpha_0} + \hat{\alpha_1}\bar{c} + \hat{\alpha_2}\bar{c}^2$.

2.2.3 Food Poverty Line: CBN approach

In the CBN approach poverty is considered as the lack of command over basic consumption needs, and the poverty line is the cost of those needs. In this approach, the food component of poverty line is estimated in four steps. The first step corresponds to the choice of finite number of commodity baskets say K. The second step corresponds to the choice of a reference frame of households consuming this basket. Let $\bar{c}_i$, denotes the average calorie consumption of the item i $\forall i \in (1, 2, .., K)$, for these households.[10] The third step corresponds to the normalization of the basket, such that the desired calorie norm is obtained. The food poverty line in the last step may be obtained as follows:

$$FPL = \sum_{i=1}^{K} \tilde{c}_i.p_i \tag{2.4}$$

where $\tilde{c}_i = \bar{c}\big(\bar{c}_i / \sum_{i=1}^{K} \bar{c}_i\big)$ and p_i, respectively denotes the normalized calorie and the price for the i^{th} item.[11]

2.2.4 Non Food Component of the Poverty Line

The main difficulty, in the computation of non food components of poverty line lies in the fact that unlike calorie norm, an equivalent norm for the non food component of poverty line is not available. Furthermore, necessities for the non food commodity vary across households. For example, a household with older members may spend more on health compared to others. Hence, setting a basket of non food commodity is not feasible in most of the time. In order to overcome these difficulties we shall follow the works of Ravallion (1992), Ravallion and Bidani (1994), Bidani and Ravallion (1993), Wodon (1997).

[10] Usually, this frame has been fixed at bottom 15% of the population (Ravallion and Bidani, 1994; Bidani and Ravallion, 1993; Ravallion and Sen, 1996; Wodon, 1997). In the next section, we shall introduce a new algorithm to choose this reference frame.

[11] For an illustration see Table 2.2, where we have presented calorie and prices, for a reference frame of households. Following equation 2.4 we have computed the daily level FPL. Multiplying the daily level FPL by 30 would give the monthly FPL, which has been presented in the bottom of the table.

Note that there are two approaches for allocating the non food components of poverty line: parametric and non-parametric approaches. Although we shall discuss both these approaches, however, we shall essentially rely on the non-parametric approach.

In the parametric approach the first step is to specify a regression equation on the Engel curve of food. Assuming the functional form to be quadratic the regression equation following the contribution of Ravallion and Bidani (1994) may be written as follows:

$$sf_i = \beta_0 + \beta_1 log(x_i/FPL) + \sum_{j=1}^{L} \theta_j D_{ij} + m_i\delta + u_i \tag{2.5}$$

where

sf_i = share of food out of total expenditure

x_i = per capita expenditure

D_{ij} = Dummy variable for region j

u_i = Error term

m_i = vector of demographic variables

Allocation of the non-food component is obtained putting $x_i = FPL$.

The dummy variable D_{ij} has been incorporated in the regression equation in order to capture the region specific prices.[12,13]

The restriction $x_i = FPL$, implies that if those households spend all their income in food, the desired calorie norm would be obtained. However, certain essential non food expenditures like medical costs, clothing etc., must be made curtailing the food components. An approximation of such non food component can be made as $NF_l = FPL(1 - \hat{sf})$, where $\hat{sf}$ is the predicted value from equation 2.5. The poverty

[12] Kakwani (2000) argued that one must have data on regional level prices of food and non-food items. Regression equations can not solve the problem.

[13] Variation of the demographic factors also allows to obtain household specific poverty line.

line is obtained in the following fashion:

$$z_l = FPL + NF_l = FPL(2 - \hat{sf_1}) \tag{2.6}$$

This is however, considered as the lower bound of the poverty line. In order to estimate the upper bound one may begin with the following equation

In order to estimate the upper bound of poverty line we consider the following estimating equation

$$sf_i = \beta_0 + \beta_1 log(zf_i/FPL) + \sum_{j=1}^{L} \theta_j D_{ij} + m_i\delta + u_i \tag{2.7}$$

Putting $zf_i = FPL$, in the above equation, we shall get the estimated share of food expenditure for the households whose food expenditure is just sufficient to meet the required calorie norms. The upper bound of poverty line may be written as follows:

$$z_u = FPL(2 - s_u) \tag{2.8}$$

where $\hat{sf}$ is the predicted value from equation 2.7.

It may be argued that these regression equations, may provide biased estimates because of the presence of per capita total or food expenditure in the right hand side. Since, the estimating equation may have problems of omitted variable bias. Furthermore, there are issues on the specification of functional form of the Engel curve. In the empirical section of the chapter we shall focus mainly on a non-parametric approach suggested by Wodon (1997). For estimation of the lower bound he suggested consideration of non food expenditure of households whose per capita expenditure is closer to the food poverty line. On the other hand for the upper bound of poverty line he considered non food expenditure of households who have food expenditure close to the FPL.

The algorithm following Wodon may be written as follows. The first step is to specify the FPL. The second step is to consider 10 intervals close to FPL, say at

$FPL \pm (i/100)FPL\ \forall i \in \{1, 2, ..10\}$. For estimation of the lower bound of the poverty line the mean values of the non food expenditure is computed for individuals whose per capita expenditure falls within the ten intervals. Thus the households closest to the FPL ($i = 1$) gets maximum weight in the sense that these households also enter in all other intervals. The upper bound of poverty line is obtained following the mean values of the non food expenditure for those individuals whose per capita food expenditures falls within the ten intervals.

2.2.5 Methodology of the Tendulkar Committee

The poverty line estimation methodology introduced by Tendulkar Committee (Government of India, 2009) can be considered as a Cost of Basic Needs (CBN) method. The expert group under Tendulkar considered the urban poverty line as appropriate. In the next step, they identified the monthly per-capita expenditure (MPCE) class in which the poverty line of urban India belongs. Poverty line basket (containing both food and non-food items) was estimated following the consumption of the households belonging in the MPCE class. The detailed lists of the consumption basket was made available in the report (see, Annexure E Government of India, 2009, pp 37). Once the consumption basket of urban India was obtained, the poverty line of rural India was obtained by the rural-urban price differentials.

There are two major flaws in this methodology. Firstly, the committee assumed that the urban poverty line is non-controversial and largely accepted for obtaining the rural poverty line. This justification has been severely criticized in the literature on the ground that it has no scientific basis (Swaminathan, 2010; Subramanian, 2011; Manna, 2012; Pathak and Mishra, 2015).

The second flaw may be considered as the fact that it is not ensured whether the food component of the PLB contains the desired calorie norm. In fact, while deriving the poverty line at no point the Committee had considered the calorie norm. However, it has been argued that "the revised minimum calorie norm for India recommended by FAO is currently around 1800 calories per capita per day which is very close to the average calorie intake of those near the new poverty lines in urban areas (1776 calories per capita) and higher than the revised FAO norm (1999 calories per capita) in rural areas in the 61st round of NSS." What the Committee has not mentioned is the fact that FAO norm is based on the assumption that all individuals are at sedentary level. Nonetheless, this is questionable considering jobs of farmers, agricultural labors, mine workers, etc., as a light activity. Hence the method has been considered to be deeply flawed by Swaminathan (2010).

Furthermore, consideration of both food and non food components in the poverty line basket is rarely done in the literature. We have mentioned the associated problems in this context in the previous section.

The controversial methodology motivated us to derive new sets of poverty line for India.

2.3 Proposed methodology

We propose a poverty line estimation methodology, which may also be termed as an iterative CBN approach. This approach is different from the others in the literature in the sense that we consider reference bundle of food basket for those households who have the purchasing power of the FPL and are expected to lie close to the poverty line.[14] The non-food component of poverty line is estimated following the non-parametric approach discussed in the earlier section.

Let there be k individuals in a society and they consume Q items. Let c_i^q be the calorie consumption of individual i in item q. Let $P = \{p_1, p_2, p_3....p_Q\}$ denote the

[14]The choice of the commodity bundle, to the best of our knowledge, has been done somewhat arbitrarily. For example, Bidani and Ravallion (1993) considered the mean consumption of a pre specified group of items viz, the poorest 15% of the population as the reference bundle. Clearly, choice of the mean consumption for the poorest 10% of the poor may actually reduce the poverty line and consequently lower poverty rates.

price vector, where p_i is the price of the i th item per unit of calorie. Further, assume that calorie norm of the society be $\bar{c}$. Consider a FEI method and $FPL^0, z_l^0,\ z_u^0$ be the estimated food poverty line, lower bound and upper bound of poverty line. For estimation of the bounds of poverty line we suggest the following steps.

Step 1: Let K^0 denote the set of individuals with income lying in the interval FPL^0 and z_u^0. Furthermore, let n_i^0 be the number of individuals in K^0 consuming the item i. Let $\bar{c}_i = \sum_{k\in K^0} c_k^i/n_i^0$ be the mean calorie consumption of item i for all the individuals belonging to the set K^0. Let $\bar{C}_0 = \{\bar{c}_1, \bar{c}_2, \bar{c}_3, .., \bar{c}_Q\}$, denote the first stage consumption bundle. In order to ensure the total calorie content of the basket as $\bar{c}$ we normalize all the elements of $\bar{C}_0$ by the ratio $\bar{k}/\bar{c}$, where $\bar{k} = \sum_{q=1}^{Q} \bar{c}_q$. Denote this new vector as $C_0^* = \{c_1^*, c_2^*, c_3^*, .., c_Q^*\}$ where $c_q^* = \bar{c}.(\bar{c}_q/\bar{k})\ \forall q \in \{1, 2, 3...Q\}$.

Step 2: In the second stage FPL is obtained following the multiplication of median price vector P and mean consumption of the calorie vector which we denote as C^*. Thus FPL is obtained as follows: $FPL^1 = \sum_{q=1}^{Q} c_q^* p_q$. Further, consider z_u^1 as the upper bound of poverty line obtained in the second stage. We obtain the calorie consumption vector for the new sets of individuals, denoted by K^1, whose incomes lie in the interval $FPL^1\ and\ z_u^1$. In the next step, we repeat this methodology and thus estimate FPL^2 and z_u^2. We shall repeat this process until a desired level of precision is obtained.[15]

2.3.1 Poverty measures

We shall now have a discussion on the FGT measure (Foster et al., 1984), for the estimation of the poverty rates. For a society with n number of individuals the poverty index may be written as

$$P_\alpha = \frac{\sum_{i\in Q} \left(1 - y_i/z\right)^\alpha}{n} \tag{2.9}$$

[15] Note that convergence of poverty line is not guaranteed.

where y_i is the income of the i^{th} individual, $Q = (i : y_i \leq z)$ is the set of poor and z is the poverty line, α is the inequality aversion parameter. Increasing α implies that the policy maker gives higher weights to the inequality among the poor. For $\alpha = 0$, P_0 measures the incidence of poverty and the index is the widely known as Head Count Ratio(HCR). If $\alpha = 1$ the poverty index is related to the poverty gap (PG). For $\alpha = 2$ we get the squared poverty gap (SPG).

In the FGT index, it is possible to incorporate either z_l or z_u as the poverty line (z). We shall also consider a fuzzy poverty index introduced by Cerioli and Zani (1990) in order to incorporate both z_l and z_u. Following this poverty index an individuals poverty status is considered as fuzzy.[16] Thus an individual lying below z_l is considered as fully poor. On the other hand individuals with income being above z_u are considered to be non poor. Rest of the individual will be considered as partially poor. The degree of poverty for an individual is associated by a fuzzy membership function (mf), in the following fashion:

$$\begin{aligned} mf_i = 1 \;\; if \;\; y_i \leq z_l \\ mf_i = ((z_u - y_i)/(z_u - z_l)) \;\; if \;\; z_l < y_i < z_u \\ mf_i = 0 \;\; if \;\; y_i \geq z_u \end{aligned} \tag{2.10}$$

The poverty index is considered as the mean of the fuzzy membership function.

$$Fuzzyhcr = \sum_{i=1}^{K} mf_i/n \tag{2.11}$$

For axiomatization of this index, See Chakravarty (2006).[17]

[16] In the classical set theory an element may either fully belong in a set or is completely absent in that set. However, in the context of fuzzy set theory some elements in a set may belong partially. The degree of association of an object is considered following a membership function. For further details see Zadeh (1965).

[17] Note that this poverty index has originally been proposed for measuring multidimensional

2.4 Empirical illustrations

In this section we shall apply the new methodology for the computation of the poverty line. We shall begin with a brief discussion of the data and then we shall have a detailed discussions on the poverty estimates.

2.4.1 Data

The main variable necessary for this analysis is income of individuals or households of a society. However, in India data on income at the national level is not available. Government of India provide estimates of the poverty rate on the basis of "monthly per capita expenditure(MPCE)"; following the quinquennial rounds of National Sample Survey Organization (NSSO) on consumption and expenditure. In this chapter we shall consider two such rounds for the analysis namely, NSSO 61st and 66th rounds. These survey rounds were conducted for the periods 2004-05 and 2009-10, respectively. NSSO provides two different types of MPCE, on the basis of two recall periods. The first one is based on an *"Uniform Recall Period (URP)"*. In URP all items are reported on a 30 days basis. A more widely used MPCE is based on a "*Mixed Recall Period (MRP)*". In a MRP; clothing, bedding, footwear, education, medical (institutional), durable goods are collected on a recall basis of 365 days. All other items are collected only on the basis of a 30 days recall period.[18] The reported MPCE,

poverty. However, in this chapter we consider a specific form of this index, assuming income as the sole dimension of poverty.

[18] In the 66^{th} round consumer expenditure survey, two types of schedules of enquiry namely Schedule 1.0 Type 1 and Schedule 1.0 Type 2; were used to collect data. The schedules differs only in terms of specification of the recall periods for reporting consumption. Type 1 schedule is exactly same as the NSSO 61st round. In the *Schedule Type 2* the very frequently used items (Edible oil; egg, fish & meat; vegetables, fruits, spices, beverages and processed foods; pan, tobacco & intoxicants) are collected on the basis of a recall period of seven days. In order to maintain the comparability of the 61 st and 66th round, we shall consider schedule type 1 data.

however, is adjusted on a 30 days basis.[19] In the entire thesis we shall consider MPCE at MRP. Unless otherwise specified, by MPCE we shall refer MPCE at a mixed recall period.

NSSO follows stratified multi-stage survey design in both these rounds. The first stage units (FSU) are the 2001 census villages in the rural sector and blocks in the urban sector. Households are the ultimate stage units in both the sectors.

2.4.2 Consumption Basket and FPL

We shall now discuss issues related to the allocation of different commodities in the consumption basket. Following this basket we shall compute the FPL. Note that in this chapter our analysis is based on two survey rounds. However, we shall consider only two basket, one for rural India and the other for the urban India. These baskets are computed from the food consumption of NSSO 61st round. Essentially we are assuming that taste remains same for both the rounds. This is done mainly to maintain comparability between two rounds (see Kakwani, 2003, for further details).

NSSO provides information on the monthly consumptions for a wide range of food items.[20] Out of these items we have chosen 13 broad categories of items in the poverty line basket (See Column 1 of Table 2.2). Further, out of these item groups there are seven items which represents a group of food item. For example, the commodity rice have two classifications : 1) rice that has been obtained from the open market and 2) rice that is distributed in the Public Distribution System (PDS). Similarly for pulses, vegetables, Sugar and products, edible oil and spices have further sub items. The details of the sub classes of the food have been presented in the bottom of Table 2.2.

In Table 2.2 we have also reported the median prices and mean calories of these

[19]This is done simply by multiplying expenditure for the 365 days scheduled items, by 30/365.

[20]The detailed lists of all the food items for the round 61st and 66th are respectively available in the reports no 513(Government of India, 2007, page no 19-23) and 540 (Government of India, 2010, page no 15-18); published by the 'Ministry of Statistics & Programme Implementation'. Furthermore, informations on the calorie content for each of the item is also available in these reports.

13 commodities following the iteration process described previously. In a nutshell the reported calories for each item corresponds to the average consumption of those households whose MPCE lies in the range of $[332.8, 614]$ for rural India, and $[356.08, 753.82]$ for Urban India.[21] The price of these commodities are obtained considering the expenditure incurred per unit of calorie. The reported price vector in Table 2.2 is based on the median prices based on the entire sample of rural/urban India.[22] Unlike calorie contents in the poverty basket, prices are allowed to vary over the 61st and 66th rounds. This allows us to adjust price over the two time points.[23]

2.4.3 Rural and Urban Poverty scenarios

In table 2.4, we present poverty lines corresponding to the Tendulkar Committee (TC) (Government of India, 2009), CBN1 and CBN2 approach. In this chapter our main analysis will be based on the CBN2 approach. We present the TC and CBN1 poverty lines only for the sake illustrations. It is readily observable that the lower bound of poverty line following the CBN1 and CBN2 approaches is very close to each other. However, the upper bound of poverty line following the CBN2 approach is much higher than that of the CBN1 approach. This implies that the non food component does not get appropriate weights in the CBN1 approach. In all the cases except for the rural 61st round, TC line lies in between z_l and z_u following the CBN2

[21] Initially we had started with the bounds: $[343.9, 492.2]$ and $[444.6, 685.5]$ respectively for rural and urban India, obtained following a FEI approach. We have repeated the process 10 items and obtained a precision level of more than 10^{-3}. It should be noted that even if we change the initial level of FPL and upper bound (obtained by the FEI approach) poverty line remains more or less same. However, it is not guaranteed that convergence will be achieved following this methodology for a different data set.

[22] Since, we have used prices at the national level, the price vector would remain unchanged in each iteration.

[23] In the forthcoming chapters we shall consider different price adjustment techniques, following spatial price indices. For the rural India we shall consider Consumer Price Index for Agricultural Labor's, whereas for the urban India we shall consider Consumer Price Index for Industrial Worker's.

approach.

In Table 2.6, we have presented the estimated HCR, PG and SPG considering the lower and upper bounds of poverty line following the CBN1 and CBN2 approaches. We have also presented the estimates of fuzzy HCR, considering both the bounds of poverty line. The 95% confidence intervals for each of the measures has been reported in parenthesis.[24]

It is clearly evident from this table that considering either lower or the upper bound of poverty line following the two different CBN approaches, ensures decline of poverty. Furthermore, notice that the lower confidence interval limit of the 61st round for both rural and urban regions is higher than that of the upper limit of the 66th round, for all the poverty measures. We consider this as a statistical validation for the decline of poverty.

2.5 State level Poverty analysis

We shall now extend this analysis for the following 16 major states of India: Andhra Pradesh, Assam, Bihar, Gujrat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharastha, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal. These states consists of more than 75% of the sample households for both the NSS rounds. We shall consider the all India level basket specified in Table 2.2, for the computation of the FPL.[25] However, we shall consider the median prices separately for each states which would reflect the differences in food price across states.

In the earlier section we have observed that the CBN2 approach fails to provide

[24]The confidence interval limits has been estimated considering the NSSO sampling survey design. Furthermore, all the estimates in this chapter is obtained considering the NSSO sampling weights.

[25]For estimation of the state specific FPL, we have normalized all the items in the basket such that total calorie content in the basket equals to the calorie norm of the corresponding state which has been specified in Table 2.3.

appropriate weights especially in the upper bounds of poverty line. Furthermore, as we have mentioned earlier there are serious issues regarding the choices of functional form of the regression equation. We shall thus consider the state level analysis only on the basis of CBN2 approach.

In Table 2.5, we have presented the estimates of lower and upper bounds of poverty lines along with the TC line. Note that the reported bounds of poverty line is based on the CBN2 approach. In the context of rural (urban) India for the 61st and 66th round, TC line lies in between the lower and upper bounds respectively for 6 and 10 (10 and 16) states.

In Table 2.7 we have presented the state specific poverty rates following the HCR, PG, SPG and Fuzzy HCR measures. We have reported the 95% confidence interval estimates in the parenthesis. In the 61st round, most of the rural regions of the states exhibits high incidences of poverty. For example, in states like Andhra Pradesh, Bihar, Gujrat, Madhya Pradesh, Maharashtra, Odisha, Rajasthan and Tamil Nadu; the estimated HCR exceeds 70% considering z_u as the poverty line. Even if we consider z_l we find that HCR exceeds 45% for these states (excluding Rajasthan). Following the fuzzy poverty measure poverty rates are higher than 50% in almost all the rural regions of the states (except for Haryana, Kerala, and Punjab).

Urban poverty for all the states of the 61st round is much smaller than its rural counterparts considering any poverty line or measure. However, considering z_u, HCR in Andhra Pradesh, Bihar, Madhya Pradesh, Maharastha, Odisha, Rajasthan, and Uttar Pradesh exceeds 50%. On the other hand, considering z_l as the poverty line it is readily observable that HCR of the urban regions of all the states of 61st round, is lower than 30%, except for Bihar and Odisha. Fuzzy Head Count Ratio, is also much lower than the rural counterparts, and only in Bihar, Madhya Pradesh and Odisha, this measure exceeds 40%.

In the 66th round poverty rates, in both rural and urban regions in general are lower than that of 61st round considering any poverty line and measure. Even if we consider z_u, we find that HCR in the rural regions is less than 60% for all the states, excluding Madhya Pradesh. If we consider z_l as the poverty line, HCR lies below 40% for all the states, excluding Bihar, Madhya Pradesh and Odisha. The fuzzy poverty index is also much smaller, compared to that of the rural 61st round. The decline of rural poverty from 61st to 66th round, can also be validated statistically considering the confidence interval limits in most of the cases. This validation is observed for all the states considering z_u as the poverty line. In fact this decline, can also be validated statistically considering z_l for all the states except for Assam, Bihar, and Madhya Pradesh.[26] Poverty decline, following the Fuzzy HCR can also be validated for all the states except Assam.

Poverty rates in the urban regions of the 66th round are also very small. In this context, none of the states has exhibited a HCR greater than 40%, even after considering the z_u as the poverty line. On the other hand, following z_l only Bihar and Uttar Pradesh exhibits a HCR higher than 20%.

For some states we have also find poverty has increased. For example, in rural Bihar considering z_l as the poverty line, we have observed that poverty has increased following the SPG measure. Note that this observation is also common with the TC line. In fact in rural India the TC line also shows evidence of increment of poverty for Assam along with Bihar. In the urban India, increment of poverty, consider either TC line or z_l, has also been observed for states like Assam, Haryana, Himachal Pradesh, Punjab. However, this increment of poverty can not be statistically validated.

2.6 Choice of Poverty Line

In this chapter we have discussed two types of approaches for the computation of the lower and the upper bounds of poverty lines, namely the FEI and the CBN

[26] In Assam, Bihar and Haryana considering z_l as the poverty line, the decline of poverty can not be statistically validated for any of the FGT measures. In Madhya Pradesh, this validation has been observed only for HCR.

approaches. As we have discussed earlier, FEI violates the consistency property of poverty measurement introduced by Ravallion and Bidani (1994). We have not reported the poverty lines and the associated measures following the FEI approach. In the context of CBN approach, we have discussed the parametric and the non-parametric approaches, which we have referred to as CBN1 and CBN2, respectively. We have seen that the CBN1 allocates a very small weight to the non food component of poverty line, especially in the upper bound of poverty line. Moreover, the non-parametric approach is free from any specification of functional form and thus it is more general than the parametric approach. Clearly, these justify the choice of CBN2 approach. In the state level analysis, we have thus considered this approach only. In fact, the iterative procedure discussed in the earlier section is also based on CBN2 approach.

Throughout this chapter our interest has been on the estimation of bounds of poverty line, namely, the lower and upper bounds, which we have denoted as z_l and z_u, respectively. Still one important question remains unanswered: which of the two bounds should be considered as the final poverty line? We recommend considering z_l as the final poverty line. The justifications for this choice are discussed below.

Individuals whose income lies below z_l may be considered as extreme poor, which we have referred to as 'fully poor' in the fuzzy poverty analysis. Furthermore, in the same section, we have referred to individuals lying in between z_l and z_u as partial poor. Now, considering z_u as the poverty line implies incorporating both the extreme and the partial poor in a poverty targeting exercise. In the context of rural India HCR following z_u crossed 69% and 50%, respectively, in the 61st and 66th rounds. On the other hand, HCR of urban India crossed 43% and 26.4% for rounds 61 and 66, respectively. Following the Census of India 2011 reports, nearly 69% of Indians live in rural India, and the rest in urban India. Assuming that the ratio of rural to urban Indians is the same as that found in Census 2011 report, the all-India level percentage of poor are approximately 60% and 43% respectively in rounds 61 and 66.

Kakwani (2003) argued that "unrealistically high poverty line that cannot be met by available resources is simply impractical". Clearly in the context of India, targeting such a huge percentage of poor people following z_u as the poverty line, is also quite impractical. For example, in 2010, the Prime minister of India expressed his reservations against Supreme Court's directive on free distribution of food grains to the poor; in his reckoning, it was unrealistic to expect that food grains could be delivered free to as many as 37% of the Indian population.

At the all-India level, the estimates of HCR following z_l boils down to 36% and 27%, respectively for the 61st and 66th rounds. Targeting these proportions of poor would be meaningful for any poverty targeting exercise. We thus recommend consideration of z_l as the final poverty line.

2.7 Poverty Decomposition Analysis

One of the principal objectives in the entire thesis is to address issues related to impacts of growth and inequality on the poverty reduction. We shall often consider different methodologies to address this issue. We shall begin here following a poverty decomposition approach suggested by Kakwani (2000). This approach allows decomposition of total changes in poverty into two components-growth and inequality. Hence, the effects of growth along with the adverse effects of poverty on inequality can be estimated.

2.7.1 Kakwani's Poverty Decomposition Methodology

Let $\Gamma_1(z, \mu_1, L_1(p))$ be a poverty measure that is fully characterized by the poverty line, mean income and Lorenz curve at the initial time point. z, μ_1 and $L_1(p)$ denote the poverty line, mean income and Lorenz curve, respectively. We are interested in the change of poverty from time point 1 to 2. We write this as

$$p_{12} = \Gamma_1[z, \mu_1, L_1(p)] - \Gamma_2[z, \mu_2, L_2(p)]. \tag{2.12}$$

Kakwani considered an axiomatic approach and decomposed p_{12} as follows:

$$p_{12} = G_{12} + I_{12} \tag{2.13}$$

G_{12} is the growth effect defined as change in poverty from time point 1 to 2, due to pure change in mean income provided relative inequality following the Lorenz curve remains constant. The author has defined the average growth effect as follows

$$G_{12} = \frac{\Gamma_1[z, \mu_2, L_1(p)] - \Gamma_1[z, \mu_1, L_1(p)] + \Gamma_1[z, \mu_2, L_2(p)] - \Gamma_1[z, \mu_1, L_2(p)]}{2}. \tag{2.14}$$

On the other hand I_{12} is the inequality effect where Lorenz curve is to change but mean income at constant price remains the same. The average inequality effect may be defined as follows:

$$I_{12} = \frac{\Gamma_1[z, \mu_1, L_2(p)] - \Gamma_1[z, \mu_1, L_1(p)] + \Gamma_1[z, \mu_2, L_2(p)] - \Gamma_1[z, \mu_2, L_1(p)]}{2} \tag{2.15}$$

The decomposition method discussed above is only applicable for bilateral comparison i.e., for two time periods. In fact the author has also generalized this approach in the context of multilateral periods. In this chapter, since we consider only two time periods of NSSO 61st and 66th rounds, we leave out discussions related to multilateral comparison.

2.7.2 Decomposition Analysis: Results

The results of poverty decomposition following the above mentioned methodology has been presented in Table 2.8 and 2.9. In the first table (Table 2.8) we have set the poverty line at the z_l. In fact we have argued in the previous section that z_l should be more appropriate as the final poverty line. However, for illustrations we have also presented the decomposition results corresponding to the upper bound of poverty line in Table 2.9. In both the tables we have also reported the growth and inequality components along with the total changes of poverty following the class of FGT poverty indices. These tables also contain the decomposition results for sixteen major Indian states. The last row of these tables corresponds to the results of rural and urban India at the national level.

Let z61 and z66 be the poverty line corresponding to round 61st and 66th round (either lower or upper bound of poverty line), respectively. We have fixed incomes of all individuals for the 61st round. However, for the 66th round we have multiplied incomes of all individuals by the ratio $\frac{z61}{z66}$. We consider poverty line as z61 for both the two rounds.[27] This also adjusts the changes of price in between these two time points.

The results at the national level of rural and urban India reveal that the decline of poverty is largely explained by the growth rate of mean incomes. However, the adverse effects of inequality on poverty reduction is also reflected in the inequality component. This effect is much higher in the urban areas. In fact considering the poverty line as z_u the inequality component following HCR is negative. Thus an increment of inequality implies decline of poverty. This is possible if under *cetirus peribus*, there is a transfer (or sequence of transfers) of income of poorer poor to a richer poor such that rank of both individuals remains unchanged.[28] Another possibility of this result

[27]These changes will not affect the FGT poverty measure because the entire class of FGT belongs to the class of relative poverty measures.

[28]For example, consider a poverty comparison exercise for a distribution at two time points, namely 1 and 2, with income profiles being $y_1 = \{2, 3, 4, 10\}$ and $y_2 = \{1, 3, 5, 10\}$ respectively. Let the poverty line for both the distributions be 4.5. It can be argued that y_2 is obtained from y_1 following a transfer of 1 unit of income from the first individual to the third individual. Clearly, the Lorenz curve of y_1 will be more closer to the egalitarian line than that of y_2. Hence inequality in y_2 will be higher. On the contrary poverty following HCR is lower in y_2 than y_1. Since, growth rate of mean income is 0, the reduction of poverty (following HCR) in this example is completely explained by the increment of inequality. Eventually, the inequality effect is negative.

might be the case that policy maker focuses largely on persons lying closer to the poverty line. In chapter 5 we have similar findings and we shall discuss this issue in further details.

In the context of the state level decomposition analysis, growth also plays an important role for explaining the decline of poverty. However, in the rural India the inequality component is negative for most of the states.

The fact that adverse effects of inequality in urban India is much higher than that in rural India is common both in state and national level poverty decomposition analysis. As we move through subsequent chapters of this thesis, we shall find that this conclusion remains unchanged even when some other methodologies are considered.

2.8 Conclusion

In this chapter we have introduced new sets of poverty lines in the context of India. We have derived the lower and the upper bounds of poverty line. A fuzzy poverty index following Cerioli and Zani (1990) has been used, that incorporates both the bounds in the poverty measurement. Empirical illustrations are provided separately for the rural and urban India, using household level data on consumer expenditure, collected by the "National Sample Survey Office", for the period of 2004-05 and 2009-10. It has been observed that the government estimates of the poverty line lies in between these two bounds, in most of the cases.

In both rural and urban India, poverty rates following the Foster et al. (1984) (see equation 2.9) class of measures (HCR, PG and SPG), has been observed to be declining regardless of whether lower or the upper bound is considered as the poverty line. In fact the findings also holds considering the fuzzy poverty index, that has been introduced by Cerioli and Zani (1990). The analysis has also been carried out separately for sixteen major states of India and the results are found to be similar to the all India level in most of the cases.

In this chapter we have discussed on the estimation of lower and upper and bounds of poverty line. However, in many policy prescription exercises one must consider a single poverty line. We have recommended consideration of lower bound as the final poverty line. This is justified in the grounds of current resource constarints of the Indian government.

India has a enjoyed a decent economic growth in the last two decades. It may be of interesting to the policy makers to see how economic growth effects poverty reduction. Furthermore, another important question may be relevant to the policy maker: whether inequality acts as an impediment on the forces of poverty reduction. Both these issues have been addressed in this chapter, considering the poverty decomposition methodology suggested by Kakwani (2000). We have observed that poverty reduction is mostly due to the economic growth. However, the adverse effects of income inequality have been observed in many cases. This adverse effects of income inequality is much higher in the urban India, compared to that of rural India.

2.9 Tables and Figures

Table 2.1: Computation of Calorie Norm for 2004-05: Task Force age sex activity status classification

Age-sex-occupation group	**Calorie Requirements**	**Weights**	
		Rural	**Urban**
1 Infants (less than 1 year)	700	1.8	1.5
2 Children:			
(a) 1 to 3 years	1240	6.8	5.2
(b) 4 to 6 years	1690	7.7	5.8
(c) 7 to 9 years	1950	7.1	5.6
3 Boys: 10 to 12 years	2190	4.3	3.3
4 Girls: 10 to 12 years	1970	3.5	3.1
5 Boys: 13 to 15 years	2450	3.4	3.2
6 Boys 16 to 18 years	2640	3.4	3.6
7 Girls: 13 to 18 years	2060	5.9	6.0
8 19 years and above:			
(I) Workers: Men			
(a) Sedentary	2425	4.4	16.4
(b) Moderate	2875	3.6	6.9
(c) Heavy	3800	16.8	3.1
(II) Workers: Women			
(a) Sedentary	1875	1.0	3.6
(b) Moderate	2225	1.7	1.4
(c) Heavy	2925	8.1	0.9
9 Non-Workers:			
(a) Men	2425	3.0	5.9
(b) Women	1875	17.6	24.2
Calorie Norm $\longrightarrow$		2365.2	2155.5

[1] **Notes :** Calorie requirements are based on the ICMR 1998 reports.

[2] Weights (Rural and Urban) corresponds to the % of individuals in the age-sex-activity status category, computed from the NSSO employment and Unemployment Round 61.

[3] Weights corresponds to the percentage of people in the age-sex-activity status category.

Table 2.2: Consumption Basket from final iteration

	Rural			*Urban*		
Commodity	**Calorie**	**Price 61**	**Price 66**	**Calorie**	**Price 61**	**Price 66**
Rice	1016.9	2.9	4.3	855.4	3.5	5.8
Wheat	731.1	2.3	3.5	692.7	2.9	4.4
Pulses and Products	37.7	8.1	19.5	36.4	8.5	20.1
Vegetables	38.3	26.3	46.3	37.9	31.1	53.3
Potato	50.2	7.7	14.4	42.2	8.2	15.5
Onion	10.7	14.5	27.3	11.7	14.5	29.1
Chicken	9.1	59.6	100.9	9.3	59.6	100.9
Egg	9.7	20.0	30.0	11.3	17.5	30.0
Banana	18.5	7.2	14.4	18.7	8.6	16.5
Milk	165.8	12.0	20.0	141.7	14.0	20.0
Sugar and Products	99.7	4.5	8.1	109.4	4.5	8.3
Edible Oil	144.4	6.2	6.3	163.8	6.2	6.7
Spices	17.8	20.9	38.6	19.7	23.0	41.3
Initial Iteration: FEI						
	Rural			**Urban**		
$(FPL, z_u) \longrightarrow$	(343.9,492.2)			(444.6, 685.5)		
Final Iteration: CBN2						
$(FPL, z_u) \longrightarrow$	(332.80,614.0)			(356.08, 753.82)		

[1] **Notes** The items correspond to average calorie consumption of the households. Initial bounds are the FEI based FPL and z_u. After 10 iterations the final estimates of FPL and z_u are obtained. The precision level was $< 10^{-3}$.

Price corresponds to the price per 1000 Kcal.

Calorie Norm : 2350 and 2150 K cal, respectively for rural and urban India.

Note that we have computed the calorie contents of the basket only for 61st round. We shall use the same basket for the 66th round.

Sub item groups : Rice : Rice Pds, Rice others (NSSO Codes 101 102) Wheat : Wheat PDS, Wheat from other sources (NSSO Codes are 107 and 108) Pulses and products : Moong, Masoor and soybean. (NSSO codes 143, 144, 147)

Edible Oil : vanaspati, margarine, mustard oil, groundnut oil, coconut oil and other edible oil (NSSO codes 170-179)

Vegetables : radish, carrot, turnip, beet, sweet potato, arum, pumpkin, gourd, bitter gourd, cucumber,parwal, patal jhinga, torai,snake gourd, papaya: green, cauliflower, cabbage, brinjal, lady's finger, palak/other leafy vegetables french beans, barbati, tomato, peas, chillis: green, capsicum, plantain: green, jackfruit: green, lemon, garlic, ginger, other vegetables (NSSO code 192 -224)

Sugar and Products : sugar - PDS, sugar - other sources, gur, candy, honey. (NSSO codes 260-269)

NB : NSSO codes corresponds to 61 st round (codes changed in 66 th round)

[2] Rural and Urban 61 and 66 imply that NSSO survey data conducted on 2004-05 and 2009-10, respectively.

Table 2.3: State specific calorie norms in Rural and Urban India

States	**Rural**	**Urban**
Andhra Pardesh	2478.1	2171.5
Assam	2335.9	2118.5
Bihar	2260.9	2143.4
Gujrat	2439.6	2156.4
Haryana	2279.2	2153.3
Himachal Pradesh	2402.8	2196.1
Karnataka	2522.6	2166.2
Kerala	2207.6	2151.4
Madhya Pradesh	2441.9	2140.7
Maharastra	2507.0	2165.3
Odisha	2361.2	2145.5
Punjab	2288.7	2145.0
Rajasthan	2333.2	2139.8
Tamil Nadu	2475.8	2182.0
Uttar Pradesh	2267.9	2130.5
West Bengal	2316.6	2161.4

[1] **Notes :** State Specific Calorie Norm, using ICMR specified age-sex and occupation status calorie norms.

Table 2.4: Poverty Lines in Rural and Urban India : Different approaches

	Rural : 61	**Urban : 61**	**Rural : 66**	**Urban : 66**
FPL	332.8	356.1	531.0	569.0
CBN Approach : Parametric				
s_1	0.6	0.6	0.8	0.7
s_2	0.6	0.5	0.7	0.6
z_l	464.6	502.7	663.6	718.1
z_u	476.6	542.0	693.7	790.1
CBN Approach : Non Parametric				
n_l	128.3	150.7	137.5	153.5
n_u	281.2	397.7	275.9	374.4
z_l	461.1	506.8	668.5	722.5
z_u	614.0	753.8	806.9	943.4
Tendulkar Committee poverty line				
	446.68	**578.8**	**672.8**	**859.6**

[1] **Notes :** z_l and z_u stands for the lower and upper bounds of poverty line. In the parametric approach s_1 and s_2 stands for the share of food respectively for lower and upper bounds (See equation 2.5 and 2.7). Whereas in the non parametric approach n_l and n_u stands for the amount of non food expenditures, following Wodon methods.
In the CBN approach the iterative method is used for the estimation of the food poverty line. Note that FPL from the items following the final iteration basket in Table 2.2.

[2] TC line refers to the Tendulkar committee poverty lines.

Table 2.5: Poverty lines for Rural and Urban States of India

	Round 61						*Round 66*					
	Rural			*Urban*			*Rural*			*Urban*		
States	**TC**	z_l	z_u	**TC**	z_l	z_u	**TC**	z_l	z_u	**TC**	z_l	z_u
Andhra Pardesh	433.4	504.6	689.6	563.2	523.0	816.1	693.8	781.9	952.0	926.4	850.0	1217.0
Assam	478.0	503.3	614.1	600.0	543.5	738.9	691.7	693.3	762.0	871.0	742.6	879.0
Bihar	433.4	406.1	500.7	526.2	439.1	595.6	655.6	594.1	676.5	775.3	610.9	750.6
Gujrat	501.6	533.2	724.4	659.2	556.8	809.6	725.9	759.2	904.6	951.4	800.2	1025.8
Haryana	529.4	488.4	675.9	626.4	534.2	850.3	791.6	745.3	898.9	975.4	808.6	1073.0
Himachal Pradesh	520.4	508.3	728.0	605.7	541.8	924.8	708.0	687.0	867.6	888.3	747.7	979.0
Karnataka	417.8	410.9	543.3	588.1	546.6	829.2	629.4	543.7	651.2	908.0	826.1	1093.7
Kerala	537.3	543.7	825.5	584.7	566.2	873.9	775.3	747.8	1039.0	830.7	799.4	1130.9
Madhya Pradesh	408.4	441.8	603.7	532.3	476.1	706.7	631.9	683.9	801.9	771.7	691.4	940.0
Maharastra	484.9	523.8	746.2	631.8	571.0	972.9	743.7	741.2	936.4	961.1	884.8	1216.2
Odisha	407.8	439.4	567.3	497.3	456.4	649.4	567.1	610.8	694.6	736.0	658.9	836.6
Punjab	543.5	478.4	683.4	642.5	513.3	829.8	830.0	734.0	936.3	960.8	802.6	1064.6
Rajasthan	478.0	503.8	666.5	568.2	522.4	761.2	755.0	776.6	945.1	846.0	776.5	977.8
Tamil Nadu	441.7	511.7	677.1	559.8	559.3	853.4	639.0	587.2	768.8	800.8	666.5	872.3
Uttar Pradesh	435.1	401.9	541.4	532.1	474.0	679.1	663.7	607.4	744.7	799.9	701.8	867.5
West Bengal	445.4	451.6	574.3	572.5	499.8	709.2	643.2	609.0	698.2	830.6	712.0	874.4

[1] **Notes :** z_l and z_u are the lower and upper bounds of poverty line following the CBN2 approach. Poverty lines has been obtained following the CBN2 approaches with FPL being obtained from the calorie consumption vectors at the all India (rural and urban) level i.e from Table 2.2. This basket has been normalized by the new state level calorie norms given at Table 2.3. Price vectors corresponds to the state level median price vector. The non food allocations has been computed using the non parametric approach.

[2] Rural and Urban 61 and 66 implies NSSO survey data for the period on 2004-05 and 2009-10 respectively.

Table 2.6: Poverty rates for Rural and Urban India following different poverty measures and poverty lines

Poverty measure	Approach	Poverty line	**Rural : 61**	**Urban : 61**	**Rural : 66**	**Urban : 66**
HCR	CBN1	z_l	45.5(44.7,46.3)	18.0(17.0,19.0)	32.5(31.4,33.5)	12.2(11.4,13.0)
-do-	-do-	z_u	48.0(47.2,48.8)	22.2(21.1,23.3)	36.6(35.5,37.6)	16.4(15.5,17.4)
-do-	CBN2	z_l	44.8(44.1,45.6)	18.4(17.4,19.4)	33.3(32.2,34.3)	12.5(11.7,13.3)
-do-	-do-	z_u	69.8(69.2,70.5)	43.0(41.6,44.3)	50.7(49.7,51.8)	26.4(25.2,27.5)
-do-	Gov	TC	41.8(41.1,42.6)	25.7(24.6,26.9)	33.8(32.8,34.9)	20.9(19.8,21.9)
PG	CBN1	z_l	10.9(10.7,11.2)	3.7(3.4,3.9)	6.9(6.5,7.2)	2.3(2.2,2.5)
-do-	-do-	z_u	11.8(11.6,12.1)	4.9(4.6,5.2)	8.1(7.7,8.4)	3.4(3.2,3.6)
-do-	CBN2	z_l	10.7(10.4,11.0)	3.8(3.5,4.0)	7.1(6.7,7.4)	2.4(2.2,2.6)
-do-	-do-	z_u	22.6(22.2,22.9)	12.7(12.2,13.2)	13.1(12.7,13.5)	6.3(6.0,6.7)
-do-	Gov	TC	9.6(9.4,9.9)	6.1(5.7,6.4)	7.2(6.9,7.5)	4.6(4.4,4.9)
SPG	CBN1	zl	3.7(3.6,3.8)	1.1(1.0,1.2)	2.1(2.0,2.3)	0.7(0.6,0.7)
-do-	-do-	zu	4.1(3.9,4.2)	1.6(1.5,1.7)	2.6(2.4,2.7)	1.1(1.0,1.1)
-do-	CBN2	zl	3.6(3.5,3.7)	1.2(1.1,1.3)	2.2(2.1,2.3)	0.7(0.6,0.8)
-do-	-do-	zu	9.4(9.2,9.6)	5.1(4.8,5.3)	4.7(4.5,4.9)	2.2(2.1,2.3)
-do-	Gov	TC	3.2(3.0,3.3)	2.0(1.9,2.2)	2.3(2.1,2.4)	1.5(1.4,1.6)
Fuzzy	CBN1	-	46.8(46.0,47.5)	20.2(19.1,21.2)	34.7(33.6,35.7)	14.2(13.4,15.0)
-do-	CBN2	-	58.5(57.8,59.2)	31.0(29.8,32.2)	42.2(41.1,43.2)	19.2(18.3,20.2)

[1] **Notes :** In the parentheses 95% confidence intervals have been reported considering NSSO sample survey design. CBN1 and CBN2 corresponds to the parametric and non parametric CBN approach, respectively.

[2] Rural and Urban 61st and 66th implies NSSO survey data conducted on 2004-05 and 2009-10 respectively.

[3] HCR, PG, and SPG stand for head count ratio, poverty gap and squared poverty gap of poverty index. Fuzzy stands for the poverty index explicitly stated in equation 2.5. Approach refers to the poverty line estimation method. ‘Gov’ refers to Planning Commission based approach. TC refers to Tendulkar Committee Line.

[4] Each figure in this table has been multiplied by 100, so as to be interpreted in terms of percentages.

Table 2.7: Poverty in the major states of India

States	Index	Line	Rural 61	Urban 61	Rural 66	Urban 66
Andhra Pardesh	HCR	TC	32.3(29.8,34.7)	23.4(20.1,26.6)	22.7(19.4,26.0)	17.7(14.8,20.5)
-do-	-do-	z_l	47.3(44.8,49.9)	19.8(16.8,22.7)	33.1(29.5,36.7)	13.7(11.1,16.4)
-do-	-do-	z_u	73.8(71.7,75.8)	50.9(46.8,54.9)	52.5(48.8,56.1)	35.8(32.1,39.6)
-do-	PG	TC	7.0(6.2,7.7)	4.8(4.1,5.5)	4.7(3.7,5.6)	3.8(3.0,4.6)
-do-	-do-	z_l	11.6(10.7,12.5)	3.5(2.9,4.1)	7.4(6.2,8.5)	2.8(2.1,3.4)
-do-	-do-	z_u	25.2(24.0,26.3)	15.1(13.6,16.7)	13.6(12.1,15.1)	9.3(8.0,10.6)
-do-	SPG	TC	2.3(1.9,2.6)	1.5(1.2,1.8)	1.5(1.1,1.9)	1.2(0.9,1.5)
-do-	-do-	z_l	4.1(3.7,4.6)	1.1(0.8,1.3)	2.5(1.9,3.0)	0.8(0.6,1.1)
-do-	-do-	z_u	10.9(10.2,11.6)	6.0(5.2,6.7)	5.1(4.3,5.8)	3.4(2.8,4.1)
-do-	Fuzzy	-	62.1(59.9,64.3)	35.8(32.3,39.3)	42.3(38.8,45.9)	24.5(21.4,27.6)
Assam	HCR	TC	36.4(32.4,40.3)	21.8(15.3,28.2)	39.9(34.2,45.5)	25.9(19.7,32.0)
-do-	-do-	z_l	41.2(37.1,45.4)	18.3(12.1,24.5)	39.9(34.3,45.6)	16.3(12.3,20.4)
-do-	-do-	z_u	62.4(58.6,66.1)	32.4(23.7,41.0)	48.7(43.2,54.2)	27.1(20.9,33.4)
-do-	PG	TC	7.0(6.0,8.0)	4.2(2.9,5.6)	7.3(5.8,8.8)	5.9(4.2,7.6)
-do-	-do-	z_l	8.6(7.5,9.8)	2.6(1.7,3.5)	7.4(5.9,8.9)	3.4(2.2,4.6)
-do-	-do-	z_u	16.3(14.8,17.9)	8.5(6.0,11.0)	10.7(8.9,12.5)	6.1(4.4,7.8)
-do-	SPG	TC	2.0(1.6,2.4)	1.1(0.7,1.6)	1.9(1.4,2.5)	2.0(1.2,2.7)
-do-	-do-	z_l	2.6(2.2,3.0)	0.6(0.3,0.9)	2.0(1.4,2.5)	1.0(0.5,1.4)
-do-	-do-	z_u	5.8(5.1,6.6)	2.9(2.0,3.8)	3.2(2.5,3.9)	2.0(1.3,2.8)
-do-	Fuzzy	-	51.3(47.4,55.3)	24.8(17.5,32.1)	44.3(38.7,49.8)	21.0(16.0,26.0)
Bihar	HCR	TC	55.7(53.0,58.4)	43.7(36.5,51.0)	55.3(51.4,59.2)	39.3(32.5,46.2)
-do-	-do-	z_l	48.0(45.3,50.7)	30.8(24.5,37.1)	43.6(39.4,47.7)	24.4(18.5,30.2)
-do-	-do-	z_u	70.6(68.2,73.0)	52.0(43.0,61.1)	58.9(55.1,62.7)	36.5(29.5,43.5)
-do-	PG	TC	12.7(11.8,13.5)	11.4(9.3,13.5)	13.5(11.9,15.0)	10.3(8.0,12.7)
-do-	-do-	z_l	10.1(9.3,10.8)	6.0(4.6,7.4)	9.7(8.4,11.1)	4.8(3.4,6.1)
-do-	-do-	z_u	19.5(18.5,20.6)	15.6(12.9,18.3)	14.8(13.2,16.4)	9.4(7.2,11.6)
-do-	SPG	TC	3.9(3.6,4.3)	3.9(3.0,4.7)	4.5(3.8,5.3)	3.7(2.8,4.7)
-do-	-do-	z_l	2.9(2.6,3.2)	1.7(1.2,2.2)	3.0(2.4,3.6)	1.4(0.9,1.8)
-do-	-do-	z_u	7.0(6.5,7.5)	6.0(4.8,7.2)	5.1(4.3,5.9)	3.3(2.4,4.2)
-do-	Fuzzy	-	60.2(57.8,62.7)	42.6(35.6,49.6)	51.2(47.4,55.0)	29.9(23.5,36.2)
Gujrat	HCR	TC	39.1(34.7,43.4)	20.1(15.9,24.2)	26.6(21.4,31.9)	17.7(13.5,21.8)
-do-	-do-	z_l	46.0(41.8,50.2)	10.6(8.0,13.1)	30.6(25.2,36.0)	9.7(6.9,12.4)
-do-	-do-	z_u	71.9(68.4,75.5)	34.9(29.4,40.5)	48.6(42.9,54.4)	21.9(17.0,26.9)
-do-	PG	TC	9.3(7.8,10.8)	3.9(3.0,4.8)	4.6(3.5,5.8)	3.6(2.6,4.6)
-do-	-do-	z_l	11.3(9.7,12.9)	1.8(1.3,2.3)	5.6(4.4,6.9)	1.7(1.1,2.2)
-do-	-do-	z_u	24.2(22.2,26.3)	8.4(6.8,9.9)	11.2(9.4,13.0)	4.8(3.6,6.0)
-do-	SPG	TC	3.2(2.4,3.9)	1.1(0.8,1.5)	1.2(0.8,1.6)	1.1(0.7,1.4)
-do-	-do-	z_l	4.0(3.2,4.8)	0.5(0.3,0.6)	1.5(1.1,2.0)	0.4(0.2,0.6)
-do-	-do-	z_u	10.4(9.2,11.7)	2.8(2.2,3.4)	3.6(2.8,4.3)	1.5(1.0,1.9)
-do-	Fuzzy	-	60.2(56.4,64.0)	22.8(18.8,26.9)	40.4(35.0,45.7)	15.9(12.2,19.6)
Haryana	HCR	TC	24.8(21.1,28.5)	22.4(16.8,28.0)	18.6(14.3,22.8)	23.0(15.2,30.8)
-do-	-do-	z_l	19.3(15.8,22.7)	14.0(9.3,18.6)	14.9(11.3,18.5)	13.6(5.3,21.8)
-do-	-do-	z_u	44.3(39.7,48.8)	44.1(37.7,50.4)	28.2(23.5,32.9)	29.7(21.7,37.7)
-do-	PG	TC	4.7(3.8,5.6)	4.9(3.3,6.6)	3.7(2.6,4.8)	4.6(2.8,6.4)
-do-	-do-	z_l	3.3(2.5,4.0)	2.7(1.5,3.9)	2.9(1.9,3.9)	1.7(1.0,2.4)
-do-	-do-	z_u	11.2(9.7,12.7)	12.7(10.1,15.3)	6.0(4.5,7.4)	6.5(4.2,8.8)
-do-	SPG	TC	1.3(1.0,1.6)	1.6(0.9,2.3)	1.1(0.7,1.5)	1.2(0.8,1.7)
-do-	-do-	z_l	0.9(0.6,1.1)	0.8(0.3,1.3)	0.8(0.5,1.2)	0.4(0.2,0.6)
-do-	-do-	z_u	3.9(3.3,4.5)	4.9(3.6,6.3)	1.9(1.3,2.5)	2.0(1.2,2.7)
-do-	Fuzzy	-	32.0(28.2,35.8)	29.5(24.1,35.0)	20.9(16.8,25.1)	21.2(13.6,28.9)
Himachal Pradesh	HCR	TC	25.0(21.9,28.0)	4.6(1.5,7.6)	9.1(6.4,11.8)	12.5(5.4,19.6)
-do-	-do-	z_l	22.8(20.0,25.7)	3.2(0.5,6.0)	8.0(5.4,10.6)	5.9(1.2,10.7)

Continued on the next page

Table 2.7 (Contd.)

States	Index	Line	Rural 61	Urban 61	Rural 66	Urban 66
-do-	-do-	z_u	54.6(51.0,58.2)	30.3(15.0,45.5)	23.7(19.7,27.8)	19.1(10.8,27.4)
-do-	PG	TC	4.2(3.5,4.9)	1.1(-0.0,2.2)	1.4(0.8,2.0)	2.4(0.6,4.2)
-do-	-do-	z_l	3.8(3.1,4.4)	0.8(-0.2,1.7)	1.2(0.6,1.8)	1.0(0.1,2.0)
-do-	-do-	z_u	14.6(13.2,15.9)	5.8(3.7,7.8)	4.1(3.1,5.1)	3.7(1.4,6.0)
-do-	SPG	TC	1.1(0.8,1.4)	0.4(-0.1,0.9)	0.4(0.1,0.6)	0.7(0.1,1.3)
-do-	-do-	z_l	1.0(0.7,1.2)	0.3(-0.1,0.7)	0.3(0.1,0.5)	0.3(0.0,0.5)
-do-	-do-	z_u	5.2(4.5,5.8)	1.9(0.9,2.9)	1.1(0.7,1.5)	1.1(0.3,1.9)
-do-	Fuzzy	-	39.6(36.4,42.9)	12.8(8.5,17.2)	15.0(11.9,18.1)	12.2(5.6,18.9)
Karnataka	HCR	TC	37.5(34.0,41.0)	25.9(21.0,30.8)	26.1(20.5,31.7)	19.5(15.5,23.5)
-do-	-do-	z_l	35.1(31.7,38.6)	21.3(16.8,25.7)	14.6(10.5,18.7)	14.6(11.3,17.9)
-do-	-do-	z_u	67.2(63.9,70.4)	48.8(43.5,54.1)	30.7(25.0,36.4)	28.7(23.3,34.0)
-do-	PG	TC	6.5(5.6,7.4)	6.2(4.6,7.8)	4.8(3.5,6.1)	4.4(3.4,5.4)
-do-	-do-	z_l	6.0(5.1,6.9)	4.9(3.5,6.2)	2.2(1.3,3.2)	3.1(2.3,3.8)
-do-	-do-	z_u	17.3(16.0,18.7)	15.2(12.8,17.6)	5.6(4.1,7.0)	7.8(6.2,9.4)
-do-	SPG	TC	1.7(1.4,2.0)	2.1(1.4,2.8)	1.3(0.8,1.8)	1.4(1.1,1.8)
-do-	-do-	z_l	1.5(1.2,1.8)	1.6(1.0,2.2)	0.5(0.2,0.8)	0.9(0.7,1.2)
-do-	-do-	z_u	5.9(5.2,6.5)	6.5(5.1,7.8)	1.5(1.0,2.1)	2.9(2.2,3.5)
-do-	Fuzzy	-	52.5(49.1,55.9)	35.2(30.3,40.1)	22.4(17.2,27.5)	22.2(17.9,26.6)
Kerala	HCR	TC	20.2(17.7,22.7)	18.4(15.0,21.7)	12.0(9.3,14.7)	12.1(9.4,14.7)
-do-	-do-	z_l	21.2(18.6,23.7)	17.2(13.9,20.6)	10.4(7.9,13.0)	10.7(8.1,13.2)
-do-	-do-	z_u	52.6(49.8,55.4)	43.1(38.9,47.4)	29.7(26.2,33.2)	29.3(25.4,33.2)
-do-	PG	TC	4.4(3.6,5.2)	4.0(3.0,5.1)	2.3(1.5,3.0)	2.1(1.5,2.8)
-do-	-do-	z_l	4.6(3.7,5.4)	3.6(2.6,4.6)	1.9(1.2,2.6)	1.8(1.2,2.4)
-do-	-do-	z_u	15.8(14.5,17.2)	12.8(10.9,14.6)	6.9(5.7,8.2)	7.2(6.0,8.5)
-do-	SPG	TC	1.5(1.1,1.9)	1.3(0.9,1.8)	0.7(0.3,1.1)	0.6(0.4,0.8)
-do-	-do-	z_l	1.5(1.1,2.0)	1.2(0.7,1.6)	0.6(0.2,0.9)	0.5(0.3,0.7)
-do-	-do-	z_u	6.5(5.7,7.2)	5.3(4.2,6.3)	2.4(1.7,3.0)	2.5(1.9,3.0)
-do-	Fuzzy	-	37.5(34.9,40.2)	29.7(25.9,33.4)	19.9(16.9,22.8)	20.3(17.1,23.5)
Madhya Pradesh	HCR	TC	53.6(50.4,56.8)	35.1(30.0,40.1)	42.0(37.6,46.4)	22.9(19.0,26.8)
-do-	-do-	z_l	60.3(57.3,63.4)	27.3(23.0,31.6)	50.8(46.3,55.4)	17.7(14.2,21.2)
-do-	-do-	z_u	82.7(80.5,84.9)	54.4(48.9,59.8)	64.8(60.4,69.3)	35.7(30.6,40.9)
-do-	PG	TC	12.6(11.5,13.7)	8.6(7.2,10.0)	10.6(9.0,12.2)	5.6(4.4,6.7)
-do-	-do-	z_l	15.9(14.7,17.2)	5.9(4.8,7.0)	13.4(11.6,15.1)	3.8(2.9,4.7)
-do-	-do-	z_u	31.4(29.9,32.8)	17.5(15.3,19.8)	19.9(17.9,22.0)	10.0(8.3,11.7)
-do-	SPG	TC	4.2(3.7,4.7)	2.9(2.4,3.5)	3.7(3.0,4.5)	1.8(1.4,2.3)
-do-	-do-	z_l	5.6(5.0,6.2)	1.8(1.4,2.3)	4.9(4.1,5.8)	1.2(0.8,1.5)
-do-	-do-	z_u	14.3(13.4,15.2)	7.4(6.3,8.5)	8.2(7.0,9.3)	3.8(3.0,4.6)
-do-	Fuzzy	-	73.5(71.0,76.0)	41.4(36.6,46.3)	58.0(53.7,62.4)	27.1(22.9,31.4)
Maharastra	HCR	TC	47.9(45.1,50.6)	25.6(22.6,28.6)	29.5(26.0,33.0)	18.3(15.5,21.0)
-do-	-do-	z_l	54.8(52.0,57.5)	20.4(17.5,23.2)	29.1(25.7,32.6)	14.2(11.8,16.6)
-do-	-do-	z_u	79.9(77.9,81.9)	51.8(48.4,55.2)	51.7(48.0,55.4)	30.2(26.9,33.5)
-do-	PG	TC	11.9(10.9,13.0)	6.5(5.5,7.5)	5.7(4.8,6.6)	4.0(3.2,4.7)
-do-	-do-	z_l	14.9(13.7,16.0)	4.7(3.9,5.5)	5.6(4.7,6.5)	2.9(2.3,3.5)
-do-	-do-	z_u	31.0(29.6,32.4)	18.0(16.4,19.6)	13.0(11.7,14.3)	8.2(7.0,9.3)
-do-	SPG	TC	4.3(3.7,4.8)	2.3(1.9,2.7)	1.6(1.2,1.9)	1.3(1.0,1.5)
-do-	-do-	z_l	5.6(5.0,6.2)	1.6(1.2,1.9)	1.5(1.2,1.8)	0.9(0.7,1.1)
-do-	-do-	z_u	14.7(13.8,15.7)	8.2(7.3,9.2)	4.4(3.8,5.0)	3.1(2.6,3.6)
-do-	Fuzzy	-	69.0(66.8,71.3)	36.9(33.9,39.9)	40.9(37.5,44.4)	22.2(19.4,25.1)
Odisha	HCR	TC	60.8(57.5,64.0)	37.6(30.3,44.9)	39.2(35.1,43.3)	25.9(19.3,32.5)
-do-	-do-	z_l	67.3(64.3,70.2)	31.9(25.5,38.3)	46.6(42.6,50.6)	17.8(13.0,22.5)
-do-	-do-	z_u	83.0(80.8,85.1)	52.5(44.8,60.3)	59.9(56.2,63.6)	35.1(27.8,42.4)
-do-	PG	TC	17.4(15.9,18.8)	9.6(7.2,12.0)	9.0(7.7,10.3)	5.3(3.7,6.9)
-do-	-do-	z_l	20.7(19.2,22.3)	7.4(5.3,9.4)	11.5(10.0,12.9)	3.4(2.2,4.6)
-do-	-do-	z_u	33.2(31.6,34.8)	18.1(14.5,21.6)	16.5(14.8,18.1)	8.5(6.4,10.5)

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Table 2.7 (Contd.)

States	Index	Line	Rural 61	Urban 61	Rural 66	Urban 66
-do-	SPG	TC	6.6(5.9,7.4)	3.5(2.3,4.7)	3.0(2.4,3.6)	1.7(1.1,2.3)
-do-	-do-	z_l	8.4(7.5,9.2)	2.6(1.6,3.5)	4.0(3.3,4.7)	1.1(0.6,1.5)
-do-	-do-	z_u	16.0(14.9,17.1)	7.9(6.0,9.8)	6.3(5.4,7.1)	2.9(2.0,3.8)
-do-	Fuzzy	-	76.0(73.5,78.5)	43.4(35.8,51.0)	53.2(49.4,57.0)	27.3(21.3,33.3)
Punjab	HCR	TC	22.1(19.2,25.0)	18.7(15.2,22.2)	14.6(11.4,17.8)	18.0(14.3,21.8)
-do-	-do-	z_l	13.0(10.5,15.4)	7.5(5.3,9.8)	6.6(4.5,8.7)	9.9(7.4,12.4)
-do-	-do-	z_u	43.3(40.1,46.6)	34.3(30.0,38.6)	22.9(19.1,26.8)	24.3(19.8,28.8)
-do-	PG	TC	3.8(3.1,4.4)	3.2(2.5,3.9)	1.9(1.4,2.5)	3.8(2.9,4.6)
-do-	-do-	z_l	1.9(1.4,2.4)	0.7(0.5,1.0)	0.8(0.5,1.1)	1.6(1.1,2.2)
-do-	-do-	z_u	9.8(8.7,10.8)	8.4(7.1,9.8)	3.8(3.0,4.6)	5.4(4.3,6.6)
-do-	SPG	TC	1.0(0.7,1.2)	0.8(0.6,1.0)	0.4(0.3,0.6)	1.1(0.8,1.4)
-do-	-do-	z_l	0.4(0.3,0.6)	0.1(0.1,0.2)	0.2(0.1,0.2)	0.4(0.2,0.6)
-do-	-do-	z_u	3.1(2.6,3.5)	2.8(2.2,3.3)	0.9(0.7,1.2)	1.7(1.3,2.2)
-do-	Fuzzy	-	28.1(25.4,30.8)	20.9(17.5,24.3)	14.7(11.8,17.6)	17.0(13.6,20.5)
Rajasthan	HCR	TC	35.8(32.9,38.8)	29.7(23.9,35.5)	26.4(22.5,30.2)	19.9(15.5,24.4)
-do-	-do-	z_l	42.2(39.2,45.2)	22.6(17.3,27.9)	29.1(25.2,33.1)	14.2(10.7,17.7)
-do-	-do-	z_u	72.7(70.2,75.2)	51.8(45.0,58.6)	51.9(47.8,56.1)	31.4(26.1,36.6)
-do-	PG	TC	7.0(6.2,7.8)	5.7(4.3,7.2)	4.3(3.5,5.2)	3.8(2.8,4.7)
-do-	-do-	z_l	8.7(7.8,9.6)	4.0(2.9,5.1)	5.0(4.1,5.9)	2.6(1.8,3.3)
-do-	-do-	z_u	20.9(19.6,22.1)	14.8(12.1,17.5)	11.3(9.9,12.6)	6.7(5.3,8.1)
-do-	SPG	TC	2.0(1.7,2.3)	1.7(1.2,2.2)	1.1(0.8,1.4)	1.1(0.7,1.5)
-do-	-do-	z_l	2.6(2.2,3.0)	1.1(0.7,1.5)	1.3(0.9,1.6)	0.7(0.4,1.0)
-do-	-do-	z_u	7.9(7.2,8.5)	5.6(4.4,6.7)	3.5(2.9,4.0)	2.1(1.6,2.7)
-do-	Fuzzy	-	58.6(55.9,61.3)	38.5(32.0,45.0)	40.2(36.3,44.1)	22.6(18.3,26.9)
Tamil Nadu	HCR	TC	37.5(34.7,40.3)	19.7(17.2,22.2)	21.2(17.8,24.5)	12.8(10.6,14.9)
-do-	-do-	z_l	52.5(49.7,55.3)	19.7(17.2,22.2)	14.6(11.7,17.5)	5.3(4.2,6.4)
-do-	-do-	z_u	74.8(72.5,77.1)	48.8(44.9,52.7)	35.9(32.2,39.6)	17.3(14.6,20.0)
-do-	PG	TC	7.4(6.6,8.2)	4.1(3.4,4.7)	3.7(2.9,4.5)	2.1(1.7,2.6)
-do-	-do-	z_l	12.6(11.6,13.6)	4.1(3.4,4.7)	2.5(1.9,3.1)	0.8(0.6,1.1)
-do-	-do-	z_u	25.4(24.2,26.7)	15.0(13.5,16.4)	7.9(6.7,9.0)	3.2(2.6,3.8)
-do-	SPG	TC	2.1(1.8,2.4)	1.3(1.0,1.5)	1.0(0.7,1.3)	0.6(0.4,0.7)
-do-	-do-	z_l	4.1(3.7,4.6)	1.2(1.0,1.5)	0.6(0.4,0.8)	0.2(0.1,0.3)
-do-	-do-	z_u	10.7(9.9,11.4)	6.0(5.3,6.7)	2.5(2.0,2.9)	0.9(0.7,1.1)
-do-	Fuzzy	-	65.1(62.6,67.5)	35.6(32.4,38.9)	25.3(22.1,28.5)	10.8(9.1,12.6)
Uttar Pradesh	HCR	TC	42.7(40.9,44.6)	34.1(29.7,38.4)	39.3(36.8,41.8)	31.7(27.8,35.6)
-do-	-do-	z_l	35.2(33.4,37.1)	25.1(21.4,28.9)	29.9(27.5,32.3)	22.6(19.4,25.8)
-do-	-do-	z_u	64.7(63.0,66.5)	51.4(46.8,55.9)	52.0(49.4,54.6)	37.4(33.2,41.6)
-do-	PG	TC	9.2(8.6,9.7)	7.8(6.7,8.9)	7.6(6.9,8.3)	7.3(6.3,8.3)
-do-	-do-	z_l	6.7(6.2,7.2)	5.1(4.3,6.0)	5.1(4.6,5.7)	4.5(3.8,5.2)
-do-	-do-	z_u	18.1(17.3,18.8)	15.4(13.6,17.1)	11.8(11.0,12.6)	9.4(8.2,10.7)
-do-	SPG	TC	2.8(2.5,3.0)	2.5(2.1,3.0)	2.1(1.9,2.4)	2.4(2.0,2.8)
-do-	-do-	z_l	1.9(1.7,2.1)	1.5(1.2,1.8)	1.3(1.1,1.5)	1.3(1.0,1.6)
-do-	-do-	z_u	6.6(6.3,7.0)	6.1(5.3,6.9)	3.7(3.4,4.0)	3.3(2.8,3.8)
-do-	Fuzzy	-	50.8(49.1,52.5)	39.0(34.8,43.3)	41.2(38.8,43.6)	30.3(26.6,34.0)
West Bengal	HCR	TC	38.2(35.6,40.9)	24.4(20.8,28.0)	28.8(25.5,32.0)	21.9(18.2,25.7)
-do-	-do-	z_l	39.8(37.1,42.4)	16.4(13.6,19.3)	24.1(21.0,27.2)	13.1(10.5,15.7)
-do-	-do-	z_u	63.8(61.3,66.4)	39.3(35.0,43.6)	39.6(36.2,43.1)	25.1(21.3,29.0)
-do-	PG	TC	7.9(7.2,8.7)	5.3(4.4,6.2)	5.3(4.4,6.1)	4.5(3.7,5.4)
-do-	-do-	z_l	8.3(7.6,9.1)	3.0(2.4,3.7)	4.1(3.3,4.9)	2.4(1.8,3.0)
-do-	-do-	z_u	17.9(16.8,19.0)	10.3(8.9,11.7)	7.5(6.5,8.6)	5.5(4.5,6.5)
-do-	SPG	TC	2.4(2.1,2.6)	1.6(1.3,2.0)	1.4(1.1,1.8)	1.4(1.1,1.8)
-do-	-do-	z_l	2.5(2.2,2.8)	0.9(0.6,1.1)	1.1(0.8,1.4)	0.7(0.5,0.9)
-do-	-do-	z_u	6.6(6.1,7.1)	3.8(3.2,4.4)	2.2(1.8,2.6)	1.8(1.4,2.2)

Continued on the next page

Table 2.7 (Contd.)

States	Index	Line	Rural 61	Urban 61	Rural 66	Urban 66
-do-	Fuzzy	-	53.0(50.4,55.6)	27.8(24.2,31.3)	31.0(27.9,34.2)	19.0(15.8,22.2)

NB : State specific poverty rates (HCR, PG and SPG) have been obtained considering the state specific poverty lines (CBN2) specified in Table 2.5, for the two NSSO survey rounds of 61st and 66th ones. In the parentheses we have reported the 95% confidence intervals of the poverty measures considering the NSSO multi stage sampling design. Each figure in this table has been multiplied by 100, so as to be interpreted in terms of percentages.

Table 2.8: Bilateral poverty decomposition of all-India and major states of India from 2004-05 to 2009-10 corresponding to the lower bound of poverty line

	Rural India									*Urban India*								
	HCR			***PG***			***SPG***			***HCR***			***PG***			***SPG***		
States	Δp	Δg	ΔI	Δp	Δg	ΔI	Δp	Δg	ΔI	Δp	Δg	ΔI	Δp	Δg	ΔI	Δp	Δg	ΔI
Andhra Pardesh	-14.17	-14.51	0.34	-4.24	-4.64	0.40	-1.65	-1.87	0.22	-6.03	-7.69	1.66	-0.77	-1.65	0.88	-0.24	-0.55	0.31
Assam	-1.32	-8.34	7.03	-1.27	-2.81	1.54	-0.63	-1.01	0.38	-2.03	-2.68	0.65	0.74	-0.54	1.27	0.33	-0.17	0.50
Bihar	-4.48	-6.16	1.68	-0.31	-2.07	1.76	0.13	-0.79	0.92	-6.41	-6.01	-0.40	-1.26	-1.70	0.45	-0.35	-0.58	0.24
Gujrat	-15.38	-15.07	-0.31	-5.67	-4.50	-1.18	-2.46	-1.71	-0.75	-0.93	-4.13	3.20	-0.14	-0.86	0.72	-0.07	-0.26	0.19
Haryana	-4.33	-2.36	-1.96	-0.36	-0.42	0.06	-0.04	-0.13	0.09	-0.40	-5.17	4.78	-0.97	-1.34	0.36	-0.41	-0.38	-0.03
Himachal Pradesh	-14.84	-14.70	-0.14	-2.55	-2.69	0.13	-0.67	-0.75	0.08	2.69	-3.83	6.52	0.30	-0.78	1.08	-0.02	-0.26	0.24
Karnataka	-20.52	-19.59	-0.93	-3.76	-4.20	0.43	-0.98	-1.22	0.24	-6.68	-8.88	2.20	-1.78	-2.60	0.83	-0.65	-0.97	0.32
Kerala	-10.73	-11.38	0.65	-2.64	-2.70	0.06	-0.96	-0.92	-0.04	-6.57	-8.72	2.15	-1.80	-1.93	0.13	-0.67	-0.64	-0.03
Madhya Pradesh	-9.50	-11.15	1.65	-2.57	-4.82	2.25	-0.69	-2.18	1.49	-9.55	-10.54	0.99	-2.13	-2.87	0.74	-0.69	-1.08	0.39
Maharastra	-25.62	-20.75	-4.87	-9.26	-6.97	-2.29	-4.04	-2.84	-1.19	-6.17	-7.62	1.45	-1.81	-2.29	0.49	-0.67	-0.86	0.20
Orissa	-20.66	-18.64	-2.01	-9.29	-8.27	-1.02	-4.36	-3.93	-0.43	-14.14	-17.39	3.25	-3.95	-4.94	0.98	-1.50	-1.83	0.32
Punjab	-6.39	-6.88	0.49	-1.09	-1.04	-0.05	-0.29	-0.25	-0.04	2.37	-1.02	3.40	0.91	-0.11	1.02	0.27	-0.03	0.30
Rajasthan	-13.03	-12.23	-0.81	-3.67	-3.32	-0.35	-1.32	-1.12	-0.20	-8.42	-8.25	-0.17	-1.41	-1.73	0.32	-0.37	-0.53	0.17
Tamil Nadu	-37.85	-35.59	-2.26	-10.15	-9.78	-0.36	-3.53	-3.50	-0.03	-14.46	-11.57	-2.88	-3.24	-2.48	-0.76	-1.04	-0.78	-0.26
Uttar Pradesh	-5.30	-1.78	-3.53	-1.58	-0.55	-1.02	-0.57	-0.18	-0.39	-2.54	-9.81	7.26	-0.64	-2.90	2.26	-0.18	-1.03	0.85
West Bengal	-15.67	-10.21	-5.46	-4.25	-2.55	-1.70	-1.45	-0.87	-0.58	-3.31	-4.48	1.17	-0.63	-1.02	0.39	-0.16	-0.34	0.18
All India	-11.54	-11.66	0.12	-3.64	-3.82	0.18	-1.38	-1.50	0.12	-5.92	-7.80	1.87	-1.40	-2.00	0.61	-0.47	-0.70	0.23
All India	-11.54	-11.66	0.12	-3.64	-3.82	0.18	-1.38	-1.50	0.12	-16.58	-18.48	1.90	-6.38	-7.36	0.99	-2.89	-3.42	0.53

Notes

[1] This table corresponds to the decomposition of poverty rates into growth and inequality components following Kakwani (2000) method. Δp represents the total change of poverty, Δg denotes the growth component and ΔI is the inequality component. The exercise has been repeated for three different poverty measures HCR, PG and SPG which stand for Head Count Ratio, Poverty Gap and Squared Poverty Gap, respectively.

[2] The decomposition exercise is carried out over the entire sample rural and urban India and also for major states, separately for rural and urban regions. Poverty line corresponds to the CBN2 approach. Poverty lines for all-India and that for the states are provided respectively in Table 2.4 and 2.5. In order to account for the changes in prices in these two periods, incomes of all individuals for the 66th round has been multiplied by the ratio $\frac{z61}{z66}$ where z61 and z66 denote the lower bound of poverty line for the 61st and 66th round, respectively.

[3] Each figure in this table has been multiplied by 100, so that it can be interpreted in terms of percentages.

Table 2.9: Bilateral poverty decomposition of all-India and major states of India from 2004-05 to 2009-10 corresponding to the upper bound of poverty line

	Rural India									*Urban India*								
	HCR			***PG***			***SPG***			***HCR***			***PG***			***SPG***		
States	Δp	Δg	ΔI	Δp	Δg	ΔI	Δp	Δg	ΔI	Δp	Δg	ΔI	Δp	Δg	ΔI	Δp	Δg	ΔI
Andhra Pardesh	-21.30	-22.41	1.11	-11.55	-12.02	0.48	-5.84	-6.14	0.31	-15.07	-15.28	0.21	-5.79	-6.71	0.92	-2.50	-3.16	0.65
Assam	-13.70	-19.65	5.95	-5.65	-7.93	2.29	-2.67	-3.47	0.80	-5.25	-8.87	3.62	-2.39	-3.91	1.53	-0.90	-1.71	0.82
Bihar	-11.72	-12.74	1.02	-4.74	-6.45	1.71	-1.87	-3.02	1.16	-15.53	-12.66	-2.87	-6.20	-5.80	-0.40	-2.67	-2.77	0.10
Gujrat	-23.31	-24.72	1.41	-12.99	-12.37	-0.62	-6.89	-6.10	-0.78	-12.98	-15.00	2.02	-3.59	-4.81	1.23	-1.33	-1.93	0.60
Haryana	-16.04	-11.97	-4.07	-5.25	-4.45	-0.81	-1.96	-1.85	-0.11	-14.38	-20.71	6.34	-6.15	-8.02	1.86	-2.93	-3.60	0.67
Himachal Pradesh	-30.87	-31.91	1.04	-10.50	-10.72	0.22	-4.05	-4.17	0.12	-11.19	-22.43	11.24	-2.07	-6.66	4.59	-0.78	-2.79	2.01
Karnataka	-36.47	-34.46	-2.01	-11.78	-11.72	-0.06	-4.34	-4.54	0.20	-20.12	-20.83	0.71	-7.44	-8.39	0.95	-3.58	-4.20	0.62
Kerala	-22.88	-25.27	2.39	-8.88	-9.49	0.61	-4.08	-4.24	0.16	-13.85	-16.08	2.23	-5.55	-6.57	1.01	-2.80	-3.14	0.35
Madhya Pradesh	-17.89	-17.54	-0.34	-11.43	-13.26	1.83	-6.14	-7.81	1.67	-18.66	-17.83	-0.83	-7.54	-8.09	0.55	-3.60	-4.10	0.51
Maharastra	-28.13	-26.24	-1.88	-18.04	-15.51	-2.53	-10.31	-8.54	-1.76	-21.61	-23.64	2.03	-9.84	-10.81	0.97	-5.14	-5.66	0.52
Orissa	-23.05	-22.45	-0.59	-16.72	-15.76	-0.95	-9.73	-9.13	-0.60	-17.45	-22.04	4.59	-9.59	-11.58	1.99	-4.98	-5.85	0.87
Punjab	-20.39	-20.31	-0.08	-5.95	-6.07	0.12	-2.14	-2.16	0.01	-10.02	-13.94	3.92	-3.01	-4.78	1.78	-1.04	-1.97	0.93
Rajasthan	-20.72	-21.66	0.94	-9.58	-9.36	-0.22	-4.39	-4.15	-0.24	-20.41	-18.76	-1.65	-8.11	-8.12	0.02	-3.41	-3.57	0.16
Tamil Nadu	-38.92	-35.79	-3.12	-17.57	-16.76	-0.81	-8.22	-7.95	-0.27	-31.49	-27.86	-3.64	-11.76	-10.15	-1.61	-5.12	-4.35	-0.77
Uttar Pradesh	-12.71	-11.86	-0.85	-6.29	-5.09	-1.20	-2.95	-2.25	-0.70	-13.94	-20.59	6.65	-5.94	-9.36	3.42	-2.78	-4.57	1.78
West Bengal	-24.19	-21.29	-2.90	-10.36	-8.20	-2.16	-4.42	-3.39	-1.03	-14.16	-15.38	1.22	-4.86	-5.57	0.71	-2.01	-2.37	0.35
All India	-19.07	-19.03	-0.05	-9.52	-9.67	0.14	-4.72	-4.85	0.13	-16.58	-18.48	1.90	-6.38	-7.36	0.99	-2.89	-3.42	0.53

Notes

[1] This table corresponds to the decomposition of poverty rates into growth and inequality components following Kakwani's (1999) method. Δp represents the total change of poverty, Δg denotes the growth component and ΔI is the inequality component. The exercise has been repeated for three different poverty measures HCR, PG and SPG which stands for Head Count Ratio, Poverty Gap and Squared Poverty Gap, respectively.

[2] The decomposition exercise is carried out over the entire sample rural and urban India and also for major states, separately for rural and urban regions. Poverty line corresponds to the CBN2 approach. Poverty lines for all-India and that for the states are provided respectively in Table 2.4 and 2.5. In order to account for the changes in prices in these two periods, incomes of all individuals for the 66th round has been multiplied by the ratio $\frac{z61}{z66}$ where z61 and z66 denote the upper bound of poverty line for the 61st and 66th round, respectively.

[3] Each figure in this table has been multiplied by 100, so that it can be interpreted in terms of percentages.

Chapter 3

Applications of Stochastic Dominance: A study on India

3.1 Introduction

Since independence of India the topic of estimation and reduction of poverty has remained a major issue of debate and discussion among all the intellectual sections of the society. Researchers from those days expressed interests not only on poverty comparison over time, but also focused on the subgroups being more vulnerable to remain in poverty.

Sundaram and Tendulkar (2003) investigates the prevalence, depth and severity of poverty in both rural and urban India following the National Sample Survey Rounds(NSSO) and finds that poverty in the 1990s is higher among SC and ST households[1]. Similar results are also obtained by Meenakshi et al. (2000) for the year

[1]The Indian Constitution specifies the list of castes and tribes included in these two categories, and accords the scheduled castes and scheduled tribes special treatment in terms of affirmative action quotas in state and central legislatures, the civil service and government-sponsored educational institutions (Revankar, 1971). The scheduled castes correspond to the castes at the bottom of the hierarchical order of the Indian caste system and were subject to social exclusion in the form of untouchability at Indian Independence (August 15, 1947), while the scheduled tribes correspond to

1999.

In any poverty evaluating exercise, it has been observed that in most developing nations the poorer people usually have higher household size. However, as pointed out by Lanjouw and Ravallion (1995), the relationship between poverty and household size is largely explained by the economies of scale factor. In an interesting article, Dreze and Srinivasan (1997) finds poverty is usually higher among the male headed households compared to those of female headed households. However, incorporating the economies of scale alters the result. The main objective of this chapter is to re-examine these facts, considering a robust poverty ordering technique named "*Stochastic Dominance*".

In the previous chapter poverty ordering was based on the lower and upper bounds of poverty line. Following the lines of Atkinson (1983) "There is no one line of food intake required for subsistence, but rather a broad range where physical efficiency with falling intakes of calories and proteins"(See Atkinson, 1983, page no 226). The main departure in this chapter is consideration of the fact that any point in the real line may be a possible poverty line. Further, instead of considering the Foster et al. (1984) class of poverty index we would consider a wide range of poverty indices. We shall consider stochastic dominance analysis for the comparison of different income distributions. These dominance implies not only reduction of poverty, but also an increment of welfare[2] (Foster and Shorrocks, 1988b,a). In this chapter we shall use data sets similar to the previous one, i.e National Sample survey Organization (NSSO) consumer expenditure rounds 61st and 66th, survey dates corresponds respectively 2004-05 and 2009-10. We shall order income distributions over time and also for different subgroups of population namely general, SC-ST, male and female headed households, to address issues of poverty for these groups. We shall also consider sim-

the indigenous tribal population mainly residing in the northern Indian states of Bihar, Gujarat, Maharashtra, Madhya Pradesh, Odisha, Rajasthan, and West Bengal, and in North-Eastern India.

[2]Stochastic dominance might also be related with pro poor growth. In the next chapter we shall discuss in details on this link.

ilar exercise in the context of poverty comparison for general *verses* SC-ST, and male headed *verses* female headed households. Furthermore, the results will be validated by considering economies of scale.

It should be noted that stochastic dominance are based on very robust ordering approaches in terms of indexes and their parameters. However, unlike the previous chapter or following any complete ordering approach it is not possible to quantify poverty in numbers. These conditions are based on partial ordering of income (or any related welfare measure) distributions and there is a possibility of getting an inconclusive result. As we move through this chapter we shall see there are certain techniques that partially solves this problems. For example, if the first order stochastic dominance breaks it is possible to get conclusive result by considering second (higher) order dominance exercises. Since the orderings are based on survey data, it is necessary to test whether these results holds asymptotically. Thus it is necessary to test the dominance conditions statistically. We shall use a Kolmogrov Smirnov (KS) type of test statistics Barrett and Donald (2003) for the statistical validation of the obtained results.

The chapter has been organized in the following fashion. In section 3.2 we provide a brief review of stochastic dominance and some results associated with it. In section 3.3 we discuss very briefly on economies of scale. In section 3.4 we present a brief discussions of the NSSO data. The empirical illustration is provided in section 3.5. The concluding part of the chapter in section 3.6, highlights the main empirical results.

3.2 Stochastic dominance

Let $F(y)$ be the cumulative distribution function of income representing the percentage of individual lying below y, in a distribution F. Furthermore, let Π be the set of all income distributions, defined on the domain $[0, \infty)$. Stochastic Dominance of one distribution over the other is defined in the following fashion:

Definition 1: Stochastic dominance : Given two income distributions $F, G \in \Pi$, we say that F stochastically dominates (SD) G by r+1 th order/degree ($F \succ_{r+1} G$) if $F^{r+1}(s) \leq G^{r+1}(s)\ \forall\ s\ \in [0, \infty)$ and strictly less than for at least one s, where $F^{r+1}(s) = \int_0^s F^r(s)$ and $G^{r+1}(s) = \int_0^s G^r(s)$, $\forall s\ \in [0, \infty)$ and $r \geq 0$ is an integer.

In some cases we shall also require inverse stochastic dominance. We define the p^{th} income quantile function as $y_F(p) = F^{-1}(p) = inf\{y : F(y) \geq\ p\}$. Let $F^{-(r+1)}(p) = \int_0^p F^{-(r)}(p)\, dp$ where $r \geq 0$ is an integer.

Definition 2 : Inverse Stochastic dominance : F dominates G by (r+1)th order/degree Inverse Stochastic Dominance (ISD) if $F^{-(r+1)}(p) \geq G^{-(r+1)}(p)\ \forall p \in [0, 1]$ and $>$ for at least one p.

The stochastic dominance criterion are nested in the sense that lower order SD/ISD implies higher order. However, the reverse may not be true. Following Zoli (1999) SD implies ISD and vice versa for $r \leq 2$. In the empirical section of this chapter we shall focus mainly on first and second order ISD. Nevertheless, this is equivalent to SD. We shall plot income quantiles of two distributions, say F and G. If the quantiles of the distribution F lies completely above G we shall refer there is as a conclusive statement on the fact that: F stochastically dominates (first order) G. If the first order SD fails to provide conclusive result we shall move to second order SD. We shall plot the mean of bottom $p\%$ of population of distribution F and G, which we denote as $\mu_F(p)$ and $\mu_G(p)$ respectively. Note that we cal also write $\mu_S(p) = \int_0^p y_S^t(p)\, dp\ \forall S \in F, G$. It is readily observable that if $\mu_F(p) \geq \mu_G(p) \forall p$ and $>$ for at least one p, implies evidence of second order ISD (SD) of F over G. A figure with $\mu_F(p)$ on the vertical axis and p on the horizontal axis is also referred as Generalized Lorenz Curve (GLC) (Shorrocks, 1983).[3]

[3]GLC has been introduced in the literature following the seminal contribution of Shorrocks (1983). GLC is obtained by multiplying all the points of Lorenz Curve by the mean income of the society. Empirical result shows that GLC curve provides conclusive results in many cases compared to the Lorenz Curve.

We shall fix the number of quantiles as 20. Although we have chosen large number of quantile[4], it must be validated following a statistical test of stochastic dominance. We shall return on this issue latter.

3.2.1 Stochastic Dominance $\iff$ Poverty and welfare ordering

Poverty analysis has often been carried out by a fixed poverty line. While comparing poverty between two countries or between two periods the ranking may change as a result of change in the poverty line. The ranking may also give some ambiguous result as a result of change of the poverty index. In order to rule out this inconsistencies Atkinson (1987) in his seminal paper relates poverty ordering to that of stochastic dominance. He shows in that paper: if there exists a first order stochastic dominance of one distribution over the other poverty would decrease for any poverty index which is continuous in income profiles, non-increasing in income and non decreasing in poverty line. Foster and Shorrocks (1988a,b) propose poverty ordering condition and show relationship between FGT index (Foster et al., 1984) and stochastic dominance. The FGT index of Poverty might be written as follows

$$P_\alpha = \frac{1}{z^{\alpha-1}} \int_0^{F(z)} [z - F^{-1}(p)]^{\alpha-1} dp \tag{3.1}$$

where z is poverty line and α denotes the degree of inequality aversion parameter. P_1 is the Head count ratio, P_2 as the income gap measure and P_3 as the squared Poverty gap measure. The poverty ordering condition as proposed by Foster and Shorrocks (1988a,b) $F(P_\alpha)G \iff F \succ_\alpha G$. These implies if F stochastically dominates G by α order then for any poverty line poverty in F is lower than that of G provided one considers P_α as the poverty index.

[4]There are evidence of choice of smaller number of quantile in many cases, e.g Son (2004) considered the number of quantile as 10.

Stochastic dominance condition may also be related to that of welfare dominance. Consider $\mathbb{U}$ as the class of social welfare function of the form $U(F) = \int_0^{\bar{z}} u(x)dF(x)$ where $u(x) : \Re_+ \to \Re$ is any continuous function may represented as the utility function. Let $\mathbb{U}_1 \subset \mathbb{U}$ and $u'(x) > 0$, $\mathbb{U}_2 \subset \mathbb{U}_1$ and $u''(x) < 0$, and $\mathbb{U}_3 \subset \mathbb{U}_2$ and $u'''(x) > 0$. Now define welfare dominance as $FU_\alpha G \; iff \; U(F) > U(G) \forall U \in \mathbb{U}_\alpha$. Again $FU_\alpha G \; iff \; F \succ_\alpha G$.

3.3 Economies of Scale

In developing economies it is often noticed that larger households tend to be poorer. However, certain goods such as water taps, cooking utensils, fuels, etc., can be shared in large households. There might also be other reasons since larger households usually purchase commodities in bulk and thus more likely to get some discount on these items. Thus at a same level of expenditure a larger household is able to achieve higher utility compared to that of smaller households. The issue would be important while comparing female headed and male headed households since female households are usually smaller in size. Table 3.1 also shows, among all households, the mean household size for the female headed households is the lowest.

Following Dreze and Srinivasan (1997) we consider scale adjusted per-capita expenditure (y') as follows

$$y' = y/n^\theta \tag{3.2}$$

where θ is a parameter varying between 0 and 1, which captures the extent of scale economies. Clearly, when $\theta = 1$ it implies no economies of scale and y' is the scale adjusted per-capita expenditure. Considering $\theta = 0$, y' is equal to total household consumption; this can be thought of as a case where consumption entirely takes the form of 'public goods' which are shared within the household without any 'rivalry' (i.e., one person's consumption does not reduce anyone else's consumption). We shall consider the following four different economies of scale: 1, 0.8, 0.4 and 0.

3.4 Data

In continuation to the previous chapter we have also considered NSSO consumer expenditure data for 61st and 66 th round (Schedule Type 1). Our benchmark of analysis is the monthly per-capita expenditure(MPCE) for the mixed recall period of 365 days. We would like mention this once again that income data is generally not available in India and expenditure is considered as a proxy. From now on by income, we would mean expenditure.

One important aspect in this context is the comparability of results between the two rounds. The survey designs for both the rounds are the same and hence this is not a problem. Furthermore, both these rounds provide information on the MPCE at mixed recall period. Thus comparability among the two rounds is also not problematic in this regard. However, one must adjust changes in price that occurs in between these the two time points. We shall follow a methodology that has been adopted by the Planning Commission of India. In order to make these two rounds comparable we have converted incomes of all individuals of 66th round in terms of prices of 61st round. Further, we have used price indices supplied by the Ministry of Labor, Government of India. In case of rural India, we have used the Consumer Price Index for Agricultural Labor (CPIAL), whereas in the urban India the Consumer Price Index for Industrial Workers (CPIIW).[5]

In this chapter, we would also like to compare distributions of Male Headed (MHH) and Female headed households (FHH). Furthermore, we shall also compare general *verses* backward caste households. NSSO provides informations on the sex of all

[5] The same procedure has also been adopted by the Planning Commission of India, following the recommendations of Task force for updating poverty lines (Government of India, 1993). The Task Force set up by the Planning Commission, estimated the poverty line to be Rs 49.09 and Rs 56.64 per capita per month at 1973-74 prices for rural and urban India, respectively. Poverty lines for the subsequent years have been obtained considering the CPIAL and CPIIW as the price deflators, for rural and urban India, respectively.

individuals, including head of household. Thus we form two subgroups of population on the basis of the sex of household head. NSSO also provides informations on the social group in which a household belongs. The categories in social group are as follows: scheduled tribe, scheduled caste, other backward class, others. We shall consider the SC and the ST households as backward class (bc) and the rest as general (gen) category households.

3.5 Empirical Illustrations

In this section we will evaluate performances of different subgroups of Indian population using stochastic dominance. We will address the following questions here

1) Has poverty declined for all the subgroups from 2004-05 to 2009-10 ?

2) Is poverty higher among the backward caste households compared to that of the general categories ?

3) Is poverty higher for the FHH compared to MHH ?

We shall begin with an usual approach by specifying a poverty line and poverty index in order to answer the above mentioned questions. For the sake of brevity, we shall consider three poverty line namely Tendulkar committee line (TC), and the lower and upper bound of poverty line following non parametric costs of basic needs approach (CBN2) estimated in Chapter 2 of this thesis, See Table 2.4. Furthermore, we shall consider the poverty rates following the FGT class of poverty index, that has been defined in equation 2.9.

In Table 3.1 we have reported the sample size, mean income, household size and the FGT class of poverty measures (See equation 2.9). If we observe the figures closely it is readily observable that poverty has declined in both rural and urban India for all the groups. Furthermore, it is also observable that poverty for the backward caste households are higher than the general households. In the comparison of MHH *verses* FHH it is clearly observable that there is a difference in the pattern of rural and urban poverty orderings. In this context, we find HCR being lower for the FHH in rural India, which on the other hand is higher for the same group in urban India. This verdict slightly changes once we consider more distributional sensitive poverty index like PG or SPG in the context of rural NSSO 61 st round, where we find again higher poverty for the FHH. However, in the 66th round, it is readily observable that poverty among the FHH is smaller than MHH, for all the poverty lines and measures.

Given the fact that average household size of the female headed households is low it may be expected that the economies of scale will play an important role in this context. We shall also address the three questions raised in the beginning of this section considering economies of scale in the analysis.

3.5.1 Stochastic Dominance over time

We shall now address the issue whether poverty has declined from 61st to 66th round for all the groups of Indian population, that has been discussed earlier. Recall that earlier we have pointed out that first and second order SD and ISD are equivalent. We shall address the issues with first order ISD. We shall plot the income quantile function of two distributions say F and G. We shall restrict the number of quantiles to 20. If the quantiles of F lies above G for all the points we shall refer that F first order stochastically dominates G.

In figure 3.1, we plot the income quantiles for the rural and urban regions of 61st and 66th round, for different population groups, namely full sample, gen, BC, FHH and MHH. We shall also see whether our conclusions depends upon the choice of the economies of scale parameter or not. We have thus considered four different parameters of economies of scale $\theta = \{1, 0.8, 0.4, 0\}$, corresponding to $e = \{1, 2, 3, 4\}$. Each panel in the figure 3.1 thus corresponds to the income quantile plots of 61st and 66th round for one of the groups and parameter e.

The dotted line represents the distribution of the 66th round and the plain line represents that of 61st round. If we observe the figure closely, it may be readily observable that the dotted line (66th round) lies above the plain line (61st round), for all groups and also for any choice of e. This implies that for all the groups: round 66 stochastically dominates round 61. Hence, poverty (welfare) is lower (higher) in round 66 compared to that of 61. Furthermore, the result also holds considering economies of scale in the analysis.

Since, stochastic dominance are nested, first order stochastic dominance implies higher order. Hence, we do not plot any figure for higher order dominances.

3.5.2 Comparison: General *verses* Backward class

In continuation with the approach discussed in the earlier subsection, our main objective in this section is to see whether the general households stochastically dominates the backward class.

In Figure 3.2 we plot the income quantile function of rural and urban regions for the two round 61st and 66th. In each frame we have incorporated the income quantiles of the *"gen"* and *"bc"* households. The *"gen"* category households has been represented by the dotted line, whereas the *"bc"* by the plain line. It is readily observable that the "*gen*" households stochastically dominates the *"bc"*, since the dotted line lies above the plain line for all the points. Furthermore, the conclusions remains unchanged even after considering the economies of scale in the analysis.

3.5.3 Female Headed Households *verses* Male headed households

We shall now see whether MHH stochastically dominates the FHH, or vise versa. We shall also plot the income quantiles for these groups of households, to address this issue. Recall that in table 3.1, we have observed that HCR in rural regions of 61st round is lower for the FHH compared to MHH. This conclusion is exactly opposite when we consider the PG and/or SPG. This clearly implies that first order stochastic dominance will lead to inconclusive statements. Thus higher order stochastic dominance seems to be applicable in this context. Hence, in this comparison exercise, beside the income quantile function we shall also plot the Generalized Lorenz Curve (GLC) for both FHH and MHH.

In Figure 3.3 we have plotted income quantiles function and have incorporated that of MHH and FHH in each panel. The dotted line represents the income quantile function for the MHH and the plain line for the FHH. Similarly in Figure 3.4, we have plotted the GLC curves for the MHH and FHH. The dotted line represents the GLC of MHH and the plain line represents that of FHH.

It is readily observable that in the context of rural India at 61st round, the first order stochastic dominance breaks for $e = 1$ (i.e comparisons by average income). Even the GLC also crosses, see Figure 3.4. Hence we can not say anything in this regard, unless we put additional restrictions. However, in the context of rural 66th round, a clear verdict of first order stochastic dominance in favor of FHH is observed. This implies that poverty is lower for the FHH. However, once we incorporate economies of scale, and move from mild to high economies of scale (i.e from 1 towards 0), it might be readily observed that the dotted curves moves upwards and crosses the plain curve. This implies a verdict of stochastic dominance in favor of MHH. Hence, considering economies of scale into account, leads to higher poverty is observed among the FHH. In the context of urban India, the dotted line, in general lies above the plain line implying that poverty among FHH is higher with or without incorporating economies of scale.

3.5.4 Tests for Stochastic Dominance

We shall validate the ordering exercise following a test for stochastic dominance. We consider Barrett and Donald (2003) Kolmogorov-Smirnov(KS) type of test statistics for testing Stochastic Dominance. The main difficulty with this tests lies in the construction of an appropriate rejection regions for conducting the tests for Stochastic dominance (SD) of order j to be represented by SD_j for j larger than 1, e.g in the case of SD2 and SD3 will depend on the underlying distributions. The test statistics is based on the assumptions that both the CDF's used for the analysis are continuous and have a common support. They also assume the CDFs are calculated using independent random samples. Another assumption is that the number of samples in both distribution approaches to infinity the ratio of sample of one distribution to the total sample tends to a finite constant lying between 0 and 1. We apply here the KS1 and KS2 tests based on alternative approaches of simulation to compute the p values. While testing Stochastic dominance between two distributions F and G, one has to test whether F dominates G and also whether G dominates F. One can conclude F stochastically dominates G, for a certain order only when one can reject the null hypothesis G dominates F and fails to reject the null that F dominates G.[6]

In Table 3.2, we have presented the SD tests, to see whether reduction of poverty that has been obtained from 61st to 66th in the earlier section is statistically supported or not. See in the left hand side all the p values for both the statistics are much larger than the usual rejection rate (0.05). Thus we can not reject the fact that there is first order SD of 66 th round over the 61st round. On the other hand in the right hand side all the values are much less than usual rejection rates, thus we reject the fact there is a SD of 61st round dominates 66th round. Combining both these facts we have a clear support of the results that has been obtained in the descriptive statistics and the graphical representations. Following, Table 3.3, our conclusion for the general *verses* backward households also remains same. In the context of FHH *verses* MHH comparison in Table 3.4 we get conclusive results in all the cases, thus the inconclusive cases predicted in the graphically, no longer holds. It should be studied with a more robust test statistics that considers the survey design in order to compute the p values.

[6]Note that this test statistics are based on independent and identical sample. However, NSSO considers a stratified sampling design, thus the results may be questionable. However, we present this result to see whether our analysis simply based on graphs are supported or not.

3.6 Conclusion

In this chapter we have addressed problems related to the poverty ordering of rural and urban India for the year 2004-05 and 2009-10. Further, we have also evaluated whether poverty is higher for the general or the backward categories household. Furthermore, we have also conducted exercises related to ranking male and female headed households in terms of poverty ordering. These issues has been addressed by many papers in the literature. However, the main contribution of this chapter is to consider a robust ordering exercise named stochastic dominance. The stochastic dominance analysis is a partial ordering approach, and results may be inconclusive for certain cases. However, in case where conclusive results are obtained then it is possible to order distributions in terms wide range of poverty measures and some of the parameters related to it. For example, we have seen that the MPCE of rural India for the year 2009-10 first order stochastically dominates that of 2004-05. This implies that poverty is less for the year 2009-10 for any possible poverty line and also a wide range of poverty measures that is declining in income and is increasing in poverty line. In the poverty ordering literature one important aspect is less often taken into account namely the economies of scale. Thus often it has been observed that the larger households are poorer compared to the smaller one. We have also incorporated economies of scale in the analysis while comparing income distributions.

The main findings of the chapter might be summarized as follows

1) The recent data of monthly per capita expenditure for rural and urban India provided by NSSO Quinquennial round 66 (2009-10) shows evidence of strict first order stochastic dominance compared to the previous Quinquennial round 61 (2004-2005). In fact similar results has also been observed for other groups of population like general, backward class, male headed and female headed households both at rural and urban India. Kolmogorov-Smirnov (KS) type of test for stochastic dominance introduced by Barrett and Donald (2003) also supports these results. The results also holds even after considering the economies of scale in the analysis.

2) The evidence of higher poverty rates among the backward category households is also supported by the stochastic dominance analysis. In fact the results also holds true even after accounting economies of scale.

3) While comparing poverty situations among the female headed and the male headed households of rural India in terms of per capita expenditure, the stochastic dominance analysis ends up inconclusively for the 61st round. However, in the same context, a clear verdict of first order stochastic dominance, is obtained in favor of the female headed households for the 66th round. Thus poverty in 66th round is lower among the female headed households compared to the male headed households. Nonetheless, this is true only with per-capita expenditure. Incorporating economies of scale, in the analysis reverts the ordering. This is because of the fact that female headed households have smaller household size. In urban India poverty is usually lower among male headed households, with or without accounting the economies of scale.

On the basis of this finding we recommend that female headed households in both rural and urban India should be considered into account in any poverty targeting exercise.

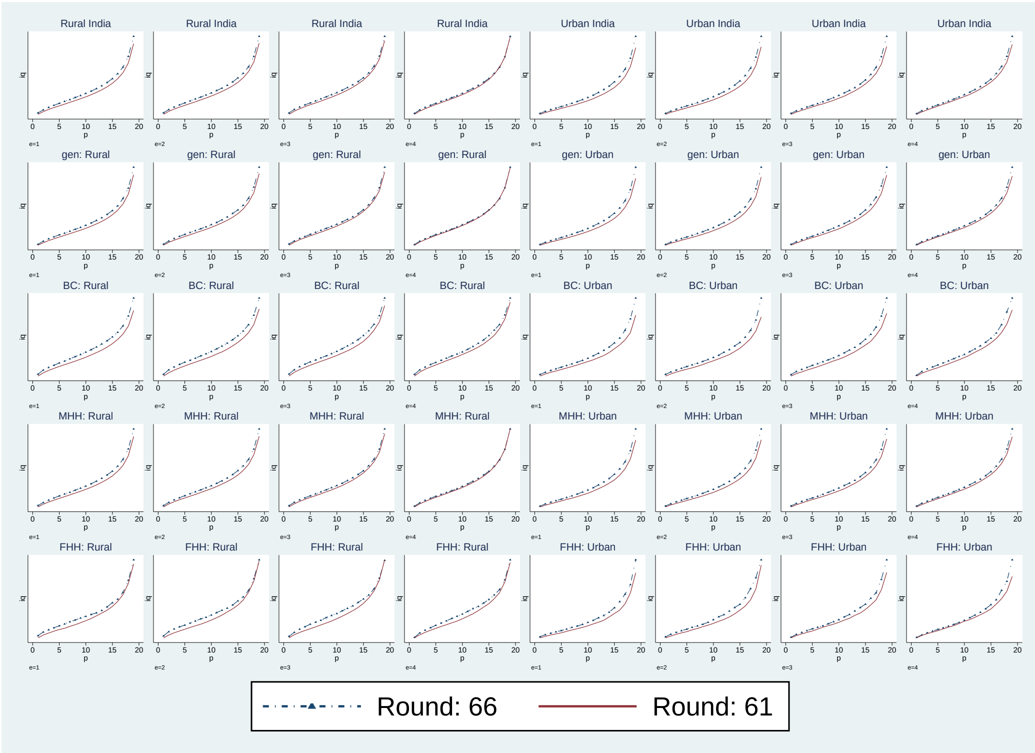
3.7 Tables and Figures

Table 3.1: Descriptive statistics for different groups of Indian population

Round	Sector	Sample	MPCE	H.Size	HCR			PG			SPG		
					TC	z_l	z_u	TC	z_l	z_u	TC	z_l	z_u
Full Sample													
61	Rural	79298	579.2	6.1	41.8	44.8	69.8	9.6	10.7	22.6	3.2	3.6	9.4
66	Rural	59119	953.0	5.8	33.8	33.3	50.7	7.2	7.0	13.1	2.3	2.2	4.7
61	Urban	45346	1104.6	5.6	25.7	18.4	43.0	6.1	3.8	12.7	2.0	1.2	5.1
66	Urban	41736	1856.0	5.3	20.9	12.5	26.4	4.6	2.4	6.3	1.5	0.7	2.2
General Category Households													
61	Rural	52737	625.8	6.2	35.4	38.3	64.5	7.4	8.3	19.3	2.2	2.6	7.6
66	Rural	38641	1026.5	5.9	28.4	27.9	45.3	5.6	5.5	10.8	1.7	1.6	3.7
61	Urban	35432	1170.6	5.6	22.7	15.9	39.4	5.1	3.1	11.2	1.7	0.9	4.4
66	Urban	32676	1954.2	5.3	18.3	10.6	23.4	4.0	2.0	5.5	1.3	0.6	1.9
Backward class Households													
61	Rural	26561	477.9	5.8	55.8	58.9	81.5	14.4	15.8	29.7	5.1	5.8	13.4
66	Rural	20478	804.1	5.6	44.7	44.1	61.8	10.4	10.2	17.6	3.5	3.4	6.7
61	Urban	9914	814.9	5.6	39.2	29.3	58.6	10.2	6.7	19.2	3.7	2.2	8.3
66	Urban	9060	1423.9	5.5	32.2	20.6	39.5	7.6	4.1	10.1	2.6	1.2	3.6
Male Headed Households													
61	Rural	70781	575.5	6.2	41.9	44.9	70.2	9.6	10.6	22.6	3.1	3.6	9.4
66	Rural	52849	947.1	5.9	34.2	33.7	51.3	7.3	7.1	13.2	2.3	2.2	4.7
61	Urban	39854	1104.5	5.6	25.5	18.1	42.8	6.0	3.7	12.6	2.0	1.1	5.0
66	Urban	36687	1847.6	5.4	20.8	12.5	26.4	4.6	2.4	6.3	1.5	0.7	2.2
Female Headed Households													
61	Rural	8517	623.4	4.7	41.0	43.4	65.2	10.2	11.2	22.2	3.6	4.0	9.6
66	Rural	6270	1020.7	4.9	29.3	28.6	44.6	6.2	6.1	11.3	2.0	1.9	4.0
61	Urban	5492	1106.0	5.1	28.8	21.4	45.2	7.2	4.7	14.0	2.6	1.6	5.9
66	Urban	5049	1946.4	4.8	21.3	12.6	26.7	4.8	2.5	6.6	1.6	0.8	2.3

[1] **Notes :** Sample, MPCE, H.Size, represents sample size, average per capita expenditure, average household size respectively. Poverty rates following subgroups of population for poverty lines TC z_l z_u corresponds to the Tendulkar Committee Line, Lower bound and upper bound following estimates of the Chapter in this thesis, (see Table 2.4).

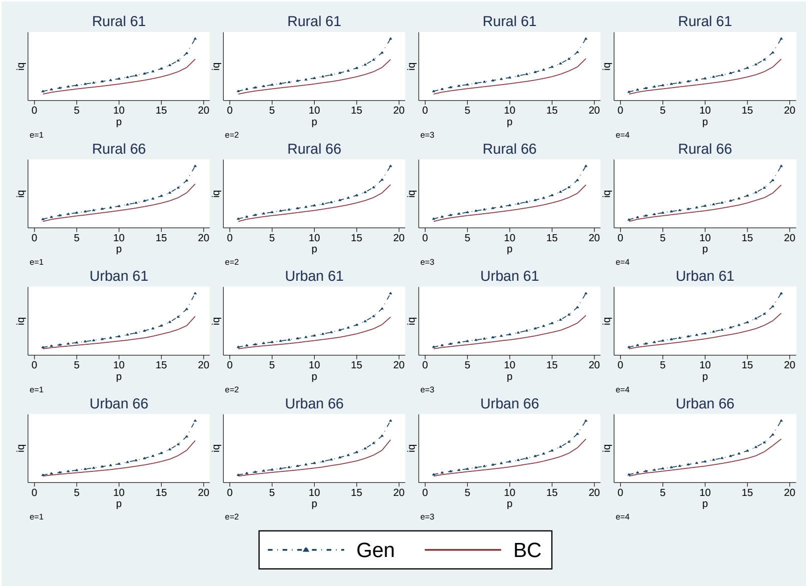
Figure 3.1: First Order Stochastic Dominance Over Time: Rural India



Each panel in the figure represents the income quantiles of different Indian population groups for the 61st and 66th round. In the horizontal axis we plot MPCE quantiles iq(p) against the p th quantile measured in the vertical axis. The income quantiles has been computed for four different economies of scale parameter: $\theta = (1, 0.8, 0.4, 0)$, which has been represented by e=(1,2,3,4) respectively. The dotted line is the iq(p) for the 66th round and the plain line represents that of 61st round. The number of quantiles is 20. The population groups are as follows:

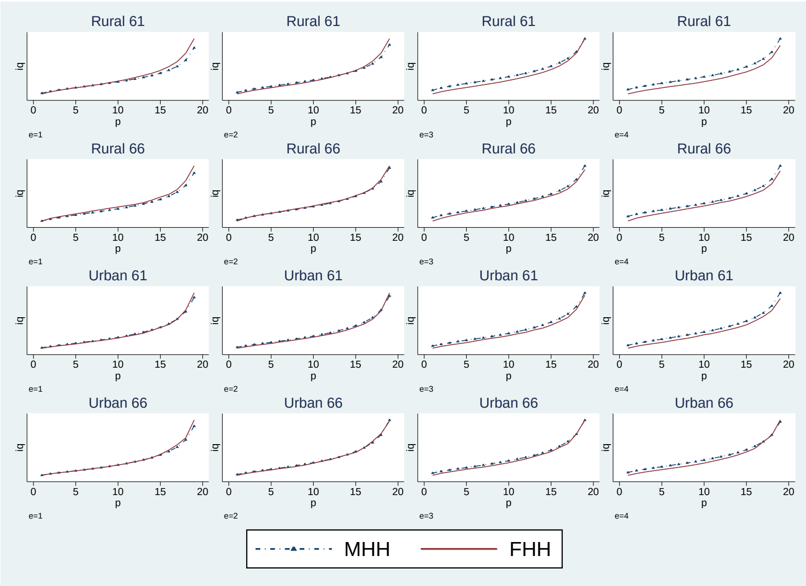
Rural India: Full sample rural India, Urban India: Full sample urban India, gen=General Households, BC=Backward class (SC and ST), FHH=Female Headed Households, MHH=Male Headed Households.

Figure 3.2: Comparing general and the backward class households by first order stochastic dominance



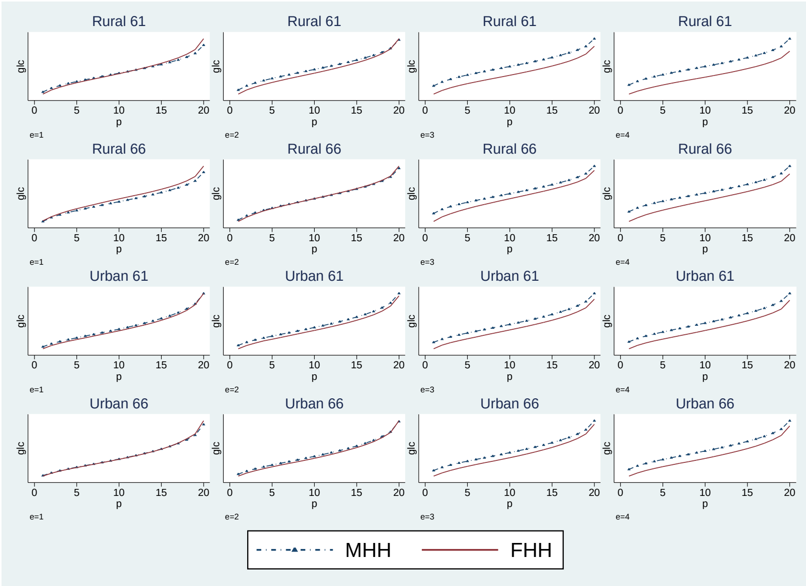
Each panel in the figure represents the income quantiles of general and backward class (sc and st) households. In the horizontal axis we plot income quantiles iq(p) against the p th quantile measured in the vertical axis. The income quantiles has been computed for four different economies of scale parameter: $\theta = (1, 0.8, 0.4, 0)$, which has been represented by e=(1,2,3,4) respectively. The dotted line is the iq(p) for the general households (gen) round and the plain line represents that of backward class (bc) households. The number of quantiles is 20.

Figure 3.3: Comparing the male and the female headed households by first order stochastic dominance



Each panel in the figure represents the income quantiles of male headed (MHH) and female headed (FHH) households. In the horizontal axis we plot income quantiles iq(p) against the p th quantile measured in the vertical axis. The income quantiles has been computed for four different economies of scale parameter: $\theta = (1, 0.8, 0.4, 0)$, which has been represented by e=(1,2,3,4) respectively. The dotted line is the iq(p) for the MHH and the plain line represents that of FHH. The number of quantiles is 20.

Figure 3.4: Comparing the male and the female headed households by second order stochastic dominance



Each panel in the figure represents the generalized Lorenz curve for the male headed (MHH) and female headed (FHH) households. In the horizontal axis we plot glc(p) against the p th quantile measured in the vertical axis. GLC has been computed for four different economies of scale parameter: $\theta = (1, 0.8, 0.4, 0)$, which has been represented by e=(1,2,3,4) respectively. The dotted line is the glc(p) for the MHH and the plain line represents that of FHH. The number of quantiles is 20.

Table 3.2: Stochastic Dominance tests : round 66 versues 61

Group	**Sector**	**Test**	θ	**Round 66 *versus* 61**			**Round 61 *versus* 66**		
All	Rural	ks1	1	1.000	0.960	0.910	0.000	0.000	0.000
All	Rural	ks2	1	1.000	0.980	0.960	0.000	0.000	0.000
All	Rural	ks1	.8	1.000	0.970	0.940	0.000	0.000	0.000
All	Rural	ks2	.8	1.000	0.970	0.940	0.000	0.000	0.000
All	Rural	ks1	.4	1.000	0.970	0.940	0.000	0.000	0.000
All	Rural	ks2	.4	1.000	0.940	0.900	0.000	0.000	0.000
All	Rural	ks1	0	1.000	0.920	0.890	0.000	0.000	0.000
All	Rural	ks2	0	1.000	0.980	0.940	0.000	0.000	0.000
All	Urban	ks1	1	1.000	0.920	0.890	0.000	0.000	0.000
All	Urban	ks2	1	1.000	0.940	0.890	0.000	0.000	0.000
All	Urban	ks1	.8	1.000	0.940	0.880	0.000	0.000	0.000
All	Urban	ks2	.8	1.000	0.930	0.860	0.000	0.000	0.000
All	Urban	ks1	.4	1.000	0.930	0.890	0.000	0.000	0.000
All	Urban	ks2	.4	1.000	0.910	0.880	0.000	0.000	0.000
All	Urban	ks1	0	1.000	0.910	0.870	0.000	0.000	0.000
All	Urban	ks2	0	1.000	0.890	0.870	0.000	0.000	0.000
Gen	Rural	ks1	1	1.000	0.930	0.890	0.000	0.000	0.000
Gen	Rural	ks2	1	1.000	0.930	0.890	0.000	0.000	0.000
Gen	Rural	ks1	.8	1.000	0.920	0.870	0.000	0.000	0.000
Gen	Rural	ks2	.8	1.000	0.930	0.870	0.000	0.000	0.000
Gen	Rural	ks1	.4	1.000	0.890	0.870	0.000	0.000	0.000
Gen	Rural	ks2	.4	1.000	0.940	0.910	0.000	0.000	0.000
Gen	Rural	ks1	0	1.000	0.880	0.860	0.000	0.000	0.000
Gen	Rural	ks2	0	1.000	0.880	0.860	0.000	0.000	0.000
Gen	Urban	ks1	1	1.000	0.910	0.890	0.000	0.000	0.000
Gen	Urban	ks2	1	1.000	0.940	0.890	0.000	0.000	0.000
Gen	Urban	ks1	.8	1.000	0.910	0.900	0.000	0.000	0.000
Gen	Urban	ks2	.8	1.000	0.970	0.920	0.000	0.000	0.000
Gen	Urban	ks1	.4	1.000	0.940	0.900	0.000	0.000	0.000
Gen	Urban	ks2	.4	1.000	0.960	0.910	0.000	0.000	0.000
Gen	Urban	ks1	0	1.000	0.950	0.930	0.000	0.000	0.000
Gen	Urban	ks2	0	1.000	0.930	0.920	0.000	0.000	0.000
BC	Rural	ks1	1	0.999	0.990	0.970	0.000	0.000	0.000
BC	Rural	ks2	1	0.999	0.940	0.920	0.000	0.000	0.000
BC	Rural	ks1	.8	0.996	0.970	0.970	0.000	0.000	0.000
BC	Rural	ks2	.8	0.996	0.950	0.920	0.000	0.000	0.000
BC	Rural	ks1	.4	0.985	0.960	0.960	0.000	0.000	0.000
BC	Rural	ks2	.4	0.985	0.960	0.940	0.000	0.000	0.000
BC	Rural	ks1	0	0.932	0.940	0.890	0.000	0.000	0.000
BC	Rural	ks2	0	0.932	0.920	0.890	0.000	0.000	0.000
BC	Urban	ks1	1	1.000	0.970	0.960	0.000	0.000	0.000
BC	Urban	ks2	1	1.000	0.990	0.960	0.000	0.000	0.000
BC	Urban	ks1	.8	1.000	0.970	0.960	0.000	0.000	0.000
BC	Urban	ks2	.8	1.000	0.990	0.960	0.000	0.000	0.000
BC	Urban	ks1	.4	1.000	0.960	0.950	0.000	0.000	0.000
BC	Urban	ks2	.4	1.000	0.960	0.950	0.000	0.000	0.000
BC	Urban	ks1	0	0.998	0.980	0.940	0.000	0.000	0.000
BC	Urban	ks2	0	0.998	0.980	0.950	0.000	0.000	0.000
MHH	Rural	ks1	1	1.000	0.960	0.940	0.000	0.000	0.000
MHH	Rural	ks2	1	1.000	0.950	0.920	0.000	0.000	0.000
MHH	Rural	ks1	.8	1.000	0.970	0.910	0.000	0.000	0.000
MHH	Rural	ks2	.8	1.000	0.990	0.920	0.000	0.000	0.000
MHH	Rural	ks1	.4	1.000	0.910	0.870	0.000	0.000	0.000
MHH	Rural	ks2	.4	1.000	0.940	0.870	0.000	0.000	0.000

Continued on the next page

Table 3.2 (Contd.)

Group	Sector	Test	θ	Round 66 *versus* 61			Round 61 *versus* 66		
MHH	Rural	ks1	0	1.000	0.950	0.930	0.000	0.000	0.000
MHH	Rural	ks2	0	1.000	0.940	0.910	0.000	0.000	0.000
MHH	Urban	ks1	1	1.000	0.950	0.920	0.000	0.000	0.000
MHH	Urban	ks2	1	1.000	0.950	0.940	0.000	0.000	0.000
MHH	Urban	ks1	.8	1.000	0.960	0.950	0.000	0.000	0.000
MHH	Urban	ks2	.8	1.000	0.960	0.930	0.000	0.000	0.000
MHH	Urban	ks1	.4	1.000	0.970	0.970	0.000	0.000	0.000
MHH	Urban	ks2	.4	1.000	0.950	0.930	0.000	0.000	0.000
MHH	Urban	ks1	0	1.000	0.940	0.930	0.000	0.000	0.000
MHH	Urban	ks2	0	1.000	0.950	0.890	0.000	0.000	0.000
FHH	Rural	ks1	1	1.000	0.950	0.900	0.000	0.000	0.000
FHH	Rural	ks2	1	1.000	0.930	0.870	0.000	0.000	0.000
FHH	Rural	ks1	.8	1.000	0.930	0.890	0.000	0.000	0.000
FHH	Rural	ks2	.8	1.000	0.910	0.850	0.000	0.000	0.000
FHH	Rural	ks1	.4	1.000	0.920	0.900	0.000	0.000	0.000
FHH	Rural	ks2	.4	1.000	0.910	0.890	0.000	0.000	0.000
FHH	Rural	ks1	0	1.000	0.930	0.880	0.000	0.000	0.000
FHH	Rural	ks2	0	1.000	0.880	0.860	0.000	0.000	0.000
FHH	Urban	ks1	1	1.000	0.960	0.940	0.000	0.000	0.000
FHH	Urban	ks2	1	1.000	0.930	0.900	0.000	0.000	0.000
FHH	Urban	ks1	.8	1.000	0.970	0.930	0.000	0.000	0.000
FHH	Urban	ks2	.8	1.000	0.930	0.870	0.000	0.000	0.000
FHH	Urban	ks1	.4	1.000	0.960	0.940	0.000	0.000	0.000
FHH	Urban	ks2	.4	1.000	0.920	0.900	0.000	0.000	0.000
FHH	Urban	ks1	0	1.000	0.950	0.900	0.000	0.000	0.000
FHH	Urban	ks2	0	1.000	0.850	0.830	0.000	0.000	0.000

Notes : In this table *p values* corresponding to the test statistics KS1 and KS2 that has been introduced by Barrett and Donald (2003) has been presented. The main objective is to see whether the income distribution of round 66 stochastically dominates 61 or not. In fact, the analysis has been separately carried out for the following groups : *ALL, gen, bc, FHH,* and *MHH*. *ALL* represents the all-India population (rural/urban). GEN and BC stands for general category and backward caste households. FHH and MHH respectively stands for male and female headed households. *p values* corresponds to first, second and third order stochastic dominance tests, which has been denoted by FSD, SSD, and TSD, respectively. θ captures the economies of scale parameter. See Equation 3.2. 61 and 66 stands for NSSO survey rounds. Price adjustments have been done considering the CPIAL and CPIIW for rural and urban India, respectively.

Table 3.3: Stochastic Dominance tests : GEN and Backward caste headed households

Round	Sector	Test	θ	GEN *verses* BC			BC *verses* GEN		
				FSD	**SSD**	**TSD**	**FSD**	**SSD**	**TSD**
61	Rural	ks1	1	1.000	0.920	0.900	0.000	0.000	0.000
61	Rural	ks2	1	1.000	0.970	0.940	0.000	0.000	0.000
61	Rural	ks1	.8	1.000	0.950	0.930	0.000	0.000	0.000
61	Rural	ks2	.8	1.000	0.970	0.940	0.000	0.000	0.000
61	Rural	ks1	.4	1.000	0.930	0.890	0.000	0.000	0.000
61	Rural	ks2	.4	1.000	0.950	0.880	0.000	0.000	0.000
61	Rural	ks1	0	1.000	0.930	0.910	0.000	0.000	0.000
61	Rural	ks2	0	1.000	0.940	0.910	0.000	0.000	0.000
66	Rural	ks1	1	1.000	0.870	0.850	0.000	0.000	0.000
66	Rural	ks2	1	1.000	0.880	0.830	0.000	0.000	0.000
66	Rural	ks1	.8	0.999	0.830	0.800	0.000	0.000	0.000
66	Rural	ks2	.8	0.999	0.830	0.800	0.000	0.000	0.000
66	Rural	ks1	.4	0.999	0.870	0.830	0.000	0.000	0.000
66	Rural	ks2	.4	0.999	0.860	0.810	0.000	0.000	0.000
66	Rural	ks1	0	0.999	0.860	0.810	0.000	0.000	0.000
66	Rural	ks2	0	0.999	0.860	0.810	0.000	0.000	0.000
61	Urban	ks1	1	0.997	0.900	0.850	0.000	0.000	0.000
61	Urban	ks2	1	0.997	0.880	0.840	0.000	0.000	0.000
61	Urban	ks1	.8	0.997	0.880	0.840	0.000	0.000	0.000
61	Urban	ks2	.8	0.997	0.880	0.880	0.000	0.000	0.000
61	Urban	ks1	.4	0.998	0.880	0.850	0.000	0.000	0.000
61	Urban	ks2	.4	0.998	0.900	0.860	0.000	0.000	0.000
61	Urban	ks1	0	0.998	0.900	0.870	0.000	0.000	0.000
61	Urban	ks2	0	0.998	0.890	0.860	0.000	0.000	0.000
66	Urban	ks1	1	1.000	0.950	0.900	0.000	0.000	0.000
66	Urban	ks2	1	1.000	0.920	0.850	0.000	0.000	0.000
66	Urban	ks1	.8	0.998	0.930	0.890	0.000	0.000	0.000
66	Urban	ks2	.8	0.998	0.890	0.870	0.000	0.000	0.000
66	Urban	ks1	.4	0.992	0.890	0.850	0.000	0.000	0.000
66	Urban	ks2	.4	0.992	0.860	0.830	0.000	0.000	0.000
66	Urban	ks1	0	0.996	0.930	0.890	0.000	0.000	0.000
66	Urban	ks2	0	0.996	0.880	0.870	0.000	0.000	0.000

[1] **Notes :** In this table *p values* corresponding to the test statistics KS1 and KS2 that has been introduced by Barrett and Donald (2003) has been presented. The main objective is to see whether the income distribution of general category (gen) stochastically dominates the backward class (bc) or not. *p values* corresponds to first, second and third order stochastic dominance tests, which has been denoted by FSD, SSD, and TSD, respectively.

[2] θ captures the economies of scale parameter. See Equation 3.2.

Table 3.4: Stochastic Dominance tests : Male and female headed households

Round	Sector	θ	Test	FHH *verses* MHH			MHH *verses* FHH		
				FSD	**SSD**	**TSD**	**FSD**	**SSD**	**TSD**
61	Rural	1	KS1	0.208	0.486	0.636	0.000	0.000	0.000
61	Rural	1	KS2	0.208	0.461	0.601	0.000	0.000	0.000
61	Rural	0.8	KS1	0.000	0.000	0.065	0.115	0.771	0.742
61	Rural	0.8	KS2	0.000	0.000	0.069	0.115	0.752	0.718
61	Rural	0.4	KS1	0.000	0.000	0.000	0.983	0.793	0.764
61	Rural	0.4	KS2	0.000	0.000	0.000	0.983	0.778	0.746
61	Rural	0	KS1	0.000	0.000	0.000	0.999	0.796	0.773
61	Rural	0	KS2	0.000	0.000	0.000	0.999	0.798	0.737
66	Rural	1	KS1	0.98	0.749	0.718	0.000	0.000	0.000
66	Rural	1	KS2	0.98	0.761	0.74	0.000	0.000	0.000
66	Rural	0.8	KS1	0.000	0.000	0.421	0.210	0.325	0.301
66	Rural	0.8	KS2	0.000	0.000	0.421	0.210	0.342	0.315
66	Rural	0.4	KS1	0.000	0.000	0.000	0.951	0.767	0.731
66	Rural	0.4	KS2	0.000	0.000	0.000	0.951	0.778	0.73
66	Rural	0	KS1	0.000	0.000	0.000	0.999	0.760	0.719
66	Rural	0	KS2	0.000	0.000	0.000	0.999	0.748	0.716
61	Urban	1	KS1	0.000	0.000	0.000	0.663	0.822	0.798
61	Urban	1	KS2	0.000	0.000	0.000	0.663	0.828	0.785
61	Urban	0.8	KS1	0.000	0.000	0.000	0.943	0.835	0.807
61	Urban	0.8	KS2	0.000	0.000	0.000	0.943	0.845	0.808
61	Urban	0.4	KS1	0.000	0.000	0.000	1.000	0.848	0.817
61	Urban	0.4	KS2	0.000	0.000	0.000	1.000	0.827	0.792
61	Urban	0	KS1	0.000	0.000	0.000	1.000	0.835	0.801
61	Urban	0	KS2	0.000	0.000	0.000	1.000	0.806	0.747
66	Urban	1	KS1	0.000	0.007	0.488	0.061	0.099	0.097
66	Urban	1	KS2	0.000	0.010	0.475	0.061	0.100	0.097
66	Urban	0.8	KS1	0.000	0.000	0.000	0.683	0.756	0.715
66	Urban	0.8	KS2	0.000	0.000	0.000	0.683	0.770	0.738
66	Urban	0.4	KS1	0.000	0.000	0.000	0.998	0.803	0.755
66	Urban	0.4	KS2	0.000	0.000	0.000	0.998	0.820	0.782
66	Urban	0	KS1	0.000	0.000	0.000	1.000	0.804	0.766
66	Urban	0	KS2	0.000	0.000	0.000	1.000	0.808	0.752

[1] **Notes :** In this table *p values* corresponding to the test statistics KS1 and KS2 that has been introduced by Barrett and Donald (2003) has been presented. The main objective is to see whether the income distribution of FHH stochastically dominates the MHH or not. *p values* corresponds to first, second and third order stochastic dominance tests, which has been denoted by FSD, SSD, and TSD, respectively.

[2] θ captures the economies of scale parameter. See Equation 3.2.

Chapter 4

Pro poor growth: A partial ordering approach

4.1 Introduction

Most of the developing economies show evidence of increment of growth rate over the last few decades. Questions have been raised by academicians and policy makers, whether poorer section of the society enjoys the benefit from it. Thus the concept of pro poor growth evolved, mainly, to analyze the fact, whether growth is favorable to the poor or not.

The notion "*pro poor growth*" may be defined in two different senses. In general growth is said to be pro poor in an absolute sense, if it raises income of the poor and consequently poverty reduces (see Kraay, 2006) . Following Kakwani and Pernia (2000), growth is labeled as "pro-poor" in a relative sense, if it raises the incomes of poor proportionately more than that of the non poor. Osmani (2005), criticized, both these approaches. He proposed a stronger absolute definition of pro-poor growth, that growth is pro poor if the poverty reduction is higher than the benchmark level. However, establishing such a benchmark is not easy and is always debatable. On the other hand, this is also a relative approach, which can be traced back to Kakwani and Pernia (2000) approach.

Both, absolute and relative pro poor growth may be evaluated with either complete or partial ordering approach. Like the previous chapter we shall also adopt a partial ordering approach here.[1] Our main objective in this chapter is generalization of the concept of Equally Distributed Equivalent Growth Rate (EDEGR) proposed by Nssah (2005), in the partial ordering context. EDEGR is almost similar the Equally Distributed Equivalent Income introduced by Atkinson (1970). It is the growth rate socially equivalent to that of observed one, for some choice of a focal parameter, which measures the degree of inequality aversion. EDEGR may also be considered as the weighted average of the points of the growth rates of income quantiles. The relative version of EDEGR also known as Distributive Adjusted Factor (DAF). DAF is the deviation of EDEGR from the growth rate of mean. Nssah (2005) declared that absolute and relative pro poor growth occurs in the society, respectively when EDEGR and DAF are strictly positive.

However, in the formulation of EDEGR and DAF, weights has been restricted to the class of a relative extended gini weights(See, Yitzhaki, 1983). Thus following any standard critics of complete ordering index EDEGR and DAF may also be criticized in the sense that pro poor ordering may be different for different choice of the weight function. In order to overcome this problem, we consider a specific class of the weight function, on the basis of certain ethical properties. We have introduced a concept called EDEGR dominance, implying EDEGR being strictly positive for at least one of the weights and negative for the none. The dominance ordering are based on inverse stochastic dominance of logarithmic income domain of one distribution over the other. The first order EDEGR dominance corresponds to the satisfaction of weak

[1] The main difference is unlike the previous chapter where we study poverty ordering of two distributions, here we want to see whether economic growth is favorable to the poor or not. Further note that cases where we had evidence of stochastic dominance of one distribution over the other would always imply growth is pro poor in an absolute sense. However, the relative pro poor ordering is not guaranteed.

monotonicity property of growth quantiles, i.e., if growth is positive in at least one of the quantiles, then it must not be anti poor. For satisfaction of this axiom we consider only non negative class of weights in the construction of EDEGR. For the second order EDEGR dominance, we have restricted EDEGR which satisfies transfer principle. It says that for any transfer of income from the richer quantile to the poorer one would lead growth to be pro poor. For satisfaction of this axiom we restrict the weights as differentiable and the corresponding first derivative being negative. Second order EDEGR dominance is obtained if EDEGR satisfies both monotonicity and transfer axiom. Additionally we need principle of positional version of transfer sensitivity for third order EDEGR dominance. It states that transfer is valued more if it takes place at the bottom quantile of the growth profile. EDEGR satisfies this property if second derivative of the weight function is non negative. We shall further establish that first second and third order EDEGR dominance are equivalent to inverse stochastic dominance of logarithmic income of one distribution over the other. Clearly the derived dominance conditions are nested i.e lower order EDEGR dominance will always imply higher order, but the reverse is not necessarily true. Recently, Duclos (2009) suggested a relative pro poor orderings approach, based on normalizing income of all individuals by any pro poor standard. We shall show that all the results for the EDEGR dominance may also be extended in the context of DAF dominance using this normalization technique.

As we have mentioned in the previous chapter, main problem of any partial ordering approach are the inconclusive cases. Researchers have searched alternatives or restrictive approaches to conclude such situations[2]. Clearly third order EDEGR dominance is more robust compared to first and second, in terms of conclusiveness.

[2]Recall that in the earlier chapter when when first order stochastic dominance of one distribution over another failed to provide conclusive results we had shifted to higher order dominance. Similar analysis is also possible in the context of poverty ordering where one normalize both distributions with a positive constant which may be considered as a meaningful poverty line for both the distributions.

For empirical application of the third order EDEGR dominance, we have introduced a new growth curve based on the change of gini social welfare function of logarithmic income at different income quantiles. We shall also consider empirical exercises to study the performances of different growth curves in terms of conclusiveness. Further we shall also evaluate whether growth in India is pro poor or not.

So far in the current literature there has been evidence of two widely used pro poor growth curves by which growth might be analyzed pro poor or not in a partial ordering sense. The first one is Growth incidence curve (GIC) following Ravallion and Chen (2003). It is defined as the rate of change of income quantiles for two distributions. A conclusive result is obtained following GIC, if it lies strictly above zero for at least one quantile and not below zero for any other quantiles. Son (2004) developed a new approach on the basis of Atkinson (1987) theorem linking the generalized Lorenz curve and changes in poverty, and proposed a new growth rate curve namely, poverty growth curve (PGC). GIC and PGC respectively provides conclusive result if there is evidence of first and second order stochastic dominance of one distribution over the other. Since, stochastic dominance conditions are nested, PGC provides better results than GIC, in terms of conclusiveness. A relative version of GIC and PGC are derived considering their deviations from the average growth rate of the society.

Our second contribution in this chapter is to relate the absolute and relative versions of the GIC, PGC and the newly proposed growth curve. We shall show in-spite of the fact that the newly proposed growth curve is based on a different domain (logarithmic income), conclusive GIC and/or PGC ordering, appears to be a sufficient condition for the conclusive ordering of the newly proposed growth curve. Thus the newly proposed growth curve shall provide conclusive results in all cases where GIC/PGC do so. However, there are certain situations where out of these three curves only the new growth curve would provide conclusive results. The same results can be easily extended in the context of relative pro poor ordering.

It should be noted that unlike the GIC and the PGC, the proposed growth curve is not related to poverty indices. If the new growth curve provides conclusive results, it implies pro-poor growth following the wide range of pro-poor growth index, named EDEGR. Similarly the value added of the relative version of this curve can be justified in terms of DAF.

The remainder of the chapter is structured as follows. In the next section we shall begin with a formal introduction on stochastic dominance, absolute and relative pro poor growth measures and many other related topics. In section 4.3 we have introduced the new dominance result. An empirical analysis has been done in section 4.4. The first part of the empirical analysis deals with the performance of new growth curve in terms of conclusiveness. The second part is mainly to evaluate the pro poor scenarios of India for the last two decades. The chapter is concluded in section 4.5.

4.2 Preliminaries

In this section we shall have a very brief discussions on three aspects that will be essential for derivation of our main analytical results. Firstly we shall formally introduce concepts of stochastic and inverse stochastic dominance.[3] We shall then move to definitions of absolute and relative pro poor growth curves and relate this to stochastic dominance ordering. Lastly we shall have a discussion on Equally distributed equivalent growth rate. Before introducing these concepts formally, we would like to introduce some notations that we will follow throughout this chapter.

In a society, let at time point t and t-1, $y_t = (y_1^t, y_2^t ... y_n^t) \in \mathbb{R}^n_{++}$, and $y_{t-1} = (y_1^{t-1}, y_2^{t-1} ... y_m^{t-1}) \in \mathbb{R}^m_{++}$, be the vectors of incomes arranged in ascending order. Throughout this chapter our target is to evaluate whether movement of income profile y_{t-1} to y_t is pro poor or not. Let $F_t(y)$ be the empirical distribution function, representing proportion of individuals with income $\leq y$. In some cases we shall also

[3]Stochastic and inverse stochastic dominance has already been introduced in the previous chapter. However, we define this concepts here once again since we shall use these ideas frequently in the analytical derivations.

represent the distribution function as $F(y_t)$, where y_t denotes the underlying domain of the distribution function. Consider $y_t^p = F_t^{-1}(p) = inf\{y : F_t(y) \geq \ p\}$ as the p^{th} income quantile of the income distribution at time point t. Let, $\mu_t = \int_0^1 y_t^p dp$, be the mean income of the society at time t, and $g = log(\mu_t) - \log(\mu_{t-1}) = \Delta log(\mu_t)$ as the growth rate of mean.[4]

4.2.1 Stochastic and inverse stochastic dominance

If y_t is defined on a continuum, the recursive integral for the distribution function may be written as $F_t^{r+1}(y) = \int_0^y F_t^r(s)\, ds \ \forall s \ \in [0, \infty)$ where r is a positive integer $(r \geq 0)$.[5] Stochastic Dominance (SD) and Inverse Stochastic Dominance (ISD) have remained the major tools of partial ordering approaches, including partial pro poor ordering analysis. The main analytical results of this chapter are also based on this techniques.

Definition 1 ***Stochastic dominance (SD):*** *$F(y_t)$ stochastically dominates $F(y_{t-1})$ by r+1 th order/degree i.e $F(y_t) \succ_{r+1} F(y_{t-1})$ if $F_t^{r+1}(s) \leq F_{t-1}^{r+1}(s) \forall \ s \ \in [0, \infty)$, & $<$ for at least one s.*

Instead of considering a distribution function, the same purpose might be solved using the inverse distribution function. Let $F_t^{-(r+1)}(p) = \int_0^p F_t^{-(r)}(p)\, dp$ where $r \geq 0$ is an integer.[6]

Definition 2 ***Inverse Stochastic dominance (ISD):*** *$F(y_t)$ dominates $F(y_{t-1})$ by (r+1)th order/degree Inverse Stochastic Dominance i.e $F(y_t) \succ_{-(r+1)} F(y_{t-1})$ if $F_t^{-(r+1)}(p) \geq F_{t-1}^{-(r+1)}(p) \ \forall p \in [0, 1]$ & $>$ for at least one p.*

[4]Throughout this chapter we shall denote the operator Δ as difference of the function between time point t and t-1; e.g $\Delta x_t = (x_t - x_{t-1})$

[5]For $r = 0$, $F_t^1(y)$ denotes the underlying cumulative distribution function.

[6]For expressions of $F_t^{r+1}(y)$ and $F_t^{-(r+1)}(p)$ on discrete domain, See Chakravarty (2009)

SD and ISD are nested, i.e lower order implies higher order dominance. However, the reverse is not necessarily true. SD implies ISD and vice versa only for $r < 2$. For further details on these issues, See Hadar and Russell (1969).

4.2.2 Absolute and Relative Pro poor growth

We will now formally introduce the concepts of absolute and relative pro poor growth. In a nutshell a growth is said to be pro poor in an absolute sense if it raises the income of the poor Kraay (2006). It may also be defined as follows :

Definition 3 ***Absolute Pro Poor growth :*** *A change from y_{t-1} to y_t is said to be pro-poor in an absolute sense whenever as a result of growth, poverty declines, for some choice of a poverty measure.(Kraay, 2006).*

Consider $g > 0$, and for a given poverty index and poverty line, if poverty declines we would say growth is pro poor in an absolute sense, following a complete pro poor ordering approach. The absolute pro poor growth might be accessed by considering the growth elasticity of poverty, which measures the percentage change in poverty as a result of increment of 1% growth. Thus, following the above definition, if the elasticity is negative, growth is considered to be pro poor. However, as a result of choice of a different poverty index or poverty line might alter the result. In order to rule out these inconsistencies, Ravallion and Chen (2003), considered a partial ordering approach based on first order SD and proposed Growth Incidence Curve (GIC). GIC is the rate of change of y_t^p, which can be represented as $GIC(p) = \Delta log(y_t^p)$. If $GIC(p) \geq 0 \; \forall \; p \;\&\; > 0$ for at least one p we refer the situation as pro poor growth or $GIC(p) \succ \; 0$. Whereas $GIC(p) \leq 0 \; \forall \; p \;\&\; < 0$ for at least one p the situation is defined as Anti poor growth or $GIC(p) \prec \; 0$. Son (2004) considered poverty growth curve (PGC) on the basis of second order stochastic dominance. The proposed growth curve is the rate of change of generalized Lorenz curve of two distributions, $PGC = \Delta log(\mu_t^p)$, where μ_t^p might also be interpreted as the mean of poorest $100p\%$

of population. Since, GIC and PGC are respectively based on first and second order stochastic dominance, conclusive ordering of these curves would also imply decline of poverty for a wide range of poverty index and also poverty line (See, Atkinson, 1987, for further details).

Kakwani and Pernia (2000) introduced the concept of relative pro poor growth, where the focus is mainly based on the income growth rate of the poor. The formal definition may be written as follows

Definition 4 ***Relative Pro poor growth :*** *A movement from y_{t-1} to y_t is said to be pro poor in a relative sense, if the growth rate of income of poor is greater than that of the non poor.(Kakwani and Pernia, 2000)*

It should be noted that the above definition remains unchanged, even if we simply replace "*growth rate of the non poor*", by the growth rate of average income the society. The relative versions of GIC and PGC might be obtained by considering its deviation from growth rate of mean income. Further following Nssah (2005) these curves may also be related to the Lorenz curve. Thus

$$\begin{aligned} g_1 &= GIC - g = \Delta L_t'(p) \\ g_2 &= PGC - g = \Delta L_t^p \end{aligned} \tag{4.1}$$

where L_t^p and $L_t'(p)$ stand for Lorenz curve and slope of Lorenz curve respectively. Thus growth is pro poor following GIC and PGC in a relative sense, if and only if the slope of the lorenz curve and lorenz curve does not cross respectively. The ordering g_1 and g_2 might also be obtained following a normalization approach suggested by Duclos (2009). If we normalize income of all individuals at time point t and $t-1$ by their respective means and denote the domains $\bar{y}_t$ and $\bar{y}_{t-1}$ respectively, it can be shown that GIC and PGC ordering, will essentially lead to g_1 and g_2 ordering, where

$$\begin{aligned} \bar{y}_t &= \{y_t^1/\mu_t, y_t^2/\mu_t, ..y_t^n/\mu_t\} \\ \bar{y}_{t-1} &= \{y_{t-1}^1/\mu_{t-1}, y_{t-1}^2/\mu_{t-1}, ..y_{t-1}^n/\mu_{t-1}\} \end{aligned} \tag{4.2}$$

It should be noted that the approach suggested by Duclos (2009) is more general in the sense that the normalization is not necessary to be by the mean income of the society. It may be any summary statistics, which the policy maker is actually interested in, e.g Median, Percentiles etc.. However, in order to make it comparable with relative versions of the GIC and PGC ordering defined in 4.1, we consider the pro poor standard as mean income.

4.2.3 Equally Distributed Equivalent Growth Rate

Nssah (2005) considered a complete ordering approach and defined Equally Distributed Equivalent Growth Rate(EDEGR) as growth rate socially equivalent to the observed growth for some choice of the focal parameter which captures the degree of inequality. EDEGR might be considered as the weighted average of the points of GIC

$$\zeta = \int_0^1 v(p)\Delta log(y_t^p)dp = \lambda\bar{v}\left(1 - \frac{cov\left(\Delta\tilde{y}_t^p, v(p)\right)}{-\lambda\bar{v}}\right) \tag{4.3}$$

where $v(p)$ is the weight attached to p^{th} quantiles and $\bar{v} = \int_0^1 v(p)dp$, λ being the growth rate of geometric mean or average growth rate of societies. The operator "cov" denotes the covariance of two variables. Nssah considered weights as $v(p) = v(1-p)^{v-1}$, where v is an indicator of aversion of inequality. The choice of specific weight function leads to $\bar{v} = 1$, thus from equation 4.3, ζ takes the form of EDEGR, almost similar to Equally Distributed Equivalent Income proposed by Atkinson (1970). However, for any choice of weight function $w(p) = v(p)/\bar{v}$, EDEGR might be obtained from 1 provided $\bar{v} \neq 0$, and finite.

Thus from 4.3 we can write

$$\zeta^* = \lambda\left(1 - \frac{cov\left(\Delta\tilde{y}_t^p, w(p)\right)}{-\lambda}\right) \tag{4.4}$$

A relative version of EDEGR might also be obtained following its deviation from the average growth rate. Nssah (2005) termed it as distributed adjusted factor (DAF).

$$\begin{aligned} DAF &= \zeta^* - g \\ &= \int_0^1 w(p)\Delta log(y_t^p/\mu_t)dp \end{aligned} \tag{4.5}$$

It is possible to obtain the DAF dominance, similar to g_1 and g_2 ordering, by considering the normalization approach suggested by Duclos (2009). However, we have to consider a logarithmic transformation of all the points of domain $\bar{y}_t$ and $\bar{y}_{t-1}$. Let the new domain is defined as $\bar{l}_t$ and $\bar{l}_{t-1}$, where

$$\begin{aligned} \bar{l}_t &= \{log(y_t^1/\mu_t), log(y_t^2/\mu_t), ..log(y_t^n/\mu_t)\} \\ \bar{l}_{t-1} &= \{log(y_{t-1}^1/\mu_{t-1}), log(y_{t-1}^2/\mu_{t-1}), ..log(y_{t-1}^n/\mu_{t-1})\} \end{aligned} \tag{4.6}$$

In the next section we shall introduce our first main result on the generalization of EDEGR in a partial ordering sense. It should be noted that EDEGR is based on the anonymity axiom of growth profiles. Hence it remains invariant with respect to permutations of initial and final incomes, which also amounts to paying no attention to the possible re-ranking of individuals caused by the distributional change (See Grimm, 2007, for further details). Further as a result of this property, growth can be deemed to be pro-poor even if some of the initial poor are penalized by the change. For the sake of simplicity we have also considered the anonymity assumption. A future research plan in this direction might be to generalize EDEGR without the anonymity axiom.[7]

[7]Note that empirical applications with relaxation of the anonymity condition is possible only when we have repeated cross sections over time or panel data of individual incomes. However, in large developing countries like India, panel data on individual level are usually not available. Results derived in this chapter shall be useful for such applications.

4.3 A new dominance result

In this section we shall introduce a new dominance result, based on the restrictions of the weight function on an ethical point of view. Since, EDEGR is weighted average of all income quantile, our domain of interest will be logarithmic income denoted by $\tilde{y}_t = \{log(y_1^t), log(y_2^t)...log(y_n^t)\}$. Essentially we establish relationship between EDEGR dominance and inverse stochastic dominance based on this domain. Before introducing the dominance results and discussing on the restrictions necessary on the weight function, we formally introduce the concept of EDEGR dominance as follows.

Definition 5 ***EDEGR Dominance :*** *For a class of weights $W_R \in W$ that satisfies properties* R*, EDEGR dominance occurs when $\zeta^*(w) \geq 0 \; \forall w \; \in W_R$ and $\zeta^*(w) > 0$ for at least one $w \in W_R$ or $\zeta^*(w) \succ 0$.*

4.3.1 Restrictions on EDEGR

The first restriction we would like to impose is similar to the monotonicity property of a poverty index. We will consider the case, such that, if there is positive growth for at least one quantile given other quantiles remains unchanged, growth rate must not be anti pro poor. Let x be the growth profile consisting of all the points of GIC, and x_i denotes the GIC for the i^{th} quantile. Let D^n denotes the set of all growth profiles and $N = \{1, 2..n\}$ denotes the set of integers of order n, where n is the number of quantiles.

Axiom 1 ***Week Monotonicity (WM) :*** $\forall x \in D^n, \; \forall \; i, j \in N, \;\; x_j > 0, \;\; \& \; x_i \geq 0, \; \forall j \; \neq i \implies EDEGR(x) \geq 0.$

The second restriction is essentially on the line of transfer axiom as proposed in the inequality literature. It is likely that in a society, a rank preserving progressive (regressive) transfer of income from the richer to poorer quantile, would lead to an increase (decrease) of EDEGR.[8] The definition of rank preserving transfer might be formally written as follows[9]

Definition 6 ***Rank Preserving Transfer(RPT) :*** *Let $x, z \in D^n$ be the growth profiles, x is obtained from z by a rank preserving Transfer, if for some i, j $(i < j)$ & l such that $x_l = z_l$, $\forall l \neq \{i, j\}$, $x_i - z_i = z_j - x_j = \delta$, where $\delta \leq \frac{z_j - z_i}{2}$ if $j = i+1$ and $\delta \leq min\{(z_{i+1} - z_i), (z_j - z_{j-1})\}$ if $j > i+1$.*

The transfer is progressive and regressive if $\delta > 0$ and $\delta < 0$ respectively. Let $x(i, j)$ denotes that in a growth profile x, a RPT takes place from j to i. The transfer is progressive and regressive if $j > i$ and $j < i$, respectively.

Axiom 2 ***Week Transfer Principle (PT) :*** *$\forall x \in D^n$, $\rho \in N$ and $1 < \rho < n$, $EDEGR(x(i+\rho), i) \geq EDEGR(x)$ and $EDEGR(x(i, i+\rho)) \leq EDEGR(x)$.*

Our next axiom will be introduced mainly to consider the fact that transfer will be valued more if it takes place at the bottom of the distribution.

Axiom 3 ***Week Principle of Positional Version of Transfer Sensitivity(PPTS) :*** *$\forall x \in D^n$, $\rho, i, l \in N$ and $1 \leq \rho \leq n - l$, $i < l$, then $EDEGR\big(x(i, i+\rho)\big) \geq EDEGR\big(x(l, l+\rho)\big)$ and $EDEGR\big(x(i+\rho, i)\big) \leq EDEGR\big(x(l+\rho, l)\big)$.*

We will use the following lemma that essentially establish the relationship between the weights function of EDEGR and the axioms discussed above.

Lemma 1 *Any EDEGR satisfies WM if $w(p) \geq 0$, satisfies PT if $w(p)$ is differentiable and $w'(p) \leq 0$ and satisfies PPTS if $w(p)$ is twice differentiable and $w''(p) \geq 0$.*

[8] It is difficult to imagine the transfers between the quantiles. However, using this axiom, comparison of pro poor growth performances between different societies is possible.

[9] See Chakravarty (2009) page 3 for details.

Let the class of weight functions be represented as

$$w_1(p) = \{w(p) \in W : w(p) \geq 0\} \tag{4.7}$$

$$w_2(p) = \{w(p) \in W : w(p) \geq 0 \; \& \; w'(p) \leq 0\} \tag{4.8}$$

$$w_3(p) = \{w(p) \in W : w(p) \geq 0, \; w'(p) \leq 0 \; \& \; w''(p) \geq 0\} \tag{4.9}$$

For w_1 EDEGR satisfies WM, for w_2 WM and PT and lastly for w_3 WM, PT and PPTS. Using the above set of weight functions, we will now introduce our first main result of the article, that essentially establish a partial ordering of EDEGR dominance and inverse stochastic dominance.

Theorem 1 $\zeta^*(w_i) \succ 0$ *iff* $F(\tilde{y}_t) \succ_{-i} F(\tilde{y}_{t-1})$ $\forall i \in \{1,2,3\}$ *and additionally* $\lambda \geq 0$ *for i=3.*

where λ is the growth rate of geometric mean. Even if $\lambda < 0$, but $\hat{g} \succ 0$, EDEGR dominance is obtained. For example, if one sets weights for the richest quantile as 0 i.e $w_4 = \{w(p) \in W : w(p) \geq 0, \; w'(p) \leq 0, \; w''(p) \geq 0 \; \textit{and} \; w(1) = 0\}$ then $\hat{g} \succ 0 \Rightarrow \zeta^*(w_4) \succ 0$. Weights adopted by Nssah (for $v \geq 2$) is a subset of w_4. It should be further noted that since ISD are nested, would imply EDEGR dominance derived in this article are also nested. Thus our next corollary as a by product of Theorem 1 :

Corollary 1 *Lower order EDEGR dominance implies higher order, however, the reverse is not essentially true.*

It is important to emphasize that, the 3rd order EGEDR dominance, will be most robust in terms of conclusiveness. For the empirical application of the third order EDEGR dominance, in the next section we shall introduce a new pro poor growth curve.

4.3.2 A new pro poor growth curve

The dominance result derived in the previous section, essentially are based on ISD on log transformed incomes. The empirical applications of the first and second order EDEGR dominance might be easily obtained constructing GIC and PGC on this domain. For application of the third order EDEGR dominance, we propose a new growth curve as the change of gini social welfare functions of logarithmic income for the poorest 100p% of population. The gini social welfare function also known as Sen's welfare function, is the product of mean and one minus gini coefficient thus captures notions of both equity and efficiency. Thus the new growth curve is written as $\hat{g} = \Delta w_t^p = \Delta\tilde{\mu}_t^p(1 - \tilde{g}_t^p)$, where w_t^p, $\tilde{\mu}_t^p$ and $\tilde{g}_t^p$ are the gini social welfare function, mean and gini coefficient respectively of logarithmic incomes for the poorest 100p% of population. We will use a result of Zoli (1999) in order to establish relationship between ISD and $\hat{g}$.

Lemma 2 *If* $\hat{g} \succ 0 \iff F(\tilde{y}_t) \succ_{-3} F(\tilde{y}_{t-1})$

Our next target is to relate GIC, PGC and $\hat{g}$ ordering. Since, the domain of the first two curves are different from that of $\hat{g}$, we will consider our next Lemma in order to relate them. We have derived this result partially using the relationship between SD and Welfare dominance by Foster and Shorrocks (1988a,b), which we consider as our next Lemma.

Lemma 3 $F(y_t) \succ_{-2} F(y_{t-1}) \implies \int_0^1 u(y_t)dF > \int_0^1 u(y_{t-1})dF$ *where* u *is twice differentiable and* $u' > 0$ *and* $u'' < 0$ *(Foster and Shorrocks, 1988a,b)*

Using the above Lemma[10], we derive a new lemma, which basically relates the EDEGR dominance on log transform domain and income domains.

[10] For income domain being continuous the result was derived in Foster and Shorrocks (1988a), while for discrete domain Foster and Shorrocks (1988b).

Lemma 4 *$GIC \succ 0 \iff F_t(\tilde{y}_t) \succ_{-1} F_{t-1}(\tilde{y}_{t-1})$ and $PGC \succ 0 \Rightarrow F_t(\tilde{y}_t) \succ_{-2} F_{t-1}(\tilde{y}_{t-1})$*

Using Lemma 4 and nested property of ISD, it can be shown that PGC ordering might be considered as a sufficient case for $\hat{g} \succ 0$. However, the reverse is not true, thus the new growth curve provides conclusive results in many cases where both GIC and PGC fails to do so. Hence,

Proposition 1 *If $PGC \succ 0 \Rightarrow \hat{g} \succ 0$*

Although, the new growth curve provides conclusive results in cases the PGC fails to do so. However, it should be noted that unlike PGC where pro poor growth and poverty indexes might be related, it is not possible for the new growth curve. The rationale, for the choice of this curve, is that the third order EDEGR dominance is obtainable using the new growth curve. A conclusive $\hat{g}$ ordering is sufficient to say that growth is pro poor at least for the class of EDEGR as suggested by Nssah defined in equation 4.4, for $v \geq 2$.

4.3.3 Relative Pro-poor growth

So far our discussion was based on the absolute notion of pro poor growth. It is possible to extend the dominance condition also in the context of relative pro poor ordering. Similar to EDEGR dominance, DAF dominance might also be considered provided domain is considered as $\bar{l}_t$ (See equation 4.6).

Let $\bar{l}_t^p$, denotes the p^{th} quantile based on $\bar{l}_t$. Thus the next theorem essentially establish relationship between DAF dominance and inverse stochastic dominance on the domain $\bar{l}_t$. Like third order EDEGR dominance an extra condition is also required for DAF dominance $\beta = \int_0^1 \Delta \bar{l}_t^p dp \geq 0$, which again can be relaxed for choice of w_4.

Theorem 2 *For any EDEGR with weights being w_j, $DAF(w_j) \succ 0$ iff $F_t(\bar{l}_t) \succ_{-j} F_{t-1}(\bar{l}_{t-1}) \forall j \in 1, 2$ and $DAF(w_3) \succ 0$ iff $F_t(\bar{l}_t) \succ_{-3} F_{t-1}(\bar{l}_{t-1})$ and $\beta \geq 0$.*

Like the EDEGR dominance results our next corollary will essentially imply DAF dominance is also nested.

Corollary 2 $DAF(W_1) \succ 0 \Rightarrow DAF(w_2) \succ 0 \Rightarrow DAF(w_3) \succ 0.$

The third order DAF dominance is the most general in terms of conclusiveness. It might be obtained by computing $\hat{g}$ on $\bar{l}_t$, or might also be accessed by considering the curve $g_3 = \hat{g} - g$. The g_3 curve might also be related to g_1 and g_2 defined in 4.1.

Proposition 2 $g_1 \succ 0 \implies g_2 \succ 0 \implies g_3 \succ 0.$

Essentially the proposition shows that g_3 might conclude in many situations where g_1 and g_2 fails to do so. A conclusive ordering of the g_i curve would imply conclusive ordering of $g_j \forall \{i, j\} \in 1, 2, 3$ and $i < j$.

We will now investigate on the relationship between DAF dominance and EDEGR dominance. Our next proposition essentially says that DAF dominance is a sufficient condition for EDEGR dominance if the growth rate of mean $g > 0$. On the other hand, DAF dominance will always hold if EDEGR dominance occurs provided $g < 0$. Hence our next proposition

Proposition 3 *If* $g > 0,\ DAF \succ 0 \implies EDEGR \succ 0$ *and if* $g < 0,\ EDEGR \succ 0 \implies DAF \succ 0.$

In the next section we will consider the performances absolute and relative versions of GIC, PGC and the newly proposed growth curves empirically.

4.4 Empirical analysis

Our aim in this section is twofold. Firstly, using major states of rural and urban India, we will analyze the performances of GIC, PGC and $\hat{g}$ along with their relative versions $g_1,\ g_2$ *and* g_3. Secondly, we shall discuss on pro poor scenarios of rural and urban

India, mainly for the last two decades. In continuation with the previous two chapters we shall also use Monthly per capita expenditure (MPCE) on a mixed recall period basis, from National Sample Survey Office (NSSO) consumer expenditure rounds. We shall use five consecutive NSSO rounds data on consumer expenditure vij 43rd, 50th, 55th, 61st and 66th, which provides information's respectively for the period of July 1987 - June 1988, July 1993 - June 1994, July 1999- June 2000, July 2004-June 2005, and July 2009-June 2010. In fact our analysis would also based on the same variable Monthly per capita income on a mixed recall period basis (MPCE).[11]

In order to account for the price adjustments, we have adjusted MPCE of rural India using consumer index for agricultural laborer (CPIAL), whereas consumer price index for Industrial workers(CPIIW) for urban India.[12] For both the state and all India study we consider the number of quantiles chosen as 20.

4.4.1 Performance of GIC, PGC and $\hat{g}$

We will evaluate the performance of both absolute and relative versions of GIC, PGC and the newly proposed growth curves, using 20 states for rural India and 17 for Urban states of India. The number of years considered in this study is 5. We consider all possible combinations of state and year.[13] Thus we have altogether 4950 and 3570 pairs of distribution respectively for rural and urban India for this comparison.

[11]Recall that in Chapter 2 and 3 we have considered only data for 61 st and 66 th round. Comparison in terms of survey design is same for all the rounds. However, 55th rounds contains information of both 7 days and 30 days recall period and is likely to create problems in comparability issues. See Deaton et al Deaton and Kozel (2005). Although there are several methodologies available for the adjustments of this recall error, we will not consider these complexities for the sake of simplicity.

[12]The same procedure was also used in the chapter 3.

[13]Note that ideally pro poor growth should have been computed for same state over any two period. In that case we would end with only 200 and 170 rural and urban comparison exercise. Even in that analysis the results remains more or less same. However, to increse the number of observations exercises we consider all possible comparison exercises in this case, e.g., Bihar 61st round *verses* Madhya Pradesh 55 th.

For each states, we compute GIC, PGC and $\hat{g}$ following the MPCE as obtained from the five consecutive NSSO rounds. In Table 4.1, we have reported the number of pro poor, anti poor, inconclusive and inconsistent conclusive (IC) cases along with the percentage of conclusive cases (CC). IC refers to the number of cases where lower order dominance provides conclusive result but the higher order fails to do so. Theoretically this is not possible, it arises due to choice of small number of income quantiles.[14] If the number of quantiles is increased substantially, the conclusive results as shown by GIC and/or PGC in these cases eventually turns out to be inconclusive.

The last column of Table 4.1 refers to the percentage of conclusive cases, excluding IC. GIC provides conclusive statements nearly about 40% cases in both rural and urban India. However, the performance of its relative version g_1 is very poor and provides less than 1% cases in both rural and urban India. PGC on the other hand provides conclusive statements on 80% cases, but its relative version performs poorly and more than 40% cases remains as inconclusive. The performance of the newly proposed growth curve is not only better in terms of the absolute sense but also in a relative sense. For both the cases, it is possible to conclude in more than 80% cases.

4.4.2 Pro poor evaluation in Rural and Urban India

Our target in this part is to see whether the evidence of sustained GDP growth in India is favorable to the poor or not. Growth process started mainly on the 1990s when liberalization took place in India, and policies changed substantially at that point.[15] Using NSSO data for the last five quinquennial rounds, we will evaluate the

[14]It has been observed that for all these cases the inconsistency arises at the lowest quantiles.

[15]In the 1980's India lacked the confidence of international community on her economic viability, and the country found it increasingly difficult to borrow internationally. Since, after early 1990s, a structural change took place in policies, like loosening government regulations, especially in the area of foreign trade. Many restrictions on private companies were also lifted, and new areas were opened to private capital. There had been a strong opposition of these policies, especially among the trade unions belonging in the left wing. However, Indian GDP has been steadily increasing after

pro-poor all possible spells of rural and urban India. Since, one of our data point is before 1990 (43rd round), we thus also have the opportunity to evaluate pro poor scenarios before and after liberalization.

All comparison results has been provided in Table 4.2. It is readily observable that, for both rural and urban India, growth is pro poor in an absolute sense, following PGC and $\hat{g}$. GIC fails to provide conclusive results in almost all cases. However, it has been observed that in almost all the cases inconsistency arises due to a negative value in the last quantile. Since, the last quantile in GIC is the growth rate of the maximum values, there is every possibility that the inconsistency arises due to presence of outliers in the data.[16]

Following g_3, it has been observed for any comparison of other rounds with the pre liberalization period, growth is pro poor in relative sense in the rural India. The conclusion remains same even if we simply replace the data point by just after the period of liberalization i.e 1993-94. However, for the remaining spells of comparisons, growth is favorable to the rich.

Pro poor scenario in urban regions of India, are almost opposite to that of her rural regions. Here, we get six out of the ten cases as anti poor in a relative sense. Only in one case i.e. for 55 th *verses* 43 rd round, following g_3 we found growth is pro poor in a relative sense. However, since there are comparability problems of the 55th round data, this result should be reported with caution. An example of inconsistent conclusive case might be observed in the comparison of 55 *verses* 43 round. In this case although the relative PGC provides conclusive result, but the newly proposed fails to do so. Perhaps a better way to deal this situations is to consider different statistical tests for Stochastic dominance that has been proposed in the literature.

these changes.

[16]The inconclusive situations of GIC, might be concluded using a technique called restricted stochastic dominance. Income of the richer individuals thus have to be censored by a constant usually by poverty line. It is possible to obtain conclusive results by GIC, using such restricted analysis.

We consider this as our future research plan.

4.5 Conclusion

The main contribution of the chapter is to generalize the Equally distributed equivalent growth rate (EDEGR) originally proposed by Nssah (2005), in a partial ordering approach. EDEGR may be represented as the weighted average of the points of growth rate of income quantiles, where the weights has been restricted to the class of relative extended gini type(See, Yitzhaki, 1983). We have introduced three types of EDEGR dominance based on the restrictions of the weights. For the first order EDEGR dominance we restricts weights to be non negative for all quantiles. For second order order EDEGR dominance we additionally need weights to be differentiable in the quantiles, with negative first derivative. Furthermore we need additionally positive second derivative for the third order dominance. The axiomatic properties of these weights has been studied borrowing some standard welfare axioms from the literature. We have shown that first, second and third order EDEGR dominance are equivalent to inverse stochastic dominance of logarithmic incomes of one distribution over the other of same order.

Our second contribution is introduction of a new pro poor growth curve based on the change of Gini social welfare function on the quantiles of logarithmic income. For empirical applications of third order EDEGR dominance this growth curve can be used. If the growth curve provides conclusive results then a wide range of EDEGR index including that of Nssah (2005) implies growth is pro poor. Previously there has been evidence of wide usage of two popular pro poor growth curves, namely, the Growth incidence curve(GIC)(Ravallion and Chen, 2003) and Poverty Growth Curve(PGC)(Son, 2004). GIC and PGC provides conclusive results when there is first and second order dominance for incomes of one distribution over the other. It has been established that, in spite of the fact that the domain of the growth curves being different, conclusive GIC/PGC appears to be a sufficient condition for the ordering of newly proposed growth curve. Furthermore it has been shown that the newly proposed growth curve may provide conclusive results in many cases where GIC/PGC fails to do so.

We have considered an empirical exercise to analyze the performance of the newly proposed growth curve along with its relative version. We have used data for Monthly per capita expenditure for the major states of India following five consecutive NSSO quinquennial rounds, vij 43rd, 50th, 55th, 61st and 66th round. The surveys was conducted respectively for the periods 1987-88, 1993-94, 2004-05 and 2009-10. Our results show that the absolute and relative version of the newly proposed growth curve provides conclusive results nearly in 80% of the cases. The same percentages for absolute and in particular the relative version of PGC and eventually for GIC are much less.

We have also considered an empirical exercise in order to address whether the growth process started in the early 1990s is pro poor or not. Instead of considering subgroups of rural and urban states of India, this exercise is based on the full sample of rural and urban India. Thus for the five data points we have 10 spells of comparisons separately for each sector. For adjustments of prices, we have transformed incomes of all individuals to that of 61st round. For price adjustments we have used the Consumer Price Index of Agricultural Labor in rural India and that of Industrial Workers in urban India. It has been observed that, growth is, in general, pro poor in an absolute sense in both rural and urban India, for all the spells of NSSO rounds. This is similar to the findings of the previous chapter. However, the relative pro-poor growth reveals exactly opposite conclusion, especially in the case of urban India. Growth is anti poor, in a relative sense, in all the comparisons made for urban India. This implies that the poorer section of the society gains much lesser compared to the richer households. In fact, such conclusions have also been observed in rural India, following the recent rounds of comparison i.e., the 61st *verses* 66th rounds.

In the empirical analysis, we found that in a very few cases, lower order dominance provides conclusive results, but higher order fails to do so. This arises due to choice of low number of income quantiles, and the inconsistency disappears once we increase the number of quantiles. We refer these cases as inconsistent conclusive results. A future research program in this direction will be to derive the asymptotic properties of the newly proposed curves, and on the construction of the confidence intervals.

4.6 Appendix

Proof of Theorem 1

Proof : For $i = 3$ the proof is similar to Zoli (Zoli, 1999) on Yaris social welfare function and ISD. We will prove for $i = \{1, 2\}$

Case 1 : i=1

(Sufficiency) If $F(y_t) \succ F(y_{t-1}) \iff GIC \succ 0 \iff \Delta log(y_t^p) \succ 0$, since $w(p) \geq 0$, thus $\zeta^*(w_1) = \int_0^1 w(p)\Delta log(y_t^p)dp \geq 0$. Clearly if $w(p) > 0 \ \forall p \in [0, 1] \Rightarrow \zeta^* > 0$.

Necessary : We begin with the assumption, that, GIC fails to provide conclusive results. Thus in interval $u_1 = (\bar{p}, \bar{\bar{p}}) \subset (0, 1)$, $GIC(p) < 0 \forall p \in u_1$ and $> 0 \forall p \in [0, 1] - u_1$. Consider the following weight function

$$\begin{aligned} w(p) &= a > 0 & \forall p \in (0, \bar{p}) \\ &= b > 0 & \forall p \in (\bar{p}, \bar{\bar{p}}) \\ &= c > 0 & \forall p \in (\bar{\bar{p}}, 1) \end{aligned}$$

Considering the weight structure mentioned above we get the following expression for $\zeta^* = a\int_0^{\bar{p}} \Delta log(y_t^p)dp + b\int_{\bar{p}}^{\bar{\bar{p}}} \Delta log(y_t^p)dp + c\int_{\bar{\bar{p}}}^1 \Delta log(y_t^p)dp$. Clearly for b chosen very high and low compared to a and c, would lead to $\zeta^* < 0$ and $\zeta^* > 0$ respectively. The last part $F_t(\tilde{y}_t) \succ_{-1} F_{t-1}(\tilde{y}_{t-1}) \iff F_t(y_t) \succ_{-1} F_{t-1}(y_{t-1})$ is trivial and is left to the reader.

Case 2 : i=2

(Sufficiency) Integrating by parts ζ^* we get

$$\zeta^* = \int_0^1 \Delta log(y_t^p)dp - \int_0^1 w'(p)\left(\int_0^s \Delta log(y_t^s)ds\right)dp \tag{4.10}$$

$F_t(y_t) \succ_{-2} F_{t-1}(y_{t-1}) \Rightarrow \int_0^s \Delta log(y_t^s)ds \geq 0 \forall s$ and > 0 for some s. Thus the second term is always > 0 given $w'(p) \leq 0$. Since the first term is always positive whenever $F_t(y_t) \succ_{-2} F_{t-1}(y_{t-1})$ holds. Hence $\zeta^* \geq 0$. Choosing weights such that $w'(p) < 0 \ \forall p \in [0, 1]$, would always lead to $\zeta^* > 0$.

Sufficient : Let $F_t(y_t) \not\succ_{-2} F_{t-1}(y_{t-1})$, consider the following weight functions

$$
\begin{aligned}
w(p) &= a - L_1 p > 0 && \forall p \in (0, \bar{p}) \\
&= b - L_2 p > 0 && \forall p \in (\bar{p}, \bar{\bar{p}}) \\
&= c - L_3 p > 0 && \forall p \in (\bar{\bar{p}}, 1)
\end{aligned}
\tag{4.11}
$$

where all the parameters a, b, c, L_1, L_2 and L_3 are positive. From 4.10 we can always get $\zeta^* < 0$ and $\zeta^* > 0$ for choice of high and low values of L_2, provided a, b, c L_1 and L_3 has been restricted accordingly. Hence EDEGR dominance breaks.

Proof of Theorem 2

Proof : Similar to Theorem 1.

Proof of Lemma 3 : For domain being continuous see Foster and Shorrocks (1988a), while domain being discrete see Foster and Shorrocks (1988b).

Proof of Lemma 4

Proof : The first part i.e $GIC \succ 0 \iff \hat{g} \succ 0$ is trivial and is left to the author.

For the second part essentially, have to show $F(y_t) \succ F(y_{t-1}) \Rightarrow F(\tilde{y}_t) \succ F(\tilde{y}_{t-1})$. Consider, income profiles are discrete (for the sake of simplicity) and population size being fixed.

$$F(y_t) \succ F(y_{t-1}) \Rightarrow \sum_{i=1}^{i} y_t^i \succ \sum_{i=1}^{i} y_{t-1}^i \tag{4.12}$$

Similarly, considering logarithmic income domain

$$F(\tilde{y}_t) \succ F(\tilde{y}_{t-1}) \Rightarrow \sum_{i=1}^{i} \tilde{y}_t^i \succ \sum_{i=1}^{i} \tilde{y}_{t-1}^i \Rightarrow \prod_{i=1}^{i} y_t^i \succ \prod_{i=1}^{i} y_{t-1}^i \tag{4.13}$$

We shall show 4.12 $\Rightarrow$ 4.13, by method of induction. For $n = 1$, it would be a trivial exercise. For $n = 2$, if 4.12 holds we can write

$$y_t^1 \geq y_{t-1}^1 \tag{4.14}$$

$$y_t^1 + y_t^2 \geq y_{t-1}^1 + y_{t-1}^2 \tag{4.15}$$

with strict inequality for at least one case.

If $y_{t-1}^2 \leq y_t^2$ it would be once again a trivial exercise to show that $y_t^1 y_t^2 \geq y_{t-1}^1 y_{t-1}^2$. For $y_{t-1}^2 > y_t^2$ we replace the maximum value of y_{t-1}^2, following 4.15 can written as $z_{t-1}^2 = y_t^1 + y_t^2 - y_{t-1}^1$. It can be shown

$$y_t^1 y_t^2 \geq y_{t-1}^1 z_{t-1}^2 \tag{4.16}$$

whenever 4.14 holds. Clearly, if we consider any smaller value than z_{t-1} the inequality would always hold. For $n = 3$ the same results can also be proved easily.

Without loss of generality assuming the equivalence is established for $n = k$, where k is any integer and $k > 3$. We will establish the relationship for $n = k + 1$.

Clearly, the conditions implies a generalized Lorenz dominance of income distribution t over t-1. Following Lemma 3 $\sum_1^{k+1}(u(x_t) - u(x_{t-1})) > 0$, for any $x > 0, u'(x) > 0$ & $u''(x) < 0$. Putting $u(x) = log(x)$ satisfies both the conditions. Hence we can write $\sum_{i=1}^{k+1}(y_t^i - y_{t-1}^i) > 0 \Rightarrow \prod_{i=1}^{k+1} y_t^i > \prod_{i=1}^{k+1} y_{t-1}^i$. Hence proved.

If population size is not fixed, let y_t^m and y_{t-1}^n be m times replication of all individuals of the first distribution and n times replication of all individuals in the second distribution. It is well known that stochastic dominance relationship are replication invariant, thus $F_t(y_t) \succ_{-r} F_{t-1}(y_{t-1}) \iff F_t(y_t^m) \succ_{-r} F_{t-1}(y_{t-1}^n)$, r being an integer. Thus the analysis again might be thought as a comparison exercise on fixed population size.

Proof of Proposition 1

Proof : Following Lemma 4 we can write $PGC \succ 0 \implies F(\tilde{y}_t \succ_{-2} F(\tilde{y}_{t-1})$. Since, ISD is nested $F(\tilde{y}_t \succ_{-2} F(\tilde{y}_{t-1}) \implies F(\tilde{y}_t \succ_{-3} F(\tilde{y}_{t-1}) \implies \hat{g} \succ 0$. *Hence Proved*

Proof of Proposition 2 *Proof :* Using nested property of ISD $g_1 \succ 0 \implies g_2 \succ 0$. The last part is similar to Proposition 1, only domain being different.

Proof of Proposition 3 *Proof :* The proof is easy, and might be constructed computing EDEGR on domain $\bar{l}_t$ defined on 4.6, which is eventually DAF.

4.7 Tables

Table 4.1: Performances for different growth curves

States of Rural India					
Index	Inconclusive	Anti Poor	Pro poor	IC	CC
GIC	2804	724	1422	173	39.86%
PGC	917	1121	2912	122	79.01%
$\hat{g}$	616	1171	3163	NA	87.56%
g_1	4932	11	7	7	0.22%
g_2	2084	946	1920	107	55.74%
g_3	659	1434	2857	NA	86.69%
States of Urban India					
Index	Inconclusive	Anti Poor	Pro poor	IC	CC
GIC	2026	424	1120	85	40.87%
PGC	675	738	2157	77	78.94%
$\hat{g}$	418	915	2237	NA	88.29%
g_1	3556	13	1	5	0.25%
g_2	1532	1361	677	66	55.24%
g_3	572	1886	1112	NA	83.98%

[1] **Notes :** Results are based on spells of 20 major states of Rural India and 17 major states of urban India for the July 1987 - June 1988, July 1993 - June 1994, July 1999- June 2000, July 2004-June 2005, and July 2009-June 2010. The results of pro poor conclusions are based on any two possible combinations of state and round. Thus we have altogether 4950 and 3570 pairs of distributions, for computation of the growth curves.

[2] GIC, PGC, $\hat{g}$, g_1, g_2 and g_3 are computed from MPCE data of NSSO consumer expenditure rounds. GIC, PGC, $\hat{g}$ represents the absolute pro poor growth curves and the rest are their relative versions i.e. their deviations from their mean. The choice of number of quantile is 20.

[3] IC represents inconsistent conclusive cases, due to low number of quantiles, these cases eventually turn inconclusive by sufficient increasing the number of quantiles (not reported here). CC represents the % of conclusive results, excluding the IC cases.

Table 4.2: Pro poor growth scenarios in India

	GIC	PGC	$\hat{g}$	g_1	g_2	g_3
Rural India						
2009-10 vs **1987-88**	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\succ 0$	$\succ 0$
2004-05 vs **1987-88**	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\succ 0$	$\succ 0$
1999-00 vs **1987-88**	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\succ 0$	$\succ 0$
1993-94 vs **1987-88**	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\succ 0$	$\succ 0$
2009-10 vs 1993-94	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\nsucc 0$	$\succ 0$
2004-05 vs 1993-94	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\succ 0$	$\succ 0$
1999-00 vs 1993-94	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\succ 0$	$\succ 0$
2009-10 vs 1999-00	$\succ 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\prec 0$	$\prec 0$
2004-05 vs 1999-00	$\succ 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\prec 0$	$\prec 0$
2009-10 vs 2004-05	$\succ 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\prec 0$	$\prec 0$
Urban India						
2009-10 vs **1987-88**	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\prec 0$	$\prec 0$
2004-05 vs **1987-88**	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\nsucc 0$	$\prec 0$
1999-00 vs **1987-88**	$\succ 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\nsucc 0$	$\succ 0$
1993-94 vs **1987-88**	$\succ 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\succ 0$	$\nsucc 0$
2009-10 vs 1993-94	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\prec 0$	$\prec 0$
2004-05 vs 1993-94	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\prec 0$	$\nsucc 0$
1999-00 vs 1993-94	$\succ 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\nsucc 0$	$\nsucc 0$
2009-10 vs 1999-00	$\nsucc 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\prec 0$	$\prec 0$
2004-05 vs 1999-00	$\nsucc 0$	$\nsucc 0$	$\nsucc 0$	$\nsucc 0$	$\prec 0$	$\prec 0$
2009-10 vs 2004-05	$\succ 0$	$\succ 0$	$\succ 0$	$\nsucc 0$	$\prec 0$	$\prec 0$

[1] **Notes :** GIC, PGC, $\hat{g}$, g_1, g_2 and g_3 are computed from MPCE data of NSSO consumer expenditure rounds. GIC, PGC, $\hat{g}$ represents the absolute pro poor growth curves and the rest are relative based on their deviations from their mean. The choice of number of quantile is 20.

[2] $\succ 0$, $\prec 0$ *and* $\nsucc 0$ implies conclusive pro poor, conclusive anti poor and inconclusive cases respectively.

[3] The data points July 1987 - June 1988, July 1993 - June 1994, July 1993 - June 1994, July 1999- June 2000, July 2004-June 2005, and July 2009-June 2010 corresponds to round 43, 50 ,55, 61 and 66 respectively.

Chapter 5

Impacts of growth and inequality on poverty of India: A spatial approach

5.1 Introduction

India is one of the largest growing economies in the world. During the last two decades, she has not only been able to maintain a sustained growth, but also been able to reduce poverty steadily. However, neither growth rate nor poverty reduction, is uniform across regions of India. The non-uniformity might be either due to economic growth, or due to different aspects of poverty-reducing impact of that growth.[1]

Our objective in this chapter is to explore not only the role of growth, but also that of distributional effects of income distribution, on poverty reduction of some regions of Indian states. Thus we will also focus on the fact, whether the reduction of poverty is embedded due to unequal incomes. Addressing this problem is not new

[1] The divergence of the poverty estimates is readily available following the poverty estimates that has been computed in chapter 2 of the proposed thesis. For further details on the issues of non uniformity, See Ravallion and Datt (1998).

in the literature, and many theoretical and empirical researches have been done in this direction. The central theme of research agenda in this context has been based on estimation of a summary index called growth elasticity of poverty (GEP). The indicator GEP is important in terms of policy prescription in the sense that it captures the responsiveness of poverty as a result of increase (decrease) of 1% growth. Our main contribution in this chapter is to incorporate spatial dependencies of the regions in the estimation of these elasticities. So far we have seen, all the studies in this area are based on the fact that regions or units of analysis are independent and identically distributed. This might actually be a meaningful assumption in the context of cross country studies. However, in our context individuals within each units migrate from one part to the other frequently. Further, neighboring regions actually may belong under the same local government, where policies on poverty reduction may remain same. Further, price of one region may depend to its neighbor. Furthermore, regions closer to developed cities or towns may enjoy certain facilities which actually can play an important role in their poverty reduction. For example, it has been observed that in one of the largest state of India, Uttar Pradesh, the percentage of poor in the western part is 34%, which on the eastern part is much higher (nearly 54%). Since, the western part shares a common boundary with Delhi, the development schemes of country's capital might have been trickled down to its neighbor. There are many such observations in this direction, which further motivates us to consider an econometric model with spatial dependencies. Ignoring these dependency, would lead to biased and inconsistent estimates of the parameters (See Anselin, 2009, for further details). Our analysis is also new in the sense that instead of considering a state level analysis we move to a deeper micro level analysis of the regions of state. It should be noted that consideration of such a micro level analysis not only increases efficiency merely increasing the number of observations, but also allows us to study on many hidden aspects of heterogeneities within the states, which would have been missed out otherwise.

In Chapter 2 of this thesis we had studied the decomposition of poverty reductions on growth and inequality components following the contributions of Kakwani (2000). Usually when we have data on the entire income distributions these analyses are the most general approaches. In fact we shall also consider a similar study in this chapter and estimate the Poverty Equivalent Growth Rate (PEGR) that has been introduced by Kakwani and Son (2008). PEGR takes into account both the growth rate in mean income and how the benefits of growth are distributed between the poor and the non-poor. PEGR is defined as the growth rate that would result in the same proportional change in poverty as the present growth rate if the growth process was not accompanied by any change in relative inequality (i.e., when everyone in society received the same proportional benefits of growth). Thus following PEGR it is possible to evaluate the effects of growth and inequality on poverty reduction.

However, as pointed out by Zaman and Khilji (2013) these studies capture only short run relationships on growth poverty and inequality. In order to estimate long-term GEP, one has to consider regression based approaches, similar to those mostly applied in the context of cross country studies.[2] For example, using data sets on cross section of countries, Ravallion (1995) considered an econometric model with poverty reduction as a a function of growth rate of average income. Further, the model was generalized by considering endogeneity of income in the poverty estimating equation. However, the model is based on cross sectional observations and fails to capture the country specific effects. These effects are likely to be correlated with growth rate, which would lead to biased and inconsistent estimates of the parameters. In order to overcome this problem it is necessary to consider a model based on panel data. There are studies based on panel data for estimation of GEP (Ravallion and Chen, 1997; Adams, 2004; Ram, 2007; Chambers and Dhongde, 2011). It has been observed

[2]Note that in the context of cross country study we do not have full sample of observations. Thus the regression based approach is more widely used. In our context we want to estimate long term effects along with spatial dependencies. Hence we shall consider a regression model with spatial dependencies.

that in most of the studies, where poverty reduction is regressed on inequality and growth, the value GEP lies in the range -2 to -4.[3]

However, all these studies are based on a costlier assumption that the growth elasticity of poverty to be constant. Even if the model includes both mean income and the gini index as linear regressors, it does not interact with these explanatory variables, which effectively prevents inequality from affecting the magnitude of the estimated GEP. Assuming log normality of income distributions Bourguignon (2003) develops an econometric model for the poverty estimation equation. He begins with an econometric model where growth rate of poverty is regressed on growth rate of inequality and income, along with the interactions of both these variables with initial income inequality and the ratio of poverty line and mean income. The later variable is refereed to be inverse development factor. More or less model has also been applied by many researchers specially in the context of cross country studies (Fosu, 2009; Epaulard, 2003; Kalwij and Verschoor, 2007). Kalwij and Verschoor (2007), generalized the model with further specifying income as endogenous variable. The endogenity was considered mainly because of the fact that income growth rate and poverty indexes are computed from the same variable. Although the studies of Bourguignon (2003), Epaulard (2003),Fosu (2009) and Kalwij and Verschoor (2007) are based on different data sets of countries but the sign and significance of the estimates is similar for all these studies.

Since these studies are based on cross sectional or panel observations of countries,

[3] Ravallion and Chen (1997) and Adams (2004), considered not only growth rate of income but also have included growth rate of gini (as a proxy of a relative inequality measure) as explanatory variables. Adam's have shown that GEP differs substantially when growth rate of mean income and GDP, is considered as a measure of growth rate. Chambers and Dhongde (2011) considered a model which considers the nonlinearity of growth-poverty-inequality nexus, by considering a non-parametric regression model. Instead of considering the poverty estimation equation in growth terms Ram (2007) considered a model where all the variables are based on their level values. The estimated GEP and IEP for this model is substantially different from the others.

they are criticized following weak comparability of primary survey rounds in most of the cases (for details see Ravallion and Datt, 2002). Furthermore, computation of poverty estimates are based on income in some countries and expenditure for some other, which creates problems in terms of comparability. For example, it is widely known that measuring inequalities (say gini) in terms of income is expected to be higher than that of expenditure (Datt and Ravallion, 1992).

The literature discussed above, clearly shows academicians have given immense importance to these elasticities. A combination of GEP and IEP, might be very helpful for policy makers, as it helps to understand the poverty responsiveness respectively due to growth and redistribution. We shall begin with the Bourguignon (2003) type model along with two additional policy variables as female literacy rates and a proxy of environment pollution. Initially we shall begin with assuming income growth to be exogenous in the poverty estimating equation. However, at some stage we shall consider a more generalized model with endogeneity of income growth rate. Our study is different from the others in two aspects. The first one is consideration of the study in terms of a new data sets, and second in terms of the incorporation of the spatial dependencies. We have constructed a balanced panel data set from five consecutive NSSO rounds with rural and urban state regions as the panel units. The state regions are the lowest possible stratum in the multistage sampling design of National Sample Survey Office (NSSO) data. Specifically we consider data sets for 43rd, 50th, 55th 61st and 66th round data which provide informations for the period of July 1987 - June 1988, July 1993 - June 1994, July 1999- June 2000, July 2004-June 2005 and July 2009-June 2010 respectively. However, many new states has been formed over this period and NSSO has also reformulated many state regions. In order to maintain geographic identity we have to merge more than one state regions in many cases. Further, poverty, growth and inequality for these regions data sets are based on the same variable monthly per capita expenditure data. Clearly, unlike most of the cross sectional studies, comparability is not an issue in this regard, since the units we consider are independent strata and the survey design has remained unchanged over this period. Incorporation of the spatial dependency allows us to unpack many hidden aspects of the data. For example, at the end of this chapter we formulate a proposition on the effects of migration and its relationship to different poverty indexes. We relate this proposition to the empirical findings of the chapter.

The chapter has been organized in the following fashion. In section 5.2 we discuss issues and results related to the estimation of PEGR. In section 5.3 we provide a brief description of a general Bourguignon type model and related issues. Section 5.4 provides a brief description of data and also on computation of poverty rates and inequality measures. In section 5.5 we discuss on incorporation of spatial dependencies. In Section 5.6 we discuss briefly on econometric models. A general model with further considering the problems of endogeneity has been discussed in section 5.7. The chapter has been concluded in section 5.8.

5.2 Poverty Equivalent Growth Rate

Before we start discussion of the econometric model and results, we shall discuss a concept called the "Poverty Equivalent Growth Rate" (PEGR) introduced by Kakwani and Son (2008). PEGR helps us to address the problems posed in this chapter, assuming that there is no spatial dependencies between any two regions. We shall compare the results obtained following this approach to those found when spatial dependency is considered in the model.

PEGR takes into account both the growth rate in mean income and how the benefits of growth are distributed between the poor and the non-poor. PEGR is defined as the growth rate that would result in the same proportional change in poverty as the present growth rate if the growth process was not accompanied by any change in relative inequality (i.e., when everyone in society received the same proportional benefits of growth). Before describing the details of estimation of PEGR, we discuss some of the notations in this approach.

Let a society be observed for two periods t (initial period) and $t+1$ (final period), with income distributions x_t and x_{t+1}. Let μ_s be the mean income at time point $s \forall s \in \{t, t+1\}$. Let P_t be an additively decomposable poverty index (e.g FGT index defined in Chapter 1 see equation 2.9). Denote $g = \Delta log(\mu_t)$ as the growth rate of mean income. Further, let $\delta = \frac{\Delta log(P_t)}{g}$ be defined as the elasticity of poverty rate with respect to mean income.

Kakwani and Son argued that poverty reduction depends on two factors. The first is the magnitude of the economic growth rate. If growth rate is high, it is likely that a part of it would be trickled down to the poor, and ultimately there will be a reduction in poverty. The second factor is the adverse effect of inequality. Growth is generally accompanied by changes in inequality; an increase in inequality reduces the impact of growth on poverty reduction. Thus the authors have decomposed δ in the following two components:

$$\delta = \eta + \kappa \tag{5.1}$$

This decomposition actually bears a resemblance to the poverty decomposition analysis, formulated by Kakwani (2000).[4] η is defined as an estimate of the neutral relative growth elasticity of poverty, which should satisfy equation 5.1. κ represents the effect of inequality on poverty reduction. The functional form of η and κ may be written as follows:

$$\eta = \frac{ln\big[P(z, \frac{\mu_{t+1}.x_t}{\mu_t})\big] - ln\big[P(z, x_t)\big] + ln\big[P(z, x_{t+1})\big] - ln\big[P(z, \frac{\mu_t.x_{t+1}}{\mu_{t+1}})\big]}{2.g} \tag{5.2}$$

and

[4]Recall that we have adopted the decomposition exercise as suggested by Kakwani (2000) in Chapter 2 of this thesis.

$$\kappa = \frac{ln\big[P(z, \frac{\mu_t.x_{t+1}}{\mu_{t+1}})\big] - ln\big[P(z, x_t)\big] + ln\big[P(z, x_{t+1})\big] - ln\big[P(z, \frac{\mu_{t+1}.x_t}{\mu_t})\big]}{2.g}. \tag{5.3}$$

It is readily observable that adding by η and κ we get δ. The Poverty Equivalent Growth Rate (PEGR) is written as follows:

$$PEGR = \frac{\delta.g}{\eta}. \tag{5.4}$$

Note that if $PEGR > 0$ from 5.4 we can write: $\frac{\delta.g}{\eta} > 0$. Note that it is readily observable from 5.2 that η is always negative (unless g=0). Hence, a positive (negative) value of PEGR implies reduction (increment) of poverty. This is exactly equivalent to the Ravallion and Chen (2003) and Kraay (2006) absolute version of pro poor growth. This is, in fact, the weakest version of pro-poor growth. On the other hand, if $PEGR > g \implies \delta > \eta$. This is equivalent to the relative version of pro poor growth that has been developed by Kakwani and Pernia (2000). Reconciling these facts, if $g > 0$ absolute pro poor growth always implies relative pro poor growth, and if $g < 0$ relative pro poor growth implies absolute pro poor growth. This is, in fact, similar to the relationship between DAF and EDEGR dominance that we have established in Proposition 3 in the preceding chapter.

The authors have also introduced a stronger version of absolute pro poor growth: growth is pro-poor if the poor enjoy greater absolute benefits than the non-poor. Following this approach, absolute inequality would fall during the course of growth. They also defined a neutral absolute growth elasticity of poverty to be the elasticity of poverty with respect to growth when the benefits of growth are equally shared by every individual in society. The form of elasticity may be written as follows:

$$\eta^* = \frac{ln\big[P(z, x_t + \mu_{t+1} - \mu_t)\big] - ln\big[P(z, x_t)\big] + ln\big[P(z, x_{t+1})\big] - ln\big[P(z, x_{t+1} + \mu_t - \mu_{t+1})\big]}{2.g}. \tag{5.5}$$

The stronger version of absolute pro poor index may be written as follows:

$$\Theta = \frac{\delta}{\eta^*} \tag{5.6}$$

This stronger version of absolute pro-poor growth is obtained if $\Theta > 1 \implies \delta > \eta^*$. This is, in fact, similar to the relative version of pro-poor growth with the only difference being η replaced by η^*. It is readily observable that $\eta^* > \eta$. Thus the condition of absolute pro-poor growth is a stronger requirement and is even stronger than the definition of relative pro poor growth introduced by Kakwani and Pernia (2000).

5.2.1 PEGR : Results

We now apply the above mentioned methodology to address whether the growth process that began after liberalization of India is pro poor or not. We use the last five NSSO quinquennial rounds data, namely, the 43rd, 50th, 55th, 61st and 66th rounds. These data sets provide information for the period of July 1987 - June 1988, July 1993 - June 1994, July 1999- June 2000, July 2004-June 2005, and July 2009-June 2010, respectively. Further, we use the MPCE for a mixed recall period as a proxy of income, and take the poverty line as recommended by the Tendulkar Committee. The poverty line for the 66th round has been taken to inflate the same for other rounds by considering the price indices, CPIAL and CPIW, for rural and urban India, respectively.[5]

Recall that in the previous chapter we have addressed the same problem following a partial ordering approach. We have reported the results for all possible spells of comparison from 1987-88 to 2009-10 in Table 4.2.[6] It may be stated in subsequent

[5]Such considerations have already been applied by the Planning Commission. In fact, it does not violate the consistency property introduced by Ravallion and Bidani (1994) (see Kakwani, 2003, for further details).

[6]In the previous chapter, we had considered a partial ordering approach. Hence, specification of poverty line was not necessary. However, price adjustments was done by converting incomes of all individuals using the Consumer Price Index for Agricultural Labor and Consumer Price Index

sections the main findings have been found to have remained more or less the same as those in the previous one.

In Table 5.1 we have reported the estimates of PEGR for different time spans of India. From this table it is evident that PEGR is positive for all the spells of comparison. This implies that growth is pro-poor in an absolute sense following the definitions of Ravallion and Chen (2003) and Kraay (2006). Furthermore, observe that in most of these spells, PEGR for rural India is greater than the growth rate of mean income. This implies pro-poor growth in a relative sense. The last three spells of comparisons in rural India imply anti poor growth in a relative sense. In the context of urban India the result shows anti poor growth for most of these comparisons. Only for the two comparisons, 1999-00 *versus* 1987-88 and 1993-94 *versus* 1987-88 we find growth as favorable to the poor in a relative sense. The result of pro poor growth that has been obtained in this chapter is exactly similar to that of the previous one (cf. Table 4.2). Note that in the context of 1993-94 *versus* 1987-88 comparisons for urban India in Chapter 4, show inconclusive results. Since the concept of PEGR is based on a complete approach, such problems do not arise in this context. We can infer that growth is pro poor in a relative sense for all the three measures of FGT. However, this result should be reported with caution. Since the partial approach is inapplicable in this context, for some other poverty measures or lines this verdict may revert completely.

Table 5.1 also reveals that estimated values of PEGR are higher when the poverty index is SPG as compared to PG and HCR. This implies that except for few cases, in rural India, growth has a higher positive effect, on the ultra poor, i.e., those lying far below the poverty line. However, among the exceptional cases lies the two recent spells of comparisons, namely, 2009-10 *versus* 1999-00 and 2009-10 *versus* 2004-05.

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for Industrial Workers, in rural and urban India, respectively. Since this Chapter is based on a complete ordering approach, we have to specify a poverty line, and this is taken to be the Tendulkar Committee Line.

In case of urban India, high growth rate is in general more favorable to those lying closer to the poverty line.

We have presented the estimates of absolute pro poor index in Table 5.2. If we observe this table closely it is readily observable that the estimated values of this index is less than 1 in most of the cases. Thus overall the poor have not gained in absolute terms during this period. Only in few spells of rural India, there are exceptions. These periods are 1999-00 *versus* 1987-88, 1993-94 *versus* 1987-88, 1999-00 *versus* 1993-94. On the contrary, none of the spells of comparisons in urban India is favorable to the poor in an absolute sense.

The adverse effect of inequality is readily observable in this analysis. It is also readily observable that these adverse effect is more in urban India, compared to that in rural India. This finding was observed in Chapter 2 where we had performed decomposition analysis, in Chapter 4 where we had considered a partial approach of ordering pro-poor growth. In fact, as we would find, the adverse effects of income inequality captured by the inequality elasticity of poverty (IEP) is much higher in urban India than in rural India. Note that this exercise is based on the national level data. However, in the remaining part of this chapter we would emphasize on a micro level data at the level of state region.

5.3 Econometric Model

In this section we shall study on the basics of (Bourguignon, 2003) and other related models. Assuming that income follows a log normal distribution, growth and inequality elasticities of poverty has been computed analytically. The analytical forms of the growth and inequality elasticities of poverty are also available in Kalwij and Verschoor (2007). It has been observed that both these elasticities, depends on the initial inequality and ratio of poverty line and mean. The last factor is also commonly known as inverse development factor.

Let income, y_t be a random variable that follows log normal distribution with mean μ_t and variance σ^2 : $log(y_t) \sim \mathcal{N}(\mu_t, \sigma_t^2)$. Mean income can be written as $\bar{y}_t = E(y_t) = exp(\mu_t + \sigma^2/2)$. Head count ratio at time point t may be defined as follows.

$$HCR_t = \Phi(-log(\bar{y}_t/z) + \sigma/2) = Pr(y_t \leq z) \tag{5.7}$$

Change of poverty may be decomposed as follows

$$\frac{dlog(\bar{y}_t)}{dt} = e^H_{\bar{y}_t}\frac{dlog(\bar{y}_t)}{dt} + e^H_G\frac{dlog(\bar{G})}{dt} + u \tag{5.8}$$

The parameters $e^H_{\bar{y}_t}$ and e^H_G denotes the growth and inequality elasticities of poverty. For the functional forms see Kalwij and Verschoor (2007) (equation no A9 Page 823). Furthermore, it has been observed that the income and gini elasticities of poverty varies with the ratio of poverty line and mean and the initial gini coefficients. These variables finally enters in the econometric model as exogenous regressors.

In the panel data context denote P_{it}, Y_{it} and G_{it}, as the poverty, average income and income inequality of region $i \in \{1, 2, ...N\}$, at time point $t \in \{1, 2, ...T\}$, and p_{it}, y_{it}, and g_{it} as their growth rate[7]. Poverty estimating equation following Bourguignon in a panel data context may be written as follows[8]

$$p_{it} = \theta_i + \alpha_1 y_{it} + \alpha_2 y_{it} i_0 + \alpha_3 y_{it}\big(z/Y_{it}\big) + \beta_1 g_{it} + \beta_2 g_{it} i_0 + \beta_3 g_{it}\big(z/G_{it}\big) + u_{it} \tag{5.9}$$

where z and G_{i0} are the poverty line and initial income inequality(gini coefficient). θ_i is the unobserved panel heterogeneity.[9] Consider X as the set of explanatory

[7]For any variable X, we denote the growth rates as x, or $x = \Delta log(X)$

[8] Bourguignon (2003) started with a naive models as $p_{it} = \beta_0 + \beta_1 y_{it} + u_{it}$. A Standard Model, is also proposed may be written as follows $p_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 g_{it} + u_{it}$. It was noticed that R square, increases as one moves from the naive model to the standard model. R square is almost doubled if one moves from the standard model to the model specified in 5.9.

[9]On further assumptions on whether θ_i is correlated with the explanatory variables or not, i.e. whether a fixed or a random effect model is considered, we will discuss latter.

variables as denoted in equation 5.9. In matrix notation we can write the model as follows

$$p = X\beta + u \tag{5.10}$$

where X is the set of all exogenous variables and u is the residual, with usual OLS assumptions. From now we will refer X as the set of Bourguigon variables. The rationale for incorporation of this model is twofold. Firstly non linearities of the relationship between poverty-inequality-growth to some extent.[10] Secondly, we will show in the next section that GEP and IEP are not fixed and depends on the initial inequality and $\frac{z}{Y}$ ratio. Thus it is possible to capture the heterogeneity of the growth-poverty-inequality relationship across regions.

5.3.1 GEP and IEP : Functional forms

GEP and IEP are the responsiveness of poverty reduction, respectively for increment of 1% growth rate and income inequality. Once α_i and β_i $\forall i \in \{1, 2, 3\}$ are estimated from 5.9, GEP and IEP turns out to be

$$GEP = \alpha_0 + \alpha_1 i_0 + \alpha_2 (z/Y) \tag{5.11}$$

$$IEP = \beta_0 + \beta_1 i_0 + \beta_2 (z/Y) \tag{5.12}$$

The values of GEP and IEP depends on the combination of initial inequality and inverse development factor (Z/Y ratio). It should be noted, that so far or discussion, has been limited that the explanatory variables are uncorrelated with the residuals.

[10] A better way to capture the non-linearities of the relationship is to adopt a non parametric estimation equation, similar to Chambers and Dhongde (2011). However, since the state regions are based on fixed boundaries it is likely to reflect spatial dependencies among each other. Ignoring the spatial dependencies (if exist) would lead to biased and inconsistent estimates of the parameters. Inclusion of a non parametric model along with the spatial effects is beyond the scope of this article.

However, presence of income growth rate (y), really questions this assumption. Such endogenity would lead to biased and inconsistent estimates of the parameters and consequently for GEP and IEP. We will come to this issue latter.

5.4 Formation of the panel data

In continuation with the earlier chapters we shall consider National Sample Survey Organization (NSSO) quinquennial rounds data on consumption expenditure. Our unit of analysis is the lowest possible NSSO strata i.e., the rural and urban state regions. The state regions are basically combinations of different districts of a state.[11] We have constructed a balanced panel data set with the above mentioned units. The time points in this analysis are the NSSO rounds 43rd, 50th, 55th, 61st and 66th round.[12] It should be noted that the number of districts and states has changed over time. Furthermore, NSSO has also reformulated many of the state regions over this period. In order to maintain the regional identity, we have to merge more than one state regions in many cases.[13] The number of modified state regions are 128, of them 64 are rural state regions and the rest are urban state regions.

The main variable needed for establishing the empirical relationship between growth poverty and inequality is income. In continuation from the earlier chapters

[11] It seems that a possible option would have been considering an analysis at a district level. However, in the multi-stage sampling design districts are not stratum. It is possible that a given district may not have adequate observations. Further the representations of all sections of the society is also not guaranteed.

[12] The survey periods for 43rd, 55th, 61st and 66th rounds are respectively for the periods July 1987 - June 1988, July 1993 - June 1994, July 1999- June 2000, July 2004-June 2005 and July 2009-June 2010.

[13] If an estimate is consistent for two independent stratum, the estimate is also consistent even if we merge the two independent stratum. Hence merging the state regions wont create a problem, from the point of sampling design and other related issues. For further details on household surveys and related issues See Deaton (1997).

even in this exercise we consider Monthly per capita expenditure on a mixed recall period (MPCE) basis as the proxy of income. The first exercise for the poverty estimation of a society is the specification of poverty line. Since, poverty line for the state regions are not available. We have used state specific poverty line for the state regions. We shall Tendulkar Committee report poverty line, for the states and consider same poverty line for all the state regions. We shall inflate the poverty lines, using Consumer price indices for agricultural labor (CPIAL) and Consumer price indices for industrial workers respectively for rural and urban India. The growth variable has been computed following the growth rate of MPCE in real terms. The computation of real MPCE is also similar to the price updating of poverty line. Recall that in Chapter 3 and 4 we have also considered the same method for price adjustments for MPCE. However, for many cases price indices are not available, we consider the price index for these states at the national level.

Real MPCE for both rural and urban India, are obtained using these price indices. The growth rate of average real MPCE of rural and Urban state regions are considered to be the proxy of average growth rate of the society. Inequality for the state regions have been computed using the same MPCE data by computing the gini index of income inequality.

5.4.1 Policy Variables

Education : It is possible that a society is able to combat poverty better if the number of literates are higher (See Gundlach et al., 2004, for details). Education may increase growth and also have an effect on inequality.[14] Thus ignoring this variable

[14]It is logical to think that a society with higher number of literates might lead to higher growth rate. Presence of large number of literates might lead to higher productivity and consequently higher growth rates. The chain of education and inequality can also be derived logically, if we focus on the one to one relationship between corruption and inequality as pointed out by Sung and Khagram (2005). Educated people might actually raise voice against ground level corruption which often directly affects the poor.

would lead to endogeneity problem in the form of omitted variable bias.

NSSO provides data on literacy status of all the individuals coded in different groups viz, primary, secondary, higher secondary and graduates and above. We have computed the percentages of female adults (aged 15 years or more), having secondary level of education (Higher than 10 years) as a proxy of the education variable.[15] We expect a negative coefficient for the education variable, in the poverty reduction equation.

Air pollution and health hazards through energy consumption (Indoor air pollution) Air pollution might be broadly classified by two different phenomenon viz, outdoor phenomenon and indoor phenomenon. The outdoor phenomenon is largely due to the smoke produced by the factories mainly situated in the industrial areas. In developing countries this is often classified as an urban problem. On the other hand in the context of rural India indoor air pollution is a bigger problem, where people uses bulk of the fuels burned (by mass) are solids, principally wood and coal. Unlike gases and liquids, solid fuels require relatively advanced technology to be pre-mixed with air or otherwise ensure their complete combustion. The airborne emissions of incomplete combustion products, such as carbon monoxide, particulates, and volatile organic compounds, are extensive. For more details see Smith (1993) and the references cited there in. The list of health hazards as a result of the indoor pollution, that has been documented by Smith are as follows

1) Respiratory infections in young children

2) Adverse pregnancy outcomes for women exposed during pregnancy

3) Chronic lung diseases and associated heart disease in adults and

4) Cancer.

Given the data sets it is not possible to capture the outdoor smoke factor. However, NSSO collects data on principle source of cooking, which might be considered

[15] Female literacy, rates as a proxy of education following Ravallion and Datt (2002). In order to capture the hetrogeneity of state regions we consider the higher secondary level.

as an indicator of indoor air pollution. We consider the percentages of people effected directly from indoor air pollution as another explanatory variable.[16] A better indoor environment might increase physical abilities of individuals and thus help them combating poverty. For testing endogenity and its modeling we need some instruments which has been collected mostly from the NSSO employment and unemployment rounds.[17] The employment unemployment rounds are also conducted in the same period and similar survey design. Thus it is also possible to obtain consistent estimates for the same state regions.

5.4.2 Descriptive Statistics

In Table 5.3 and 5.4 we have presented the average values of poverty, income inequality, average MPCE, % of households having electricity, female literacy rates, % of households whose chief source of cooking fuels are prone to causing different health hazards and also indoor air pollution, respectively for rural and urban India. The averages has been computed over the time periods.

Less developed states like Bihar, Madhya Pradesh, etc., show poor performance in most of the indicators. If we observe the poverty rates very closely we can see there are indeed hidden dependencies which we shall refer as spatial dependency. For example the developed states of north India, like Punjab, Haryana, Delhi, Chandigarh etc have really low poverty rates. Almost similar pattern is also observe if we look the data of south Indian developed states e.g Kerala, Tamil Nadu, Karnataka and Madhya Pradesh. Furthermore, notice that results for developed states like Bihar, Orissa, Madhya Pradesh, Chattisgarh and Jharkhand and also in some regions of Uttar Pradesh have really high poverty rates. Notice that in southern parts of Odisha and in some parts of Madhya Pradesh the poverty rates are high and also have a low

[16] The % of individuals using one of the following coke, coal, firewood and chips, dung cake and charcoal are assumed to be sufferer of indoor air pollution.

[17] Recall that data on employment and unemployment rounds has also been used in chapter 2 for computation of the calorie norms.

mean income. The southern part of Odisha also known as the Kalahandi regions famous for a famine. We shall return in this issue while interpreting the fluctuations of GEP and IEP estimates. Although states seems to exhibit a spatial pattern, intra state inequalities are also observed in many cases. For example the Rural Malwa regions of Madhya Pradesh shows average HCR 37.36%, whereas in the same state the south eastern part exhibits a poverty rate of 66.05%. Similarly the western part of Uttar Pradesh (contiguous to Delhi) exhibits a poverty rate of 36% part where as the other regions shows much higher poverty rates.

In the context of the two policy variables we find that the air pollution factor captured by the usage of cooking fuels material shows huge difference between the rural and urban regions. In all cases more than 80% of the individuals use cooking fuels harmful a to health. The only exception being Delhi and Chandigarh where in the rural areas this rate is less than 20%. Notice the difference in the rural and urban female literacy rates. The figures almost doubles in most of the cases.

5.5 Spatial dependencies

The rationale of spatial dependencies is based on Tobler's first law of geography states that "**Everything is related to everything else, but near things are more related than distant things**". Poverty estimating equation 5.9, is based on the assumption that all the all observations are independent and identically distributed (iid).

We expect spatial dependency in the regions for the following reasons

1. **Policy implementation at the local level :** Poverty reduction depends on implementation of policies at the local level, like distribution of BPL cards, ensuring jobs in National rural employment guarantee (NREGA)[18], Public dis-

[18]In August 2005, the Indian Parliament passed the National Rural Employment Guarantee Act (NREGA), which mandates the provision of *hundred* days of guaranteed employment(unskilled or

tribution systems[19] etc.

If performance of a region is better in terms of implementing these policies it may be possible that would create pressure on their neighbors to perform accordingly.

2. **Spatial price dependencies :** Poor people of a society are directly affected by the fluctuations of the prices of necessary commodities like food. The connections between spatial dependency of poverty and price fluctuations may be establish using the facts that price increment raise poverty rates (for any given poverty measure) and also increase price of the neighbor regions. Thus for two regions say A and B, if price of a region A increases would lead to increment of poverty in A and consequently prices in B, which would again increase poverty in B. The link between poverty and prices can be obtained in Ivanic and Martin (2008). They finds that poor people generally appear to be net consumers of food and as such tend to be hurt by higher food prices. On the other hand for the spatial relationships in reported market prices, See Fik (1988) *"It is demonstrated that significant spatial relationships exist in reported market prices and the degree of price dispersion in geographically competitive markets."*(Fik, 1988).

3. **Migration :** The units of analysis or state regions are based on geographic boundaries. Constitution of India, in most of the cases allows individuals to freely migrate from one place to another. People basically the poorer often migrates from one place to another for the search of jobs. Clearly migration

manual work)to any rural household in India.

[19]The Public Distribution System (PDS) was institutionalized in the country in the 60s to achieve multiple objectives including ensuring stability of prices, rationing of essential commodities in case of deficit in supplies, ensuring availability of basic commodities to the poor and needy and to check the practice of hoarding and black marketing. However after poor performance of the scheme, the system was revamped and re launched as Targeted Public Distribution System (TPDS). Under this scheme, the Below Poverty Line (BPL) families would get basic commodities at a subsidized rate whereas the Above Poverty Line (APL) families would get them only at their economic cost.

of an individual from one place to another, would affect poverty in both the places.

In order to capture these dependencies, in terms of an empirical model, one must specify a spatial weight matrix. We consider a contiguous weight matrix, which takes values 1, if two region are contiguous (neighbors) to each other, else 0. Let $W_N = \{w_{ij}\}$ be a square matrix of spatial weights of size $N \times N$, N is the number of regions, where

$$\begin{aligned} w_{ij} &= 1 \qquad (if\ i\ and\ j\ are\ contigous\ and\ i \neq j) \\ &= 0 \qquad (else) \end{aligned} \tag{5.13}$$

We expect that the first two aspects i.e., "Policy implementation at the local level" and "Spatial price dependencies", can be captured considering this contiguous weight matrix. However, it is unlikely that such a simple structure of the weight matrix would capture all aspects migration, specially circular migration. Circular migration is by single men, part of the family stays behind in the area of origin, and the migrants continue to maintain close links with their areas of origin and invest their savings in the village rather than in the town (De Haan, 1997). A future research plan in this direction will be to consider a spatial weight matrix based on the informations on migration following NSSO 64 th round. Furthermore, people also migrate from one place to another due to similarities in their cultures. Spatial matrix on the basis of linguistic distance between state regions may be considered for further evaluation (See West and Graham, 2004, for further details).

Spatial dependence of the dependent variable : A modified version of equation 5.10 with spatial dependencies of the dependent variable may be written as follows

$$p = \rho W p + X\beta + u \tag{5.14}$$

The spatial autocorrelation variable is endogenous in the above equation. Thus, OLS estimation of equation 5.14 leads to a biased and inconsistent estimation of the parameters. If ρ is statistically significant, but we ignore it in the model, then the estimates would be biased and inconsistent. However consistent estimation of the parameters are possible following a Maximum Likelihood method of estimation(MLE).[20]

Spatial dependence in the error terms : It is not always necessary that the spatial dependencies exist only in the dependent variable. We can also consider a model with spatial dependencies in the residual series and/or in the dependent variable as follows

$$p = \alpha + \rho W p + X\beta + u + \lambda W_2 u \tag{5.15}$$

where W_2, denotes the spatial matrix that captures the spatial dependencies of the residual series.[21]

Ignoring the spatial dependencies in the residual series would lead to inconsistent estimation of the standard errors. However, unlike the SAR model even if the spatial dependencies are ignored estimates of the coefficient would be unbiased and consistent. In some situations it is possible that the residuals are cross sectionally dependent, and/or violates the usual assumption of OLS (autocorrelation and heteroskedasticity problems). In order to deal with such situations one may also use Driscoll Karry Standard errors (DSK SE) proposed by Driscoll and Kraay (1998).

We will estimate the spatial models both with and without consideration of the fact that income growth rate (y) is endogenous. In the first case, where 'y' is assumed to be exogenous the model will be estimated by the usual Maximum likelihood estimation methodology suggested by Anselin (2009). In the second case where we have two endogenous variables in the right hand side i.e., the spatial lag and y, it is esti-

[20]See Anselin (2009) for further details.

[21] Although it is possible to consider a different weight matrix for the dependent variable and residual series. However, in this case we will consider a simple model with a same spatial weight matrix.

mated by General method of moments. The methodology of GMM in the presence of spatial dependencies was introduced by Kelejian and Prucha (1999). Kelejian and Prucha (2004) extends the GMM methodology by including additional endogenous variables among the regressors.

5.5.1 Morans Test

Before considering an econometric model with spatial dependencies we shall consider the Moran's statistics to have an initial guess on whether there is any evidence of spatial dependency in the poverty measures (FGT). We shall compute this statistics for all the time points.

A morans test is a crude indicator for the tests of spatial dependence in the data, the morans I can be written as

$$I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{N^* \sum_{i=1}^{N}\left(X_i - \bar{X}\right)^2} \tag{5.16}$$

where $N^* = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}/N$.

The expected value and its standard error can be derived easily. Morans test reflects the spatial dependence in the cross sectional case. If the Morans I is positive(negative) then it might be concluded that the states performance is positively(negatively) effected by the neighbor. In Recall our dependent variable in the Bourguignon (2003) model is the growth rate of poverty indes. We have reported Morans I along with *Probability Values(P Values)* for tests $H_0 : I = 0$, for the choice of dependent variables, in Table 5.5. It clearly shows except for the PG and SPG in the 50 th round we have evidence of a significant spatial dependency in all cases.

5.6 Econometric Results

In Table 5.6 we present the estimates of the econometric model as specified in Equation 5.10. For the robustness of the analysis we have considered three different poverty indices viz. Head Count Ratio (HCR), Poverty Gap (PG) and Squared Poverty Gap (SPG) following Foster et al. (1984), See Equation 2.9. In order to estimate the standard errors consistently, we have used the SAR models with Driscoll and Kraay (1998) standard error (DSKSE). DSKSE captures all kinds of cross section and temporal correlation, of the residuals. Another option would have been consideration of spatial dependencies not only in the dependent variable, but also in the error part as in equation 5.15. However, we find insignificant λ in all cases, thus incorporating such models would lead to inconsistent estimation of the standard errors.[22] The sign and significance of the first six variable matches exactly to the earlier estimates based on this model for cross country studies (See Bourguignon, 2003; Fosu, 2009; Kalwij and Verschoor, 2007; Epaulard, 2003). It should be noted that the coefficients corresponding to $y(g)$ is not GEP(IEP). We shall use these estimates for computation of the elasticities, in some appropriate part later on this chapter. Policy variables female literacy rates and cooking fuels has also been found to be significant for both HCR and PG. The signs are also appropriate, i.e., female literacy rate reduces poverty and cooking fuels increase it.

Furthermore, it is readily observable that the spatial autocorrelation parameter is positive and highly significant for all the cases. As we have mentioned earlier, ignoring this dependency would lead to biased and inconsistent estimates of the parameter. The positivity of the spatial autocorrelation parameter implies that poverty rate of a region is positively related to its neighbor's poverty rate. For example $\rho = 0.17$, implies that growth rate of poverty of a region increases by 1.7%, if its neighbors poverty increases by 10%. Recall that earlier we have discussed on three possible

[22]We have not reported estimates of the model with spatial dependency in the residuals (See equation 5.15) in this thesis.

types of spatial dependencies namely dependencies of prices, local level policy implementation and migration. If we observe the results closely it may be noticed that the autocorrelation parameter (ρ) declines as we shift dependent variable from HCR followed by PG and SPG. The positivity of ρ might be due to spatial dependency in the prices and in policy implementation that has been discussed earlier. Note that the value of ρ is much higher for HCR (0.17) compared to PG (0.11) and SPG (0.10). It is possible that the spatial dependence for the households lying closer to the poverty line are affected more.

In order to explore the possible links between migration and on the different values of ρ, we have done some analytical derivations in the appendix of this chapter, in the form of Proposition 1. We assume that r number of individuals migrates from a less developed society L to a developed society D, provided D has a higher poverty line. Further to relate positivity of ρ for HCR, we assume that these poverty has increased in both the societies. Income of individuals for both the societies are assumed to remain unchanged, both before and after the migration. Under these assumptions we have derived the necessary and sufficient conditions for higher growth rate of HCR compared to PG in both the societies. The conditions appears to be only when as a result of migration mean income of the poor in both L and D increases. It is possible possible if most of migrants are non poor initially at L but when enters in D most of them become poor, but their income being close to the poverty line. This result may be partially related to the findings of Du et al. (2005) that those households near the poverty line are more likely to have a migrant compared to richer or poorer households.

It is not possible to say clearly whether the price, policy implementation or the migration factor is exactly driving this result. For further exploration of this result one may consider a future research work with data on migration of individuals from one society to other, along with other related variables say income or expenditure. Furthermore, as we have mentioned earlier spatial weight matrix with linguistic distance may capture the migration factor in a better way.

5.7 Endogeneity Problems ?

The reported results of Table 5.6 are based on the assumption that the residuals are uncorrelated with the explanatory variables. Presence of income growth, however, questions this assumption. We suspect the endogenity of income growth rate mainly because of the following reasons.

1) Poverty indices and income growth rate are computed from the same variable MPCE. Any measurement error of income might also be responsible for measurement error of poverty index.

2) As Deaton (2003) pointed out the participants of the rich are usually lower in the survey. This clearly will effect both poverty and growth.

3) Poverty of a society depends on many unobserved components which is accounted in the residuals. Since, the model is based on monetary poverty, it is likely that these components not only affects poverty rates, but also growth rate of income.

In order to deal with the problem it is necessary to find a set of instruments which are uncorrelated with poverty but are highly correlated with growth rate of income. We shall explain the details on the choice of instruments in the next section. In order to test whether income variable is endogenous, we will follow an algorithm discussed in details in Gong et al. (2005). The steps for testing endogeneity are as follows

Step 1 : Let z be the set of explanatory variables as in equation 5.9 excluding the growth rate of income or y_{it}. Also assume that there exists a set of instruments z^*, not belonging to z, which are uncorrelated with the error term of the equation 5.9 and highly correlated with y_{it}. Let Π denotes the stacked matrices z and z^*. The first stage regression

$$y = \theta_i + \nu'\Pi + \zeta \tag{5.17}$$

where ν is the vector of the parameter and ζ is the residual with usual OLS assumptions. Let ζ^* be the estimates of the residual series.

Step 2 : In the second step we modify equation 5.9, with an additional explanatory variable as $\hat{w}$, along with spatial dependencies of the dependent variable.

$$p = \theta' z + \delta y + \gamma \zeta^* + v \tag{5.18}$$

If γ is significant then it implies that y is endogenous in the above equation.[23]

5.7.1 Set of Instruments

In order to choose the instruments we consider three different development indicators of each state regions, which are 1) Employment 2) Infrastructure and 3) Technological Progress. It is logical to assume that improvement of these indicators will increase the income growth rate. Further we also assume that these indicators have no direct role in poverty estimation.

5.7.1.1 Employment

Clearly income and employment are related in an one to one basis. We will consider two main indicators in order to account the employment facilities of a state region, which are average wages (and/or salaries) and Jobs. The job opportunity variable is captures the percentage of employed individuals, and non laborers.[24] The second variable Wage and/or salary may be considered as the best proxy for income,

[23] For details see Gong et al. (2005) and the references cited there in.

[24] In the employment unemployment surveys, data on employment status of all the members of a household is available. National Classification of occupation was provided by government of India, in 1968. These codes are also known as NCO codes. NSSO collects data on NCO codes for all the members of household. Using NCO codes for the last seven days, the jobs variable has been created. It captures the percentage of individuals at the age 18-60, either not related to any elementary occupations, workers or are labourers. Recall that in chapter 1 of this thesis we have used this codes for the estimation of the average calorie norm of the society.

provided informations have been correctly provided.[25] The estimates of percentage of households having jobs and average salary are obtained from NSSO Employment Unemployment round.

5.7.1.2 Infrastructure

We consider agriculture and electricity as a proxy of the infrastructure variable. We do not have data on agriculture at the state-region level, and thus we consider %ge of land that has been cultivated as the proxy. The second proxy is electricity in the form of % of households having access to electricity.[26] We have obtained data on both these variables from NSSO consumer expenditures schedule.

5.7.1.3 Technological Progress

The questionnaire on the household level survey conducted by NSSO consumer expenditure and employment-unemployment has no direct question that might be related with technological progress. We consider % of child labour as a proxy of technological progress, as obtained from employment status of children following the NSSO employment-unemployment rounds. As pointed out by Hazan and Berdugo (2002) in the early stages of development, the economy is in a development trap where child labour is abundant, fertility is high and output per capita is low. As a result of technological progress, wage differential between parents and child increases and consequently it leads to the decline of child labour along with an increment of child education. For all the state regions, it has been observed that, child labour has been

[25]Data are collected for the wage and salary received either in cash or in kind (in terms of cash), for the last seven days. However, since, self employed individuals does not receive any salary or wage, data are missing for them. Average wage/salary for the individuals has been computed excluding self employed individuals. Another problem with this variable is misreporting of actual wages/salaries.

[26]The proxy that has been used might be considered as an crude indicator. It would have been better if it is possible to incorporate the number of roads schools, colleges or area of highways and other developed roads. However, it is difficult to obtain data in the state region level.

declining over time. State regions with faster decline of child labour might be due to higher technological advancements.

5.7.2 Endogenity tests : Results

In Table 5.7, we have reported the results of the endogeneity tests result for the choice of three poverty indexes discussed earlier. It might be noticed that the coefficient for the residual (ζ^*) is highly significant for HCR and PG (respectively at 1% and 5% level of significance). However, for SPG the coefficient turns out to be insignificant.

Since, we could not reject income growth as exogenous in equation 5.10 (except for SPG), estimates in Table 5.6 should be reported with caution. In Table 5.8 we have estimated the model considering income growth as endogenous, however, results remain more or less same.

5.8 Growth and Inequality Elasticity of Poverty

In this section our main target is interpretation of GEP and IEP that has been estimated following equation 5.11 and 5.12. In order to compute these elasticities we will use α_i and β_i $\forall i \in \{1, 2, 3\}$ from Table 5.8, where growth rate of income is considered as an endogenous variable.[27]

GEP and IEP are not constant, these elasticities depends on the initial inequality and on the ratio of poverty line and mean income ($\frac{Z}{Y}$). Thus it is necessary to specify values of initial gini and the $\frac{Z}{Y}$. We compute the elasticities for each state region and time points where the initial gini is based on the gini of 43 rd round, and $\frac{Z}{Y}$ for the respective time points. In Table 5.9, we have reported the average values of GEP and IEP for different time points, where the average has been taken over rural

[27]Since, the estimated results of the models with or without endogeneity of income growth rate is more or less same, the GEP and IEP do not change much even after considering the estimated parameters from the model with out endogeneity.

and urban state regions. As we have mentioned at the beginning of this chapter the expected sign of GEP is negative, implying that growth reduces poverty. It is readily observable from Table 5.9 that GEP and IEP are of appropriate signs. Furthermore, following the same table it is readily observable that absolute values of both GEP and IEP is much higher.[28] The estimated elasticities in the cross country studies mostly lie in the range -2 to -5 (Adams, 2004). In our context do not maintain the same bound, specially in rural India, however, the absolute values of GEP found to be grater than 1. This implies that 1% increment in income growth leads to more than 1% reduction in poverty.

In the same table expected values of IEP is positive (except for a very few cases), in fact IEP close to absolute values of GEP in many cases. The positivity of IEP implies that the existence of adverse effects of inequality somehow reduces the force of growth to reduce poverty. One such adverse effect of inequality is the inter relationship between income inequality and corruption Sung and Khagram (2005).[29]

It may be readily observed that the absolute values of both GEP and IEP increases with time. This is possible because in these long period of time mean income has increased substantially leading to decline of Z/Y ratio. It has also been observed that the absolute value of this elasticities increases as we move from HCR to PG and to SPG. This result is also intuitively justified if we focus on the axiomatic literature

[28]Recall that this is in continuation of chapter 1, where the redistribution component in the rural region was almost zero and also negative in many cases.

[29] Sung and Khagram (2005) has shown that corruption is related to greater inequalities, and the adverse effect is larger in democratic countries. Corruption on the other hand might directly effect on many policies against the poor. Government of India considers a program of targeting the most needy, a measure was developed by which families were categorized as living "**Below the poverty line**". Identified rural families that are below the poverty line are eligible for government support such as subsidized food or electricity and schemes to construct housing and encourage self-employment activities.[30] As pointed by Hirway (2003), "the rich and powerful in a village frequently pressurizes the talati and the sarpanch to include their names in BPL lists". Thus in a society with higher income inequality, instead of the poor households, rich households receive the benefits.

of poverty measurement. Head count ratio is a naive indicator and thus gives equal weight to all the poor. Thus even if income of an individual increases, HCR may remain unchanged if the increase does not allow one to cross the poverty line. Both PG and SPG would decline as a result of such changes in income distribution. This property is also widely known as Monotonicity axiom as suggested by Sen's seminal article (Sen, 1976). SPG is more general in this regard, since, it also responds to transfer of income among the poor, widely known as the transfer axiom.

We have also estimated the GEP and IEP for each state region considering the averages over the time period. In Figure 5.1, we have plotted those averages for all the regions following HCR. For the ease of interpretation we have taken the absolute values of GEP. Thus the black portion of the bar, shows the difference between GEP and IEP. It may be readily observed that the length of urban bar is greater then that of the rural, in almost all the cases. This implies absolute value of GEP is grater for the urban sector. However, IEP is also high for the urban areas, in fact the gap between the elasticities, reflected in the black portion of the graph, is higher for the rural areas in most of the cases. This naturally implies, the force of poverty reduction in urban India, as a result of higher growth rate, is largely embedded due to presence of unequal incomes. Same results also follows when we consider more distributive sensitive poverty indices, See Figure 5.2 and 5.3 respectively for poverty gap and squared poverty gap. Recall that we had exactly similar findings where we had estimated the PEGR.

Although, low IEP is desirable, in some cases economies with very low average income leads to negative IEP. (For further details, see Kalwij and Verschoor, 2007, page no 811) For example in Rural India, we find evidence of negative IEP in three cases namely southern regions of Orissa, South western regions of Madhya Pradesh and in hilly areas Manipur. The values of IEP for these regions are respectively -0.82, -0.20 and -0.07. Out of these three regions the southern part of Orissa is famous for the famine of **Kalahandi**, which took place in the 1980s, in the districts of

Kalahandi. This region historically suffers from low growth rate particularly because of the deterioration of the agricultural conditions.[31] Once we consider the more distribution sensitive poverty index like HCR or SPG these negative values of GEP and IEP gets disappeared, See figure 5.2 and 5.3. Thus it may be concluded in these regions redistribution leads to decline of poverty, however, such changes affects mostly those lying closer to the poverty line.

5.9 Conclusion

In this chapter we have studied on the impacts of growth and inequality on poverty reduction of India. We have considered two different types of model in this chapter. The first one is a non-spatial model where we have estimated the Poverty Equivalent Growth Rate (PEGR) of India for different NSSO rounds. The second one is a spatial model. Following the first model, we have observed that growth is pro poor considering absolute version of pro-poor growth following Ravallion and Chen (2003). The adverse effects of income inequality on poverty reduction has been reflected in urban India and for the recent spells of rural India. Recall that we had exactly similar findings in chapter 4 of this thesis. In this chapter we have also considered the context of absolute version of pro-poor growth. We have observed that the poor has not benefited in general, in an absolute sense, in most of the cases.

The analysis of PEGR, is based on the fact that geographical regions are not spatially dependent. In order to include this we consider a spatial econometric model. We have constructed a balanced panel data sets, with panel units as National Sample

[31] Kalahandi along with the Southern part of Madhya Prdesh are known to be a drought prone area historically, with low rainfall over decades. Low agricultural production in this region also has lead to different types of aids and supports from the government in terms of food aid. This however, lead to further decline in agricultural production incentives and also agricultural prices. Since, rural India is mostly related to agricultural productions, income growth rates also behave accordingly with the deterioration. For further details on the history of the Kalahandi famine, see Pradhan (1993).

Survey Organization (NSSO) state regions (districts with a state). The time points are the five consecutive NSSO quinquennial round. Many new states and districts have been formed in India over this period and NSSO has also reformulated the state regions. In order to maintain the regional identities we have to merge more than one state merge in many cases. In continuation with the earlier chapters we have also used Monthly per capita expenditure on a mixed recall period data as the proxy of income. Poverty rates (following Foster et al. (1984) measures), growth, and inequality (gini coefficient) has also been computed using the MPCE data. Unlike, previous chapters we consider the fact that poverty of a region may depend on their neighbors. Preliminary level of analysis considering a Moran's Test statistics also show such evidence for most of the time points.

We consider the poverty estimating model similar to that of Bourguignon (2003) in a panel data context. However, we have included spatial dependencies in the dependent variable (growth rate of poverty) and additionally at some stage we have considered endogeneity of growth rate.

The main empirical results might be summarized as follows

1. It has been found that the spatial autocorrelation parameter ρ is positive and highly significant for any choice of poverty indexes belonging to the Foster et al. (1984) class. Ignoring the dependencies would have lead to biased and inconsistent estimates of all other the parameter. The results remains unchanged even if we consider income growth as an endogenous variable. Positivity of ρ may be due to spatial dependency of prices or local level policy implementation. Furthermore we have observed that ρ is very high for HCR compared to PG and SPG. Higher values of ρ for HCR is possible if poverty of the neighbors affects mostly those closer to the poverty line.

2. Another possible reasons for the positivity of ρ is migration. In order to explain the decline positivity of ρ along with its decline from HCR to PG, we have considered an analytical exercise in the 'Appendix'. Assuming a migration takes

place from one society to another such that HCR of both the societies increases and every thing else remains unchanged. Under such conditions growth rate of poverty following HCR will be grater than that of PG if and only mean income of the poor increases in both the societies increases. In the context of rural to urban migration such results are possible if the migrants were initially non poor but enters as a poor but being very close to the poverty line.

3. The estimates of GEP and IEP emphasizes many interesting facts. We have reported average values of GEP and IEP over the rural and urban sectors of state regions, separately for five time. We have noticed that the average GEP(IEP), lies mostly in the range of -1.5(0.5) to -2.5(1.7), for HCR as the poverty index. GEP and IEP, are greater when we consider the poverty index as PG and SPG. The higher values of GEP and IEP for PG and SPG, has also been obtained in earlier studies. This is due to the fact that these indices are more sensitive on changes of income of the poor.

4. In the less developed states, it has been observed that absolute values of both GEP and IEP are lower. The micro level data sets used in this study, also allows us to evaluate the GEP and IEP fluctuations within the state regions. Huge disparities have been observed in states like Maharastha, Uttar Pradesh, Madhya Pradesh, Odisha etc. In fact in Odisha for Kalahanadi region we have obtained that GEP is very low and IEP as negative for HCR as poverty index. Thus it implies that as a result of increment in inequality poverty increases. However, this negativity disappears once we consider PG or SPG. This implies in these states reduction of poverty might occur due to increase in equality.

5.10 Appendix

5.10.1 Migration and poverty

In the empirical analysis with the Spatial autoregressive model (Equation 5.14), recall that in the empirical analysis we found the spatial autoregressive parameter (ρ) is positive and higher for HCR compared to PG and SPG (See equation 2.9). In order to relate the results with migration we shall consider a simple analytical exercise here. We begin with a hypothetical situation that spatial dependency is only due to migration. We shall now derive a necessary and sufficient condition when such migrations would increase the HCR more compared to that of PG. It is intuitive to imagine

Assumptions

1. D and L respectively be a developed and less developed society.
2. r number of individuals migrates from L to D from time t to t+1, such that income of all individuals at for both the societies remains unchanged before and after this migration.
3. Poverty line for L and Y respectively for both time point t and t+1 be z_L and z_Y and $z_Y > z_L$.
4. Among the r migrants, r_l^1 and r_l^2 are the number of poor and non poor in society L at time point t, $r = r_l^1 + r_l^2$ and $r_l^2 > r_l^1 \geq 0$.
5. Among the r migrants, r_D^1 and r_D^2 are the number of poor and non poor in society Y at time point t+1, $r = r_D^1 + r_D^2$ and $r_D^1 > r_D^2 \geq 0$

The first three assumption essentially captures the usual notion of migration from a less developed to a developed society (consider cases of rural to urban migration for illustrations). Last two assumptions essentially captures the fact that poverty has increased for both L and D following HCR.

Let HCR_t^J *and* HCR_{t+1}^J $\forall J \in L, D$ be the HCR respectively at time point t and t+1. For PG gap index we shall also follow similar notation, e.g PG_t^J poverty gap at time t for society J at time t. Further denote $hcr(J) = HCR_t^J - HCR_{t+1}^J$ and $pg(J) = PG_t^J$ *and* PG_{t+1}^J respectively as the growth rate of HCR and PG, due to migration. With all these assumptions we shall now find conditions for which $hcr(L) > pg(L)$ and $hcr(D) > pg(D)$. In particular, the proposition that has been formulated below shows that this is possible only when mean income of the poor increases for both the societies due to this migration. Let $\bar{J}_t$ and $\bar{J}_{t+1}$ be the mean income of the poor in society J, respectively at time point t and t+1.

Proposition 1 *If assumptions 1 to 5 holds*
1) $hcr(D) \geq pg(D) \iff \bar{D}_t \leq \bar{D}_{t+1}$, *and*
2) $hcr(L) \geq pg(L) \iff \bar{L}_t \geq \bar{L}_{t+1}$.

Proof : Following the FGT index 2.9, it can be shown that $PG_t = HCR_t(1 - \bar{x}_t/z)$, where z being the poverty line and $\bar{x}_t$ is the mean income of the poor. Hence, the growth rate may also be related as

$$1 + pg_t = (1 + hcr_t)\theta \tag{5.19}$$

where $\theta = \frac{z - \bar{x}_{t+1}}{z - \bar{x}_t}$. $hcr_t > pg_t \iff \theta \leq 1$. Both the conditions can be proved following Equation 5.19.

5.11 Tables and Figures

Table 5.1: Poverty Equivalent Growth Rate for India: 1987-2010

	Rural India				**Urban India**			
		PEGR				**PEGR**		
Time Period	$\Delta\mu_t$	HCR	PG	SPG	$\Delta\mu_t$	HCR	PG	SPG
2009-10 vs 1987-88	25.890	28.079	29.489	30.680	39.966	31.376	29.519	29.149
2004-05 vs 1987-88	17.016	19.002	20.811	22.273	27.633	23.483	21.699	21.495
1999-00 vs 1987-88	10.187	14.623	16.654	17.961	19.141	19.353	19.068	19.351
1993-94 vs 1987-88	0.756	2.614	3.258	3.672	7.378	8.966	8.378	8.064
2009-10 vs 1993-94	25.134	25.159	26.042	26.703	32.588	22.487	21.256	21.257
2004-05 vs 1993-94	16.260	16.257	17.489	18.476	20.255	14.525	13.323	13.531
1999-00 vs 1993-94	9.431	11.792	13.379	14.231	11.763	10.569	10.790	11.452
2009-10 vs 1999-00	15.703	12.643	12.283	12.045	20.825	11.807	10.096	9.107
2004-05 vs 1999-00	6.829	4.062	3.998	4.161	8.492	3.634	2.336	1.838
2009-10 vs 2004-05	8.874	8.826	8.244	7.805	12.333	8.642	7.908	7.379

Notes

[1] Poverty Equivalent Growth Rate for India has been measured for the poverty indices belonging to the class of FGT measures.

[2] Data Sources: NSSO Quinquennial Rounds on Consumer and Expenditure.

[3] $\Delta\mu_t$ stands for the actual growth rate (growth rate of mean MPCE)

[3] PEGR and $\Delta\mu_t$ have been multiplied by 100.

Table 5.2: Absolute Pro-poor growth index for India: 1987-2010

	Absolute Pro-poor growth index					
	Rural India			**Urban India**		
Time Period	HCR	PG	SPG	HCR	PG	SPG
2009-10 vs 1987-88	0.776	0.642	0.583	0.236	0.215	0.205
2004-05 vs 1987-88	0.899	0.742	0.688	0.388	0.298	0.264
1999-00 vs 1987-88	1.243	1.037	0.964	0.576	0.437	0.386
1993-94 vs 1987-88	3.140	2.791	2.694	0.783	0.549	0.452
2009-10 vs 1993-94	0.720	0.584	0.525	0.241	0.211	0.199
2004-05 vs 1993-94	0.802	0.654	0.601	0.354	0.262	0.234
1999-00 vs 1993-94	1.079	0.903	0.830	0.529	0.408	0.375
2009-10 vs 1999-00	0.590	0.447	0.384	0.226	0.165	0.134
2004-05 vs 1999-00	0.467	0.356	0.323	0.226	0.112	0.077
2009-10 vs 2004-05	0.722	0.528	0.437	0.313	0.231	0.189

Notes

[1] This table corresponds to the absolute pro poor index (Θ) that has been defined in equation 5.6, following the poverty measures belonging to the class of FGT poverty measures. If $\Theta > 1 \implies$ pro poor growth in a strong absolute sense.

[2] Data Sources: NSSO Quinquennial Rounds on consumption and expenditure.

Table 5.3: Descriptive Statistics : Rural India

statenames	state regions	HCR	PGR	gini	MPCE	Electricity	F.Literacy	cultivation	C.Fuels
Andhra Pardesh	coastal	32.31	7.62	27.21	983.33	69.34	8.64	8.15	83.49
Andhra Pardesh	Inland	44.86	10.18	25.94	851.52	80.94	7.45	16.51	88.94
Assam	plains east and west	49.01	10.37	22.22	798.05	34.72	10.80	27.26	91.81
Assam	Hills	52.33	12.09	19.27	732.28	26.72	11.07	53.58	92.83
Bihar	Northen	59.25	15.15	21.38	658.10	5.75	5.88	47.53	87.33
Bihar	Central	63.14	16.16	20.85	636.40	18.38	7.10	35.76	93.73
Gujrat	Eastern+Plains Northen	39.20	9.10	24.73	906.06	81.24	9.82	0.98	83.87
Haryana	Eastern	28.25	6.14	29.97	1299.12	87.46	16.11	34.86	82.30
Haryana	Western	29.13	6.70	28.35	1181.13	84.78	13.11	19.13	84.74
Himachal Pradesh	Himachal	26.64	5.05	28.41	1117.34	95.81	23.38	1.25	80.85
Jammu & Kashmir	Mountains	19.40	3.53	22.28	1085.67	93.81	18.85	0.39	84.52
Karnataka	Coastal ANd Ghat	19.64	3.99	26.14	1030.64	73.20	21.82	1.76	82.32
Karnataka	Inland Eastern	25.37	4.51	21.62	882.72	79.54	13.95	4.78	91.59
Karnataka	Inland Southern	33.85	7.55	24.42	839.42	81.25	10.18	8.10	86.47
Karnataka	Inland Northen	55.45	13.53	22.20	660.35	80.08	8.02	21.73	95.14
Kerala	Northen	32.80	7.45	30.21	1141.38	68.99	22.35	7.41	88.08
Kerala	Southern	18.58	3.86	35.18	1619.07	79.70	33.84	7.96	80.86
Madhya Pradesh	Vindhya	56.00	14.23	23.49	669.91	54.69	6.93	13.20	98.02
Madhya Pradesh	Central	60.95	16.01	24.61	654.34	66.78	2.93	10.04	97.21
Madhya Pradesh	Malwa	37.36	8.93	28.26	856.60	78.76	2.97	20.29	92.57
Madhya Pradesh	South Central	64.04	18.85	29.79	669.11	64.97	4.62	10.66	96.76
Madhya Pradesh	South Western	66.05	19.22	23.95	604.27	78.95	4.27	12.35	94.45
Madhya Pradesh	Northen	34.73	6.69	23.07	830.83	58.22	4.34	15.57	98.19
Maharastra	Coastal	38.03	9.24	29.24	1016.81	81.60	12.10	2.70	77.82
Maharastra	Inland Western	33.96	7.10	25.92	1029.30	79.69	15.66	8.20	74.92
Maharastra	Inland Northen	55.95	15.82	27.47	827.02	72.27	11.61	4.75	70.75
Maharastra	Inland Central	54.62	16.54	28.51	820.20	76.18	8.19	16.80	65.69
Maharastra	Inland Eastern	57.17	16.03	26.34	806.40	71.10	13.88	11.73	88.16
Maharastra	Eastern	69.05	19.67	24.86	720.21	59.60	10.55	3.83	90.48
Manipur	Plains	49.90	9.22	15.68	921.78	86.93	31.10	55.98	69.51
Manipur	Hills	65.46	14.78	17.58	835.23	64.68	18.11	12.45	93.70
Meghalaya	Meghalaya	27.25	4.19	19.75	898.12	53.67	9.72	2.93	97.11
Orissa	Coastal	49.05	11.29	23.65	653.96	42.76	10.81	24.85	89.57
Odisha	Southern	78.15	28.23	23.23	462.53	16.74	2.62	8.20	96.80
Odisha	Northen	61.35	17.45	25.81	586.07	24.93	7.01	10.89	94.14
Punjab	Northen	20.29	3.14	28.27	1395.62	94.14	24.52	25.35	69.19
Punjab	Southern	25.67	4.84	27.29	1299.00	93.35	14.01	30.77	75.33
Rajasthan	Western	35.23	6.99	22.49	963.85	46.27	3.02	20.30	95.33
Rajasthan	North Eastern	31.70	6.31	22.25	984.41	59.56	4.38	24.34	94.81
Rajasthan	Southern	51.95	12.23	25.93	875.64	41.80	4.25	3.17	95.04
Rajasthan	South Eastern	37.43	8.04	22.95	935.92	66.76	4.02	8.18	94.56
Sikkim	Sikkim	39.41	7.65	24.30	949.09	91.21	15.75	5.15	67.28
Tamil Nadu	Coastal Northen	48.07	12.59	30.18	812.04	81.84	15.32	6.08	80.40
Tamil Nadu	Coastal	27.74	5.35	25.70	924.83	73.23	12.94	8.35	89.59
Tamil Nadu	Southern	38.56	8.74	25.00	815.82	79.32	13.13	6.50	86.78
Tamil Nadu	Inland	37.64	8.13	30.38	920.75	79.55	11.15	3.64	76.84
Tripura	Tripura	35.74	7.22	21.40	827.76	58.06	7.40	3.60	95.31
Uttar Pradesh	Western	36.14	7.30	25.99	891.73	32.95	8.03	60.58	94.46
Uttar Pradesh	Central	50.66	13.19	25.20	747.90	11.59	6.75	22.15	96.53
Uttar Pradesh	Eastern	54.03	13.10	25.06	738.15	25.74	8.53	60.67	90.79
Uttar Pradesh	Southern	52.81	14.73	30.06	793.53	24.40	4.38	15.40	99.06
West Bengal	Himalayan	42.70	8.80	20.81	766.94	24.56	7.23	3.29	96.17
West Bengal	Eastern plains	50.99	11.34	23.98	736.40	24.92	4.79	9.05	81.40
West Bengal	Central Plains	33.84	6.65	23.62	839.78	37.30	7.71	8.18	82.92
West Bengal	Western Plains	43.76	10.07	25.85	796.29	25.95	6.84	5.42	80.27
Arunachal Pradesh	Arunachal Pradesh	41.62	10.61	30.34	1066.05	52.44	13.18	1.60	88.42
Chandigarh	Chandigarh	15.21	2.79	24.88	1619.58	89.43	21.85	21.49	18.14
Delhi	Delhi	10.96	1.72	25.32	1469.08	96.98	33.14	0.22	11.34
Goa	Goa	24.50	5.09	27.71	1524.34	98.05	29.32	1.33	45.44
Mizoram	Mizoram	30.14	5.22	20.03	1087.75	70.00	11.92	2.17	82.30
Pondicheri	Pondicheri	16.37	3.05	30.30	1231.87	78.23	17.79	5.46	74.04
Chattisgarh	Chhattisgarh	61.20	16.13	24.89	649.87	59.34	7.37	1.45	97.37
Uttarakhand	Uttaranchal	30.61	5.27	27.30	1027.59	64.38	14.06	0.64	80.14
Jharkhand	Jharkhand	59.42	15.40	22.75	653.29	22.95	5.28	1.41	96.84

[1] The Table contains average values of all the indicators

[2] F.literacy implies Female literacy, C.Fuels implies percentage of households using non combustible cooking fuels.

Table 5.4: Descriptive Statistics : Urban India

statenames	state regions	HCR	PGR	gini	MPCE	Electricity	F.Literacy	cultivation	C.Fuels
Andhra Pardesh	coastal	28.31	6.27	36.01	1709.70	88.19	27.00	0.72	35.76
Andhra Pardesh	Inland	27.85	6.11	34.00	1650.88	94.00	32.31	1.27	30.01
Assam	plains east and west	28.71	6.12	29.93	1438.55	84.54	41.52	0.61	27.61
Assam	Hills	31.80	6.98	31.57	1462.08	79.32	39.40	0.96	37.59
Bihar	Northen	50.63	13.72	30.42	950.79	46.05	24.14	3.70	61.75
Bihar	Central	44.38	11.11	31.02	1053.80	76.67	31.14	4.10	52.45
Gujrat	Eastern+Plains Northen	27.26	5.74	30.44	1564.49	93.84	35.52	0.10	20.43
Haryana	Eastern	22.66	4.97	32.11	1806.76	94.47	39.58	4.24	25.75
Haryana	Western	26.69	6.22	30.01	1568.07	93.59	36.41	2.48	34.05
Himachal Pradesh	Himachal	15.62	3.03	37.74	2137.30	96.35	56.36	0.04	15.36
Jammu & Kashmir	Mountains	9.29	1.51	27.19	1659.49	99.06	47.89	0.04	15.46
Karnataka	Coastal ANd Ghat	25.80	5.53	35.12	1726.58	95.20	43.35	0.14	35.78
Karnataka	Inland Eastern	24.89	4.85	25.95	1390.09	91.77	34.32	1.20	33.56
Karnataka	Inland Southern	13.24	2.63	31.07	1964.11	94.62	44.63	0.90	12.99
Karnataka	Inland Northen	49.79	13.58	30.18	1122.13	88.58	31.35	4.59	52.00
Kerala	Northen	30.30	6.72	37.23	1487.54	86.50	32.56	1.71	70.31
Kerala	Southern	14.29	3.00	39.46	2141.32	90.41	43.73	2.18	52.15
Madhya Pradesh	Vindhya	35.57	8.58	31.43	1157.88	91.10	28.04	1.75	54.39
Madhya Pradesh	Central	36.28	9.05	38.18	1310.27	95.88	35.91	1.64	37.73
Madhya Pradesh	Malwa	23.54	5.30	34.52	1512.02	97.42	33.25	1.70	33.25
Madhya Pradesh	South Central	36.89	9.09	35.05	1225.89	93.48	31.96	1.43	48.91
Madhya Pradesh	South Western	39.58	10.00	30.70	1076.97	95.46	30.96	1.87	41.82
Madhya Pradesh	Northen	35.09	8.56	30.72	1134.02	93.14	27.60	3.23	53.78
Maharastra	Coastal	9.07	1.49	34.13	2315.84	97.82	43.96	0.37	1.65
Maharastra	Inland Western	28.45	6.43	37.41	1832.41	93.64	39.05	0.92	14.01
Maharastra	Inland Northen	45.62	13.05	33.41	1336.43	92.56	33.11	0.75	19.56
Maharastra	Inland Central	55.18	16.74	33.86	1168.85	92.30	24.87	2.21	36.09
Maharastra	Inland Eastern	46.28	13.48	36.13	1374.77	93.03	38.00	2.40	32.01
Maharastra	Eastern	37.13	9.48	28.34	1357.22	89.99	35.03	0.42	31.83
Manipur	Plains	47.36	9.27	18.91	1081.56	94.38	45.09	37.52	39.78
Manipur	Hills	64.25	15.92	15.84	911.65	96.01	22.68	0.19	66.04
Meghalaya	Meghalaya	25.50	4.24	24.47	1503.81	96.17	46.50	0.02	33.39
Odisha	Coastal	35.81	8.20	34.69	1216.41	78.06	30.48	0.98	51.29
Odisha	Southern	39.33	12.09	35.24	1102.30	68.19	26.11	0.81	59.22
Odisha	Northen	31.15	7.43	31.09	1173.68	78.46	29.74	0.73	56.46
Punjab	Northen	22.28	4.04	31.96	1784.67	97.72	45.93	2.85	16.35
Punjab	Southern	26.03	5.49	32.87	1714.22	97.41	42.69	3.65	26.06
Rajasthan	Western	25.07	4.90	27.92	1336.65	90.84	21.09	1.00	40.31
Rajasthan	North Eastern	28.79	6.07	35.35	1523.98	91.54	29.05	1.74	42.95
Rajasthan	Southern	19.58	3.88	28.24	1556.72	94.35	30.39	0.17	29.85
Rajasthan	South Eastern	29.23	6.72	30.87	1369.06	94.92	26.30	0.58	35.58
Sikkim	Sikkim	22.72	4.33	24.04	1628.45	97.07	34.95	0.06	4.02
Tamil Nadu	Coastal Northen	20.65	4.90	36.38	1742.69	93.00	39.50	1.00	19.26
Tamil Nadu	Coastal	23.92	4.99	31.04	1401.62	88.50	33.62	1.12	38.03
Tamil Nadu	Southern	30.82	7.08	34.87	1349.42	91.91	30.57	1.40	40.38
Tamil Nadu	Inland	22.89	4.28	34.54	1510.18	90.98	29.43	0.81	30.79
Tripura	Tripura	19.39	3.45	29.77	1428.41	88.32	30.23	0.15	51.23
Uttar Pradesh	Western	33.99	8.05	34.77	1301.57	81.97	30.25	5.17	46.79
Uttar Pradesh	Central	35.21	8.85	35.91	1359.13	78.63	38.79	1.57	35.72
Uttar Pradesh	Eastern	41.70	10.22	30.94	1105.41	78.61	28.73	2.96	46.50
Uttar Pradesh	Southern	51.77	14.30	28.53	1006.81	70.92	28.69	1.13	55.09
West Bengal	Himalayan	33.47	8.13	30.56	1270.82	80.04	31.58	0.05	49.52
West Bengal	Eastern plains	39.12	9.91	32.67	1235.13	71.46	26.75	0.28	47.60
West Bengal	Central Plains	22.90	4.80	36.52	1681.03	84.64	34.68	0.59	36.83
West Bengal	Western Plains	33.50	8.12	33.39	1372.66	73.17	27.73	0.19	45.04
Arunachal Pradesh	Arunachal Pradesh	25.42	5.95	28.39	1489.13	92.94	37.53	0.06	29.63
Chandigarh	Chandigarh	10.75	2.16	40.77	3172.57	95.28	55.07	13.70	4.90
Delhi	Delhi	15.55	3.04	36.34	2467.55	98.37	49.17	0.30	2.65
Goa	Goa	15.37	2.83	33.10	2090.59	96.90	42.70	0.73	10.11
Mizoram	Mizoram	9.68	1.50	22.00	1645.24	96.21	34.20	1.04	23.19
Pondicheri	Pondicheri	13.82	3.06	30.87	1615.69	91.72	37.64	3.61	28.52
Chattisgarh	Chhattisgarh	30.36	7.18	32.66	1301.20	89.47	37.33	0.14	48.14
Uttarakhand	Uttaranchal	22.21	5.00	30.60	1518.17	95.24	43.71	0.04	19.88
Jharkhand	Jharkhand	34.25	8.67	34.51	1337.56	81.06	34.28	0.06	63.48

Table 5.5: Morans Test

Poverty Index	Round	Morans I
Growth rate of HCR	50	$0.07(0.04)^b$
-do-	55	$0.14(0.04)^a$
-do-	61	$0.14(0.04)^a$
-do-	66	$0.14(0.03)^a$
Growth rate of PG	50	$0.04(0.04)^c$
-do-	55	$0.14(0.04)^a$
-do-	61	$0.16(0.04)^a$
-do-	66	$0.14(0.03)^a$
Growth rate of SPG	50	$0.01(0.04)^c$
-do-	55	$0.13(0.04)^a$
-do-	61	$0.17(0.04)^a$
-do-	66	$0.13(0.03)^a$

[1] **Notes :** In the parenthesis we report standard errors. a, b and c implies significance at 1%, 5%, 10% respectively.(Two tailed test)

Table 5.6: Spatial Model

variables	HCR	PG	SPG
y	-6.40^{a} (0.30)	-8.31^{a} (0.27)	-9.82^{a} (0.31)
$y \times i_0$	7.22^{a} (1.10)	10.53^{a} (1.01)	12.72^{a} (1.18)
$y \times z/Y$	3.20^{a} (0.17)	3.01^{a} (0.15)	3.10^{a} (0.16)
g	4.64^{a} (0.16)	5.32^{a} (0.40)	5.81^{a} (0.65)
$g \times i_0$	-2.65^{b} (1.30)	-2.44 (1.72)	-1.81 (2.48)
$g \times z/Y$	-3.78^{a} (0.18)	-3.80^{a} (0.11)	-3.94^{a} (0.10)
$f.literacy$	-0.05^{a} (0.01)	-0.05^{a} (0.02)	-0.04 (0.03)
$cooking$	0.07^{c} (0.04)	0.09^{a} (0.02)	0.10^{b} (0.05)
ρ	0.17^{a} (0.03)	0.11^{a} (0.03)	0.10^{a} (0.02)

[1] **Notes :** Estimated results based on a Spatial Autoregressive model with Driscoll Karry Standard errors. ζ^* is the residual collected from the first stage regression.

[2] Set of Instruments are electricity consumption, average cultivated lands, % of households using non combustible cooking materials, Female literacy rates (Secondary Level) and MPCE from NSSO employment Unemployment rounds.

[3] The notations for the first six variables are similar to equation 5.9. In the parenthesis we report standard errors. a, b and c implies significance at 1%, 5%, 10% respectively.(Two tailed test)

Table 5.7: Endogenity Tests

variables	HCR	PG	SPG
y	-1.29 (1.94)	2.42 (4.88)	1.55 (7.21)
$y \times i_0$	-5.56 (4.90)	-16.32 (12.32)	-15.74 (18.18)
$y \times z/Y$	1.18 (0.79)	-1.24 (1.93)	-1.41 (2.87)
g	3.06^a (0.48)	2.01 (1.61)	2.30 (2.43)
$g \times i_0$	1.09 (1.63)	5.41 (4.08)	6.52 (6.17)
$g \times z/Y$	-3.03^a (0.30)	-2.23^a (0.76)	-2.28^b (1.14)
$f.literacy$	-0.06^a (0.01)	-0.07^a (0.03)	-0.07 (0.04)
$cooking$	0.08^c (0.04)	0.11^a (0.02)	0.12^a (0.04)
ζ^*	-5.21^a (1.75)	-10.93^b (4.89)	-11.59 (7.58)
ρ	0.17^a (0.04)	0.11^a (0.03)	0.09^a (0.02)

[1] **Notes :** Estimated results based on a Spatial Autoregressive model with Driscoll Karry Standard errors. ζ^* is the residual collected from the first stage regression.

[2] Set of Instruments are electricity consumption, average cultivated lands, % of households using non combustible cooking materials, Female literacy rates (Secondary Level) and MPCE from NSSO employment Unemployment rounds.

[3] The notations for the first six variables are similar to equation 5.9. In the parenthesis we report standard errors. a, b and c implies significance at 1%, 5%, 10% respectively.(Two tailed test)

Table 5.8: Spatial Model with endogenous income growth rate

variables	HCR	PG	SPG
y	-6.41^a (0.86)	-8.31^a (1.04)	-9.83^a (1.36)
$y \times i_0$	7.30^a (2.31)	10.55^a (2.80)	12.74^a (3.64)
$y \times z/Y$	3.20^a (0.49)	3.01^a (0.59)	3.10^a (0.77)
g	4.62^a (0.66)	5.32^a (0.80)	5.81^a (1.03)
$g \times i_0$	-2.67 (1.72)	-2.45 (2.07)	-1.81 (2.70)
$g \times z/Y$	-3.77^a (0.40)	-3.79^a (0.48)	-3.94^a (0.63)
$f.literacy$	-0.05 (0.04)	-0.05 (0.05)	-0.04 (0.06)
$cooking$	0.07 (0.05)	0.09^c (0.05)	0.10 (0.07)
ρ	0.20^b (0.08)	0.12^c (0.07)	0.10 (0.07)

[1] **Notes :** Estimated results based on a Spatial Autoregressive model with Driscoll Karry Standard errors. ζ^* is the residual collected from the first stage regression.

[2] Set of Instruments are electricity consumption, average cultivated lands, % of households using non combustible cooking materials, Female literacy rates (Secondary Level) and MPCE from NSSO employment Unemployment rounds.

[3] The notations for the first six variables are similar to equation 5.9. In the parenthesis we report standard errors. a, b and c implies significance at 1%, 5%, 10% respectively.(Two tailed test)

Table 5.9: Predicted GEP and IEP for Rural and Urban India

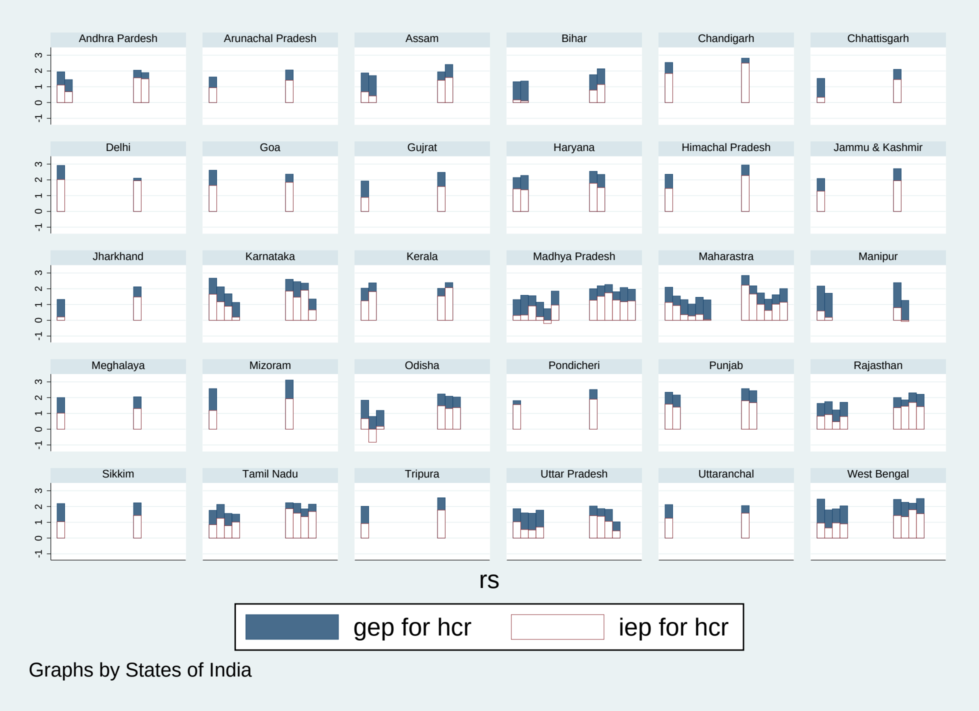
Year	GEP			IEP		
	HCR	PG	SPG	HCR	PG	SPG
Rural India						
1993-94	-1.52(0.52)	-2.69(0.56)	-3.52(0.63)	0.51(0.59)	1.24(0.60)	1.78(0.63)
1999-00	-1.70(0.55)	-2.87(0.56)	-3.70(0.62)	0.72(0.66)	1.46(0.67)	2.00(0.71)
2004-05	-1.88(0.49)	-3.04(0.54)	-3.87(0.61)	0.93(0.54)	1.67(0.55)	2.22(0.57)
2009-10	-2.08(0.48)	-3.22(0.52)	-4.07(0.58)	1.16(0.55)	1.91(0.55)	2.47(0.58)
Urban India						
1993-94	-1.88(0.48)	-2.91(0.51)	-3.68(0.57)	1.14(0.55)	1.89(0.56)	2.48(0.59)
1999-00	-2.19(0.38)	-3.20(0.46)	-3.98(0.53)	1.50(0.39)	2.25(0.39)	2.85(0.41)
2004-05	-2.25(0.41)	-3.25(0.48)	-4.03(0.55)	1.57(0.44)	2.33(0.44)	2.93(0.46)
2009-10	-2.34(0.47)	-3.33(0.49)	-4.12(0.55)	1.67(0.57)	2.43(0.58)	3.03(0.61)

[1] **Notes :** GEP and IEP are predicted from equation 5.11 and 5.12. The value of the parameters are from the spatial model with additional endogenous variable.

[2] Set of Instruments are electricity consumption, average cultivated lands, % of households using non combustible cooking materials, Female literacy rates (Secondary Level) and MPCE from NSSO employment Unemployment rounds.

[3] The notations for the first six variables are similar to equation 5.9. In the parenthesis we report standard errors.

Figure 5.1: GEP and IEP for different state regions : Poverty index HCR



In the diagram we have reported the estimated values of Growth and Inequality elasticity of poverty, see equation 5.11 and 5.12, for HCR. The values of α_i & β_i, $\forall i \in 1, 2, 3$, are obtained from Table 5.8 Further for all the regions, GEP and IEP are based on their initial inequality and average values of the ratio of mean income and poverty line. For each state, bar diagrams on the left and the right are respectively for rural and urban state regions. Absolute values of the GEP are presented in the Figure. The black portion of the bars indicate the difference between GEP and IEP.

Figure 5.2: GEP and IEP for different state regions : Poverty index PG

In the diagram we have reported the estimated values of Growth and Inequality elasticity of poverty, see equation 5.11 and 5.12, for SPG. The values of α_i & β_i, $\forall i \in 1, 2, 3$, are obtained from Table 5.8 Further for all the regions, GEP and IEP are based on their initial inequality and average values of the ratio of mean income and poverty line. For each state, bar diagrams on the left and the right are respectively for rural and urban state regions. Absolute values of the GEP are presented in the Figure. The black portion of the bars indicate the difference between GEP and IEP.

Figure 5.3: GEP and IEP for different state regions : Poverty index SPG

In the diagram we have reported the estimated values of Growth and Inequality elasticity of poverty, see equation 5.11 and 5.12, for SPG. The values of α_i & β_i, $\forall i \in 1, 2, 3$, are obtained from Table 5.8 Further for all the regions, GEP and IEP are based on their initial inequality and average values of the ratio of mean income and poverty line. For each state, bar diagrams on the left and the right are respectively for rural and urban state regions. Absolute values of the GEP are presented in the Figure. The black portion of the bars indicate the difference between GEP and IEP.

Chapter 6

Conclusions and future research directions

In this thesis we have studied on different aspects of poverty ordering and on the impacts of growth and inequality on poverty of India. We have used two alternative methodologies for the analysis, namely, complete and the partial ordering approaches. The formulations are based on new methods proposed herein and also by using different existing tools of econometrics. In almost all the chapters we find that in the poverty reduction of India, growth plays an important role. However, it has also been observed there are adverse affects of inequality which can not be neglected. Furthermore, in almost every chapters we have observed impacts of inequality on poverty reduction is much higher in the urban region compared to that of rural region.

We shall now have a very brief discussions on the main findings of this thesis.

Chapter 2, considers the problem of estimating the lower and upper bound of poverty line of India for 2004-05 and 2009-10. We have introduced an iterative Cost of Basic Needs approach. In the proposed approach the choice of the poverty line basket of food has been obtained following the average consumption bundle for a particular set of food items. The average consumption has been obtained considering a reference frame of households expected to be lying closer to the poverty line and also have purchasing power of the calorie norm. Instead of estimating a single poverty line we estimate the lower and upper bounds of poverty line. It has been observed that the lower bound of the estimated poverty line is very close to that of planning commission estimates following Tendulkar committee reports (Government of India, 2009). In the context of Urban India usually the lower (upper) bound is much smaller (higher) than the TC lines. We have observed that poverty has declined following the class of Foster et al. (1984) and Cerioli and Zani (1990) poverty indices's, at the national level, considering either the lower or the upper bound of poverty line. This analysis has also been carried out for some of the major states of India. It has also been observed that poverty has declined for most of the states. Poverty has increased for very few states, namely, the rural regions of Bihar; and urban regions of Himachal Pradesh, and Punjab. For these states poverty has also been observed to be increasing considering the Tendulkar Committee line. This chapter mainly focuses on the lower and the upper bound of poverty line. However, for policy makers it is often necessary to consider a single poverty line. We have recommended consideration of the lower bound as the final poverty line. This is justified in terms of resource constraints of the Indian government. Considering the upper bound of poverty line would result a high percentages of poor, and would have been difficult to incorporate all these poor in a poverty targeting exercise. In order to analyze the changes of poverty we have applied poverty decomposition analysis following Kakwani (2000) by which we decompose changes of poverty in terms of growth and redistribution components. It has been observed that most of poverty reduction for these two time points has been largely explained by the growth component. The redistribution component is positive implying inequality has adverse affects on reduction of poverty. The adverse effect although being small in rural India but is much larger in urban India.

It is indeed possible that the poverty ordering that has been obtained following the complete ordering approach in Chapter 2 might change as a result of choice of a different poverty index or poverty line. In order to deal with such issues in Chapter 3 we consider a partial ordering approach for ordering income distributions of rural and urban India, for the period 2004-05 and 2009-10. We have also studied on some of the subgroups of the population namely male headed, female headed, backward class and general class households. We have used stochastic dominance techniques for this analysis. We find that there is evidence of first order stochastic dominance of one distribution over the other. Thus poverty has declined for all the subgroups for any choice of any poverty line and wide range of poverty index following Atkinson (1987). Furthermore, the results remains unchanged even if we incorporate economies of scale in the comparison exercise. We then considered another exercise of comparing poverty of the male headed and female headed households. In the rural regions of India it has been observed that using per capita expenditure poverty is usually higher for the male headed households. However, incorporation of economies of scale alters the result. This findings are on the line of Dreze and Srinivasan (1997). Furthermore, our study shows that poverty for the backward class households is much higher compared to that of general class households. This is also known in the literature usually based on complete measures (Sundaram and Tendulkar, 2003). Kolmogrov smirnov based test statistics following Barrett and Donald (2003) also supports these results.

In chapter 4 we study on the issues whether growth is favorable to the poor or not. We consider notions of absolute and relative versions of pro poor growth respectively following the lines of Kraay (2006) and Kakwani and Pernia (2000). In an absolute notion growth is said to be pro poor if it reduces poverty for a given poverty measure. On the other hand growth is said to be pro poor in a relative sense if the growth rate of poor is grater than that of the non poor. Our first major contribution in this chapter is to propose a new ordering based on the absolute pro poor growth index "*Equally distributed equivalent growth rate(EDEGR)*", introduced by Nssah (2005). Our second contribution is the introduction of a new growth curve as the rate of change of gini social welfare function on logarithmic income quantiles. Our analytical derivation relates this curve to two widely used pro poor growth curves namely, Growth incidence curve(GIC)(Ravallion and Chen, 2003) and Poverty Growth curves(PGC)(Son, 2004). We have shown that conclusive ordering following either GIC or PGC appears to be sufficient condition for the newly proposed growth curve. The reverse, on the other hand, is not necessarily true. However, unlike GIC and the PGC the newly proposed growth curve can not be related to decline of poverty following poverty measures. The value added of this growth curve is justified in-terms of increment of a class of EDEGR. The relative versions of these results has also been derived following a standard normalization technique introduced by Duclos (2009). The value added of the relative version of the growth curve may also be justified in terms of "*Distributed Adjustment Factor*" (DAF), a relative pro-poor measure also introduced by Nssah. Our empirical results with MPCE data for states shows that both the absolute and the relative versions of the newly proposed growth curve provides conclusive results in more than 80% cases which is much higher than both GIC and PGC. Our finding suggests that growth is favorable to the poor in an absolute sense for all the spans of the five NSSO quinquennial rounds for both rural and urban India. However, growth is in general anti poor in a relative sense especially in urban India. Although growth has been favorable to the poor in most of the spans of rural India, but there are evidence of anti poor in the recent round 2009-10 vs 2004-05 comparisons.

In this thesis from Chapter 2-4 our study is mainly based on the assumption that poverty of one regions is not affected by that of other. However, the major departure in Chapter 5 is considering the possibility that units of analysis might be spatially dependent. The units of analysis has been considered are state regions (combinations of district of state). We have constructed a balanced panel data sets, with panel units as National Sample Survey Organization (NSSO) state regions (districts within a state). In order to maintain regional identity we have to merge many state regions. We have performed the well known Moran's test to find whether the units indeed have any spatial dependency of the poverty measures. For all the rounds we have found that the null hypothesis of spatial independence of poverty rates between the state regions is rejected.

However, it should be noted that one limitation of this analysis is that by forming the panel data we are losing valuable informations contained in the household surveys. We have thus also estimated the Poverty Equivalent Growth Rate that has been proposed by Kakwani and Son (2008). This exercise is in fact, exactly similar to the empirical section of Chapter 4, where we have addressed issues of pro-poor growth of India following the last five major quinquennial. In fact the results are also more or less same. However, one departure in this chapter is consideration of a stronger version of absolute pro poor growth, i.e., to evaluate whether the poor have gained in an absolute sense or not. We find that in a very few cases of rural India, the poor have gained in an absolute sense. Analysis on PEGR confirms the finding of the previous chapters that economic growth of India has played an important role for the reduction of poverty. However, there are adverse effects, which is, in fact, much higher in urban India compared to that of rural India. These results also has been confirmed in the spatial econometric model.

In order to incorporate the spatial dependency of poverty rates for different geographical regions, we consider an empirical model with dependent variable being growth rate of a poverty index following Foster et al. (1984) class of poverty measure. The framework has been borrowed from Bourguignon (2003) and has been generalized by considering spatial dependencies of the dependent variable i.e poverty rates. It has been found that the spatial autocorrelation parameter is positive and highly significant for any choice of poverty indices belonging to the class of FGT. Furthermore, the value of the parameter declines as we move to more distributive sensitive poverty index. It may be possible that spatial dependency plays an important role in the determination of poverty status for those lying closer to the poverty line. Estimated growth and inequality elasticities of poverty are higher in urban India compared to that of rural regions of India. In almost all the state regions, it has been observed that the absolute values of both GEP and IEP estimates are higher in rural compared to urban India. However, the difference in absolute values of GEP and IEP is higher in rural India. Thus the adverse effects of higher inequality on poverty reduction is also obtained here. The micro level data sets used in this study, also allows us to evaluate the GEP and IEP fluctuations within the state regions, in many states like Maharastha, Uttar Pradesh, Madhya Pradesh, Odisha etc. In the context of Odisha for Kalahanadi region we have obtained that GEP is very low and IEP as negative for HCR as poverty index. However, this negativity disappears once we consider PG or SPG. This region is historically known for the Kalahandi famine (See Pradhan, 1993, for further details) and has evidence of low growth rate for decades.

6.1 Directions for future research

So far our discussion is based on the assumption that poverty is based on the single dimension "Income". Poverty now a days has been accepted to be a multidimensional phenomenon, since it has been widely accepted that, well being of an individual depends on many aspects e.g literacy, health conditions, living standards (See Stiglitz et al., 2009, for further details). It is true that higher income enables individuals to perform well in non-monetary indicators. However, the biggest problem is the non-existence of market in many cases, e.g in rural India there are lack of many basic amenities in many rural villages e.g absence of electricity facilities, primary school, safe drinking water etc.

In future some of the problems that has been studied in this thesis may also be generalized in the context of multidimensional poverty. It may be interesting to see how adverse effects of inequality affects the multidimensional poverty index. Furthermore, it is likely in the regions where sufficient number of schools, electricity etc. are present poverty is expected to be lower. An interesting problem will be to see how this affects the neighboring regions poverty. Another important research problem may be on studying whether monetary poor persons are multidimensional poverty poor and vice versa. However, it is possible to conduct these studies only when we have rich sources of data on many dimensions (See Alkire and Santos, 2011, for choice of dimensions). The paucity of non-consumption data in the NSSO till now severely limits this analysis, till now.

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