Three Essays on Income Growth, Poverty and Inequality

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Submitted by

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I highly appreciate all who encouraged, trusted and supported,
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Introduction and Executive Summary

Alleviation of poverty and inequality has always been a serious concern of human societies. In addition, combating poverty has been the focal point of the altruism activities. Alongside the policy makers and humanitarian activists who take action against poverty, academia tries to play a role in favor of poverty eradication by putting the discussion of welfare, poverty and inequality in the spotlight of the academician discourse. Academics, particularly economists, argue that for making effective policies to eliminate poverty and to enhance welfare of human societies, we should be able to evaluate the scale of poverty, identify the poor people, and achieve a deeper comprehension of the poverty concept.

Based on the high demand for it, a strong literature on the subject of welfare, poverty and inequality has been developed. This literature, however, covers a vast range of issues related to general welfare and standard of living, poverty measurement analysis, and policies for welfare enhancing or poverty reduction.

This cumulative work is an attempt to take a step (even though a small one) forward in the literature. This dissertation focuses mainly on the measurement of poverty and inequalities within and between the subgroups in a society. It consists of three manuscripts, which study poverty and inequality from three different aspects. Discussing on poverty measurement, estimating gender and regional disparity of poverty, and estimating growth elasticities for Iran are the issues, which are investigated in this project. In order to achieve the goals of this project, we designed our study as an accumulation of three papers, as described in table 0.1.

Table 0.1. Articles of the Dissertation

Chapter	Author(s)	Title
Chapter 2	Mahoozi, H. and Meckl, J.	Multiple Dimensions of Impoverishment in Iran
Chapter 3	Mahoozi, H.	Gender and Spatial Disparity of Multidimensional Poverty in Iran
Chapter 4	Mahoozi, H.	Growth Elasticity of Poverty: with Application to Iran Case Study

The structure of this dissertation and a brief description of three different contributions is explained in following.

The main part of this dissertation starts with a brief literature review (**chapter 1**) focusing on the capability approach. This part is not aiming at being a comprehensive literature survey; rather it shows the line along which the relevant literature for this study has been evolving. We mainly discuss the literature on poverty measurement and particularly on the capability approach and on multidimensional poverty measurement, regarding the particular role of the capability approach and multidimensional poverty in all three essays of this cumulative work.

The first essay of this dissertation in **chapter 2** is on the debate about adequate poverty measurement, which is a controversial debate in the literature about welfare, inequality and poverty. In order to design an adequate poverty measure, many conceptual and technical issues should be addressed, such as selecting an indicator that efficiently proxies poverty, choosing a poverty line, as well as the method of aggregating and presenting the measure of poverty. Two strands of studies on poverty measurement evolved: One interprets poverty as a monetary phenomenon that should be measured by some monetary income or monetary expenditure indicator (Foster et al., 1984; Atkinson and Bourguignon, 2000; Atkinson, 1987; Clark et al., 1981; Coudouel et al., 2002). The other argues poverty is a multidimensional phenomenon and should be measured multidimensionally (Kolm, 1977; Sen, 1984; Massoumi, 1999; Klasen, 2000; Kuklys, 2005; Alkire and Foster, 2011b).

In the paper of chapter 2, we stress the demands of Sen's (1984) capabilities approach to assessment of human well-being. We estimate both the values of frequency and breadth of multidimensional poverty, and the traditional income poverty, compare the results of different measurements and demonstrate the overlaps between the results of different methods. We investigate poverty in Iran for the time-period 1999-2007, we distinguish three regions in Iran (Tehran, other urban areas and rural areas), and we estimate the poverty values for three snapshots over the time-period. The study works out significant differences in the poverty as well as the pace of poverty reduction in the three regions. The comparison of changes in poverty over the time-period also shows which measurement records faster progress or in which form of measurement economic growth has greater impact on poverty reduction. We also elaborate on the contribution of each dimension in the adjusted poverty headcount measure of each region, showing which dimensions contribute more in making the poor people to fall in poverty that can be a useful property for policy-making.

Inequalities in the distribution of welfare among individuals and special groups are another issue highlighted in this dissertation. In the second essay of this cumulative work, **chapter 3**, we tried to highlight inequalities in the distribution of welfare among the population and show how special groups are marginalized by their demographic and spatial circumstances. Measuring the multidimensional poverty ratio and the adjusted headcount ratio do not reflect the effect of the household's characteristics or region's features on incidence or intensity of poverty, besides they do not distinct poverty variation between provinces and within provinces. Hence, after identifying the poor by applying the Alkire-Foster method instead of using the counting approach, we develop multilevel regression models with the premise that households nested within the provinces. The multilevel regressions show how much the inequality in distribution of welfare relates to the province level and how much relates to the differences in the level of households. Besides, conducting a logit multilevel model we predict the probability of falling in poverty for a typical household with certain circumstances and in each province in Iran. The results show that most of the poverty incidence variation relates to within-province variation (94.5%), and only 5.5% of the poverty incidence variation relates to between-province variation. The results also indicate a remarkable disparity among the population in Iran in which female-headed households and rural households are heavily disadvantaged compared to their peers of male-headed and urban households. According to our results, the most disadvantaged households are female-headed rural households in the poorest southeast provinces, while the most fortunate households are (married, middle aged) male-headed urban households in Tehran, Bushehr and Mazandaran. The study concludes that certain households are marginalized based on their demographic and spatial circumstances.

The sensitivity of the frequency of poverty to economic growth is another central issue of the poverty and inequality discourse. The discussion on this issue has been going on for about two decades (Ravallion and Chen, 1997; Ravallion and Datt, 1998; Adams, 2000; Bhalla, 2002; Bourguignon, 2003; Kraay, 2006; Bresson, 2009). However, the more tools at our disposal, the more demand comes up for further constructive studies. In the third essay, **chapter 4** of this dissertation, we made our individual contribution by measuring the sensitivity of monetary and non-monetary deprivations to income growth. In this paper, we estimate the income growth elasticity of poverty and the income inequality elasticity of poverty using the Ravallion and Chen (1997) regression model for a panel of 28 provinces of Iran from 1999 to 2009. We also for the first time estimate the growth elasticity of multidimensional poverty (estimated using the Alkire-Foster method). We find a low income growth elasticity of poverty, and strong and significant income inequality elasticity of poverty. The results of our estimation of growth elasticity of non-monetary deprivations and multidimensional poverty also indicate rather similar results. Hence, inequality (both the initial level and its increase over time) has a negative effect on both monetary and non-monetary poverty reduction. Furthermore, high income-inequality diminishes the positive effect of income growth, especially for lower poverty lines. The results also indicate that the smaller the monetary poverty threshold, the higher is the sensitivity of poverty for changes in mean income and for changes in income inequality. The sensitivity of multidimensional poverty for changes in mean income and the sensitivity of multidimensional poverty for changes in income inequality are more than the sensitivities of monetary poverty (with upper threshold) and less than the sensitivities of monetary poverty (the lower threshold).

Chapter 1

Literature Review

1.1. The Discussion on Poverty Measurement with Emphasis on the Capability Approach

Measuring individual (or household) welfare is the basic input to all inequality and poverty analyses. Although there is agreement in economics and other social sciences that measurement of individual welfare is essential, no consensus exists for how to conceptualize welfare theoretically or how to measure it empirically (Kuklys, 2005). In economics, there are three general arguments in terms of conceptualizing and measuring welfare. The first is some notion of opulence. The second is to see the living standard as some notion of utility, the third to see the standard of living as one type of freedom (see Sen, 1985). The first approach goes back at least to Adam Smith and the modern literature on real income indicators, and the indexing of commodity bundles is the inheritor of this tradition of evaluating opulence. It is sometimes discussed as an approach with the utility approach in disguise. However, as Sen argues, there is an important difference between the two approaches even when the evaluation of real income is done in terms of an indifference map preference, since what is being evaluated is not utility as such (in the form either of desirability or of satisfaction), but the commodity basis of utility (Sen, 1985). The second argument is the dominant view that conceptualizes welfare as utility, and measures it empirically by one-dimensional indicators such as income or expenditure (Sen, 1973; Atkinson and Bourguignon, 2000). These two arguments, which are supported by "welfarists", however, are challenged by alternative views that conceptualize welfare as standard of living, quality of life, or subjective well-being, and measure welfare by multidimensional indictors (Sen, 1985, 1992; Kolm, 1977). That is known as capability approach.

The most common empirical welfare measure in economics is income. The advantage of using one-dimensional measures is their simplicity and clarity, although they can never tell the whole story (Goodman and Shepard, 2002). The income measure has been criticized for some sources of measurement error. First, individuals often underreport their income. The second source of measurement error is that, even if reported correctly, current income might not reflect appropriately the long-run level of individual welfare. This is the case when the household has a temporarily higher or lower income than usual during the period of reporting. Moreover, an income measure of welfare neglects important issues such as welfare derived from home production, non-market goods and services, and in-kind transfers (Kuklys, 2005). Employing expenditure data can be a simple solution for this problem, under the assumptions that households report expenditure more truthfully than income, and that they smooth their expenditures over time when making consumption decisions, expenditure is a better proxy of long-run welfare levels than current income (Deaton, 1997). Nevertheless, some problems remain. With respect to measurement errors, for instance, it cannot still fully reflect the long-run welfare situation of the households or individuals, when income or expenditure increase or decrease temporarily.

Moreover, the well-being of a population and hence its poverty which is a manifestation of insufficient well-being, depends on both monetary and non-monetary variables. It is certainly true that with a higher income or consumption budget, a person may be able to improve the position of some of his/her monetary and non-monetary attributes. Nevertheless, at the same time it may be the case that markets for some non-monetary attributes (e.g. some public goods) do not exist. It may also happen that markets are imperfect. Therefore, income as the sole indicator of well-being is inappropriate and it should be supplemented by other attributes or variables (Bourguignon and Chakravarty, 2003).

Sen challenges the welfare or utility approach, which concentrates on happiness, pleasure and desire fulfillment. He indicates that neither opulence (income, commodity command) nor utility (happiness, desire fulfillment) constitute or adequately represent human well-being and deprivation (see Sen, 1985, p. 670). Hence, Sen advocates a multidimensional assessment of individual welfare in the space of standard of living measures such as health, nutrition, education, or shelter. His approach is known as the capability approach (Kuklys, 2005) which its roots basically going back to Smith, Marx, and Mill, among others (see Sen, 1984), or back even to Aristotle's theory of "political distribution" and his analysis of Eudaimonia - "human flourishing" (Sen, 1993).

The capability approach is primarily and mainly a framework of thought, a mode of thinking about normative issues, hence a paradigm – loosely defined – that can be used for a wide range of evaluative purposes. The approach focuses on the information that we need in order to make judgments about individual well-being, social policies, and so forth, and consequently rejects alternative approaches those are considered normatively inadequate, like an evaluation based on monetary terms (Robeyns, 2005).

In its most basic form the capability approach conceptualizes welfare as standard of living, and measures it as function(ing)s (or dimensions). Function(ing)s are defined as the achieved states of being and activities of an individual, e.g., being healthy, being well-sheltered, moving about freely, or being well-nourished. Welfare measurement in the function(ing)s space takes into account the presence of non-market goods and services in an economy, home production, and adjusts for non-monetary constraints in decision making, because function(ing)s are outcome-based (as opposed to resource-based) welfare measures. Capability is a derived notion and reflects the various function(ing)s he or she can potentially achieve, and involves the person's freedom to choose between different ways of living (Kuklys, 2005). A series of approaches to multidimensional poverty have formed based on the capability approach.

1.2. Empirical Approaches to the Multidimensional Poverty Measurement

Sen's approach is theoretically attractive. However, to operationalize it empirically several issues arise. First of all it is not at all clear which function(ing)s or dimensions should be selected for the measurement of welfare. Additionally, it is not obvious how the dimensions should be measured. The third issue is a missing natural aggregator to summarize different dimensions in a composite standard of living measure, and finally measurement error problems.

In this section, at first we discuss about selecting dimensions, then we indicate the different methods to measure multidimensional poverty.

1.2.1. Selecting Dimensions

In practical applications of the capability approach and related multidimensional approaches, it seems that the methods for identifying capabilities or dimensions of poverty are surprisingly straightforward. Although, as mentioned initially, the discussion of the basis of choice is rarely explicit, it seems that most researchers draw implicitly on five selection methods, either alone or in combination. The five selection methods are:

Existing Data or Convention – select dimensions (or capabilities) mostly because of convenience or a convention that is taken to be authoritative, or because these are the only data available that have the required characteristics.

Assumptions – to select dimensions based on implicit or explicit assumptions about what people do value or should value. These are commonly the informed guesses of the researcher; they may also draw on convention, social or psychological theory, philosophy, religion, and so on.

Public 'Consensus' – to select dimensions that relate to a list that has achieved a degree of legitimacy due to public consensus. Examples of such lists at the international level are universal human rights, the MDGs (Millennium Development Goals); these will vary at the national and local levels.

Ongoing Deliberative Participatory Processes – to select dimensions based on ongoing purposive participatory exercises that periodically elicit the values and perspectives of stakeholders.

Empirical Evidence regarding people's Values – to select dimensions on the basis of expert analyses of people's values based on empirical data on values, or data on consumer preferences and behaviors, or studies of which values are most conducive to mental health or social benefit (Alkire, 2008).

Robeyns (2003) has proposed that authors use four procedures when identifying the relevant domains and capabilities. These are:

1. Explicit formulation: the list (of domains and/or capabilities) should be made explicit, discussed and defended: why it is claimed to be something people value and have reason to value.

2. Methodological justification: The method that has generated the list should be clarified and defended (and open to critique or modification), if this domain was chosen on the basis of a participatory exercise, or through consultation of empirical studies of human values.

3. Two stage processes, Ideal-Feasible: If a set of domains aims at an empirical application or at implementable policy proposals, then the list should be set in at least two stages. Each stage will generate a list at a different level, ranging from the level of ideal theory to the lists, which are more pragmatic. Distinguishing between the ideal and the second-best level is important, because these second best constraints might change over time, for example as knowledge expands, empirical research methods become more refined, or the reality of political or economic feasibility changes.

4. Exhaustion and non-reduction: the capabilities on the (ideal) list should include important elements: no relevant dimension should be dismissed. For example, those capabilities related to the non-market economy should also be included in economic assessments.

An example of multidimensional measure of wellbeing in terms of functioning achievements is the Human Development Index suggested by UN Development Programme (UNDP) (Streeten, 1981). It aggregates at the country level functioning achievements in terms of the attributes life expectancy, real gross domestic product (GDP) per capita and educational attainment rate. Another example suggested by Ravallion (1996) in a paper that four sets of indicators considered as ingredients for a sensible approach to poverty measurement. These are real expenditure per single adult on market goods, non-income indicators as access to non-market goods, indicators of personal characteristics, which impose constraints on the ability of an individual, such as child nutritional status, and indicators of personal characteristics, which impose constraints on the ability of an individual, such as physical handicap. A very well-known example of multidimensional index of wellbeing in terms of functioning achievements is the Multidimensional Poverty Index (MPI), developed by the Oxford Poverty & Human Development Initiative (OPHI) with the UNDP. The MPI includes three dimensions and ten indicators; Health (nutrition, child mortality), Education (years of schooling, school attendance), Living Standard (cooking fuel, sanitation, water, electricity, floor, assets).

Regarding the aforementioned discussion there is not a fixed list of capabilities in the literature as Sen (2004) mentioned "Pure theory cannot freeze a list of capabilities for all societies for all time to come, irrespective of what the citizens come to understand and value. That would be not only a denial of the reach of democracy, but also a misunderstanding of what pure theory can do." (Sen, 2004, p. 78) Or "To insist on a fixed forever list of capabilities would deny the possibility of progress in social understanding and also go against the productive role of public discussion, social agitation, and open debates" (Sen, 2004, p. 80).

In sum, Sen argues that key capabilities must be selected, but argues consistently against the specification of only one authoritative 'canonical' list of capabilities that is expected to apply at all times and all places. Hence, as the relevant literature addressed, although generally there is an agreement on some dimensions, in many cases the set of dimensions (and indicators) should be designed according to the certain time and place.

1.2.2. Methods to Measure Multidimensional Poverty

After selecting the dimensions and the threshold of deprivation, it comes to the aggregation of deprivation. There are some different methods in terms of aggregation process, namely counting, scaling, fuzzy sets theory, factor and principal component analysis, which formed different methodologies of measuring multidimensional poverty.

The "Counting" approach concentrates on counting the number of dimensions in which people suffer deprivation (Atkinson, 2003). People have scores corresponding to the number of dimensions on which they fall below some threshold specified in advance. An example that applied this approach is the human poverty index based on three sub-indices, which was provided by Anand and Sen (1997).

The method of scaling as employed by the UNDP (since 1990) in the calculation of the Human Development Index (HDI) is a technique, which is mainly targeted at solving the unit of measurement problem. Each of the variables indicating a dimension is projected linearly onto a 0-1 interval. Then the problem of aggregating several dimensions to a composite welfare measure is solved by combining the different dimensions with a weighted sum of indicators. The weights are chosen in accordance to the analyst's values. In case of the HDI each of the dimensions, health, education, and material wealth, receive the same weight of 1/3. This procedure assumes perfect substitutability between the dimensions: an individual can trade off her welfare in terms of, say, health and education with an infinite elasticity of substitution. The difficulty of the method is determining the maximum achievable level and ignoring a potential different anchoring of the scales by each individual.

Fuzzy sets theory, as applied in the empirical capability literature, is an extension of the previously described method of scaling. It was pioneered in this area by Chiappero (2000) and by Qizilbash (2002). It extends the method of scaling in two respects. First, it introduces flexibility in projecting the indicator variable onto a 0-1 interval by allowing for nonlinear projection functions, then by allowing for different weighting schemes. The analysts do not choose the weights arbitrarily, but they do based on the data.

Time Series Clustering developed as a method for measuring and aggregating dimensions, building on contributions by McGee and Carlton (1970), Piccolo (1970), and Hobijn and Franses (2000), Hirschberg et al. (2001). This method may be interpreted as a generalization of the exploratory factor analysis (EFA). As with EFA, the aim is to explore the data to find clusters of function(ing)s indicators which represent the same dimension; it extends EFA in the sense that it uses the statistical information contained in the entire distribution, not only the covariance or correlation matrices of the data. The focal point of their analysis is the identification of dimensions in the data set that have statistically similar distributions. They do this by (i) applying ARIMA models[1] to time series of 15 separate indicators; (ii) estimating non-parametric kernel densities of the residuals of these ARIMA models; and (iii) estimating the distance between the 15 densities with an entropy measure. Subsequently, those indicators that have statistically similar distributions are combined to a new variable representing a dimension. Hirschberg et al. (2001) used exclusively cardinal indicators in their application that were standardized to have unit variance and zero mean. In this way, the unit of measurement is not a problem. If ordinal indicators were used, they would have to be given a cardinal interpretation. Although measurement errors are not treated explicitly, we can interpret the combination of similar indicators as an implicit treatment of possible measurement error.

There is a variety of methods for poverty measure in the multidimensional approach as well as in the capability approach, like some we above mentioned. Researchers in this era adapt and adjust some method, and sometimes they mix two or more methods or introduce a method according

[1] An autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. Both of these models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting). ARIMA models are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied to reduce the non-stationarity.

their special cases. For instance, Alkire and Foster (2011b) in a well-known study use a 'counting' based method to identify the poor, and propose adjusted Foster–Greer–Thorbecke (FGT)[1] measures that is decomposable with population-share weights as well as reflect the breadth, depth and severity of multidimensional poverty, and which were introduced by Foster et al. (1984).

Alkire and Foster (2011b) introduce an approach to identify the poor that uses two forms of cutoffs. The first is the dimension-specific deprivation cutoff, which identifies whether a person is deprived with respect to that dimension. The second determines how widely deprived a person must be in order to be considered poor. Their approach uses a counting methodology after identifying the poor over the 'dual cutoff' procedure. This 'dual cutoff' identification system gives clear priority to those suffering multiple deprivations and works well in situations with many dimensions. The overall methodology satisfies a range of useful properties. A key property for policy is its decomposability, which allows the index to be broken down by population subgroups (such as region or ethnicity) to show the characteristics of multidimensional poverty for each group. Furthermore, it can be unpacked to reveal the dimensional deprivations contributing most to poverty for any given group (this property is not available to the standard headcount ratio and is particularly useful for policy). It embodies Sen's (1993) view of poverty as capability deprivation and is motivated by Atkinson's (2003) discussion of counting methods for measuring deprivations.

To sum up: there are several methods in this field, which can be adapted, adjusted or mixed. However, an important consideration in developing a new methodology for measuring poverty is that it can be employed using real data to obtain meaningful results.

1.3. Alkire-Foster Methodology

In this work, we mainly adapt the Alkire-Foster method for its range of advantages, some of which have been listed above. Since in the second chapter of this dissertation (first paper) we review the methodology thoroughly, we do not intend to explain the methodology in this section. However, conducting the Alkire-Foster method may rise several questions, which we usually face by presenting the results extracting by the Alkire-Foster method. Hence, in the following subsections we try to answer some of these most common questions. Then we sum up this section by numerating the properties (axioms) of the Alkire-Foster methodology.

[1] The Foster–Greer–Thorbecke indices are a family of poverty metrics. The most commonly used index from the family, FGT^2, puts higher weight on the poverty of the poorest individuals, making it a combined measure of poverty and income inequality and a popular choice within development economics. The indices were introduced in a 1984 paper by economists Erik Thorbecke, Joel Greer, and James Foster.

One of the common challenging questions are: Why do we use a composite index? Composite indices do compress information on individual trends, so we may lose some information. Why do we not use indices together in a dashboard approach (making a matrix of people's achievement in different dimension without aggregation)? Why do we aggregate if we break the index down again?

1.3.1. The Reasons Behind Using a Composite Index

In order to answer the first two questions and clear the motives behind using a composite multidimensional index (Alkire-Foster method), we propose the four following reasons.

First, designing an index should serve a specific purpose. A poverty measure is designed to help realizing who is poor actually, how many poor people are there, how poor are they, and how overall poverty has changed. They provide information that gives us some principal hints to design better poverty alleviation policies. A dashboard approach identifies who is deprived in each dimension, for example who is deprived in education, or deprived in health dimension. However, it does not identify who is actually poor. For example, consider a well-educated, wealthy person who suffers a chronic disease and identifies deprived in health dimension, while he is not actually poor. The same problem emerges with the one-dimensional method as well. As Alkire and Foster declare "when poor people describe their situation, as has been found repeatedly in participatory discussions, part of their description often narrates the multiplicity of disadvantages that batter their lives at once. Malnutrition is coupled with a lack of work, water has to be fetched from an area with regular violence, or there are poor services and low incomes. In such cases, part of the experience and problem of poverty itself is that several deprivations are coupled – experienced together." (Alkire, and Foster 2011a, p. 13).

Hence, we need a method based on a concept of poverty as multiple deprivations those are simultaneously experienced. The fact is, only the aggregate index fully bears the concept of poverty and gives a coherent summary statistical convey of how overall poverty has changed. A dashboard of marginal measures can indeed be useful for some purposes. The advantages of a dashboard approach are that it is transparent and every trend is monitored. However, it is not particularly well suited to answer aforementioned questions.

The second, practical problem with a dashboard approach is its heterogeneity. At some point, we need to use data reduction techniques to reduce the number of indicators. Hence, the dashboard's appeal has an inverse proportion to the number of poverty indicators. As the Stigliz, Sen, Fitoussi report puts it: "Dashboards… suffer because of their heterogeneity, at least in the case of very large and eclectic ones, and most lack indications about … hierarchies amongst the indicators used. Further, as communications instruments, one frequent criticism is that they lack what has made

GDP a success: the powerful attraction of a single headline figure allowing single comparisons of socioeconomic performance …" (Stiglitz et al 2009, p. 63). A single indicator that conveys the concept of poverty as the joint distribution of deprivations particularly is useful for the politicians when they report the progress of pro-poor policies or comparing socioeconomic performance.

Third, dashboard approaches also toss out information. They are insensitive to the joint distribution of deprivations. That means they are useless for measuring extreme forms of poverty and indigence. A dashboard approach reflects population deprivations within dimensions, but does not look across dimensions for the same person. For example, consider the two following matrices, when they show deprivations (denoted with 1) in four dimensions (four columns) for four persons (four rows)

$$g^0 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix} \cdots \begin{bmatrix} 0 \\ 0 \\ 0 \\ 4 \end{bmatrix}, \text{ and } \quad g^0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdots \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

In a dashboard approach, both matrices have identical marginal headcount ratios for each dimension (25%). However, they indicate two different situations; in the first matrix, one person is deprived in all dimensions while the second matrix demonstrated each of the four persons are deprived in one dimension. The disability of dashboard approach to distinguish these situations is politically important, particularly to target multiply deprived families first.

Forth, using the Alkire-foster method does not mean we deny usefulness of the other methods. However, we try to analyze additional indicators as Alkire and Foster state "our measure aims to complement income poverty measure" (Alkire, and Foster, 2011 a). We believe AF method carries some additional information. The method, using the FGT (Foster- Greer- Thorbeck) technology in a multidimensional approach, creates the opportunity to measure breadth and depth of poverty, which add the properties of the measurement.

1.3.2. The Reasons of Aggregating

The adjusted poverty headcount M_0 is an index, which benefits the decomposability axiom. After Estimating M_0 we break it down by population subgroups and dimensions to understand the relationship between dimensional policies and overall poverty impacts. It may seem we aggregate the indices and break it down to get the same indices. However, that is just a misunderstanding. M_0 is resulted of an identification process, while equals the aggregate deprivations experienced by the poor as a share of the maximum possible range of deprivations across society. As Alkire and Santos express the sub-indices are not independent, but instead rely on the joint distribution through the identification step (Alkire and Santos, 2010). Therefore, sub-indices after breaking down M_0 are showing the share of each dimension in making poor the population of each group. We believe that is a virtue of this methodology, which helps for policy targeting.

1.3.3. Axioms (or Properties) of the Methodology

The dual cutoff method enjoys a range of properties, for any given weighing vector and cutoffs, the methodology $Mk\alpha=(\varrho k, M\alpha)$ satisfies: decomposability, replication invariance, symmetry, poverty and deprivation focus, weak and dimensional monotonicity, nontriviality, normalization, and weak rearrangement for $\alpha\geq0$; monotonicity for $\alpha>0$; and weak transfer for $\alpha\geq1$ (Alkire and Foster, 2011b). The axioms that the methodology satisfies are as below:

Decomposability: a key property for AF method is decomposability, which requires overall poverty to be the weighted average of subgroup poverty levels, where weights are subgroup population shares. This characteristic allows the index to be broken down by population subgroups to show the specifications of multidimensional poverty for each group. This axiom is an extremely useful property for generating profiles of poverty and targeting high poverty populations.

Replication invariance: this property ensures that poverty is evaluated relative to the population size, and allows for meaningful comparisons across different sized populations.

Symmetry: according to symmetry, if two or more persons switch achievements, measured poverty is unaffected. This ensures that the measurement does not place greater emphasis on any person or group of persons.

Focus (poverty focus and deprivation focus): that means that the poverty measure is independent of the data of the non-poor. In a multidimensional setting, a non-poor person could be deprived in several dimensions while a poor person might not be deprived in all dimensions. There are two forms of multidimensional focus axioms, one concerning the poor, and the other pertaining to deprived dimensions. This is a basic requirement that ensures that the measurement measures poverty in a way that is consistent with the identification method (Alkire and Foster, 2011b). That is that the property is absent in a number of other methodologies. For example, the methodologies with non-composite indices may satisfy the deprivation focus, but they do not satisfy the poverty focus.

Monotonicity (weak and dimensional monotonicity): it means if poor become poorer, the measure has the ability to reflect it. Weak monotonicity ensures that poverty does not increase when there is an unambiguous improvement in achievements. Monotonicity additionally requires poverty to fall if the improvement occurs in a deprived dimension of a poor person. Dimensional monotonicity specifies that poverty should fall when the improvement removes the deprivation entirely; it is clearly implied by monotonicity (Alkire and Foster, 2011b).

Non-triviality: it ensures the indicator achieves a unique maximum value (in which all achievements are 0 and hence each person is maximally deprived) and a distinct minimum value (where all achievements reach or exceed the respective deprivation cutoffs and hence no one is deprived).

Normalization: that means that the methodology regards changes in inequality among the poor. This axiom goes further than weak monotonicity and reflects the depth of poverty, which is satisfied in Alkire-Foster Methodology by index M_1[1].

Transfer: This axiom ensures that an averaging of achievements among the poor generates a poverty level that is less than or equal to the original poverty level. This axiom alongside the Rearrangement regards changes in inequality among the poor.

Rearrangement: rearrangement among the poor reallocates the achievements of the tow poor persons but leaves the achievements of

In this chapter, we mainly discussed the literature on multidimensional poverty measurement, and particularly on the capability approach as the theory basis of multidimensional poverty measurement, regarding the particular role of multidimensional poverty in all three essays of this cumulative work. In addition to, we tried to introduce and briefly discuss the characteristics and axioms of the Alkire-Foster method, as the main technique for measuring the multidimensional poverty in this dissertation.

[1] The adjusted poverty gap M_1 is the product of the adjusted headcount ratio M_0 and the average poverty gap G. In the other words, it is the sum of the normalised gaps of the poor divided by the highest possible sum of normalised gaps. The poverty measure M_1 ranges in value from 0 to 1.

Chapter 2

Multiple Dimensions of Impoverishment in Iran

ABSTRACT

Concerning the demands of Sen's (1987) Capabilities Approach to assessment of human well-being, the paper estimates the values of frequency and breadth of multidimensional poverty in Iran, while compares those results with the results of traditional income poverty measurement. The paper detects poverty over the period 1999-2007, whilst it distinguishes specific regions as Tehran, other urban areas, and rural areas. The study reveals that over the period, with relatively high rate of GDP, the pace of income poverty reduction was much faster than the multidimensional poverty alleviation. The study also detects the pace of poverty reduction in rural areas is much slower than urban areas and the capital city, Tehran, which increases the inequality between rural and urban areas over the time. Furthermore, the paper detects the specific socio-economic group's deprivation type, which is invaluable information for an effective policy targeting.

Keywords*: multi-dimensional poverty, welfare distribution, Iran*

JEL Classification: D63, O53

2.1. Introduction

Poverty is a major problem for many less developed countries and continues serious challenges for the governments of the involved states. Not surprisingly, poverty reduction in general as well as specific approaches to overcome that problem played a significant role in the political debates during the recent decades in Iran. The Islamic revolution claimed that the social base of Iran is primarily formed by the poor. The Iranian government implemented different policies over the last three decades, ranging from extensive nationalization of central industries and heavy subsidization of a wide range of basic goods in the first decade (1980-90) to the more market-oriented reforms launched in the second and third decades. Although all these policies were explicitly designed to reduce poverty they seem to have been only partially successful. As a result, poverty is still the central issue of political debates in Iran.

Existing studies providing reliable measures about the size and the development of poverty in Iran are relatively sparse and deliver quite mixed results. Assadzadeh and Paul (2004) disentangle the effects of macroeconomic growth and redistributive policy measures on poverty for the time span of 1983 to 1993. In order to measure poverty, they apply the Foster-Greer-Thorbacke (FGT) method (cf. Foster et al., 1984) that specifies a threshold value of monetary income to identify the poor in the society[4]. To substantiate that monetary poverty line, the authors consider the cost of a balanced diet propagated by the Iranian Institute of Nutrition Science and Food Industry satisfying normal nutritional requirement at 1989 prices and augment that pure food-cost component by adding a non-food component calculated from the ratio of average non-food expenditure to average food expenditure in the country. Their results indicate that the deterioration of income inequality contributed to the worsening of poverty, while the economic growth contributed to a reduction in poverty in rural areas and an increase in urban areas. They find that poverty declined slightly in the rural sector while increasing significantly in the urban sector over that time period. Salehi-Isfahani (2009) examined the trends in poverty and inequality for the time-period 1984-2005 and compares them to the published survey results of the pre-revolution years (1970-1979). He takes per capita expenditure as a measure for individual welfare and uses the Assadzadeh and Paul (2004) poverty line to identify the poor for the time-period 1984-2005. However, since the data are not available for 1970s, he relied on the published survey results for the pre-revolution years. His study reveals that poverty declined substantially over the considered time span while inequality almost remained stable. More recently, Maasoumi and Mahmoudi (2013) also decompose the change in poverty into a growth and an inequality component. They set monetary poverty lines for

[4] The FGT method can specify frequency, breadth and depth of poverty. In the other word, FGT method besides of demonstrating poverty is able to show the income distribution among poor.

each year (2000, 2004 and 2009) based on the adjusted consumption expenditure, while they applied FGT method for measuring poverty. They found a reduction in poverty both in urban and rural areas primarily driven by economic growth for their evaluation period of 2000 to 2009.

On the background of these rather positive results on the extent of poverty reduction it rather comes as a surprise that poverty is a central issue in actual debates. In our view the positive results derived by the studies cited above are misleading since they fail to perfectly measure the actual extent of poverty by concentrating on a one-dimensional monetary concept such as real income or real consumption expenditures. Basically poor people typically go beyond income in evaluating their experience of poverty, and refer to a set of variables containing malnutrition, lack of safe water, health issues, and children out of school … in assessing their situation. As a result, a single indicator such as income or consumption is not able to capture the multiple aspects that contribute to poverty in a comprehensive way, and the pursued strategy of narrowing down the diagnosis of poverty to a pure monetary measurement falls short of covering the phenomenon adequately. The current study substantiates this critique by confronting results of the traditional one-dimensional approach with those derived from a multidimensional approach. Specifically with respect to the pace of poverty reduction our multidimensional approach clearly qualifies the results from the one-dimensional approach and thus gives good reason for the high awareness of poverty in the political agenda.

The theoretical reasons that support measuring welfare as a multidimensional phenomenon were brought forward by Kolm (1977) and Sen (1984). Both authors criticized the use of income as the sole measure of poverty on the grounds of individuals' self-assessment of being poor. Building on Kolm's and Sen's contributions, two strands of literature on multidimensional welfare measurement have emerged: the first in the theoretical literature on inequality and poverty (Atkinson and Bourguignon, 1982; Maasoumi, 1999; Bourguignon and Chakravarty, 2003); and the second in the realm of applied welfare and development economics (e.g., Klasen, 2000; Qizilbash, 2002; Kuklys, 2005). The discussion about multidimensionality of poverty has also been reflected in the United Nations Millennium Declaration and Millennium Development Goals [MDGs] (UN, 2000) which have highlighted multiple dimensions of poverty since 2000, as well as in the Human Development Reports by UNDP since 2010 (United Nations Development, 2010).

In the current paper, we calculate the changes in poverty over the time period 1999-2007 using both a traditional one-dimensional poverty measurement and a multi-dimensional approach. We find that the traditional monetary measurement delivers faster reduction in poverty than the multidimensional measurement. We also identify significant differences in poverty values and the pace of poverty reduction between three regions that we distinguish: rural areas, urban areas, and Tehran. Although Iran experienced relatively high growth rates of its real gross domestic product (GDP) and subsequent poverty reduction from 1999 to 2007, the uneven pace of poverty reduction in different areas contributed to an increase in the rural-urban gap. Since the rural-urban gap is an important source of overall inequality and affects the improvement of welfare negatively, this result can be interpreted as another reason why poverty is still a central issue in political debates in Iran.

Before developing our multidimensional framework of poverty measurement, we shortly recapitulate the political evolution of Iran over the last decades. In 1979, the Islamic revolution happened, where the former Monarchy Regime was replaced by the Islamic Republic Regime. The political changes quickly triggered economic changes including a large-scale nationalization, putting about 80% of total industrial production under the control of the government. Soon after the revolution, Iran's economy was heavily hit by the prolonged, eight-year Iran-Iraq War (1980-1988). During the 1980s, the oil production plummeted as the consequence of that war and the associated lack of investment, and consequently national income declined dramatically. During the war, however, the Islamic republic government tried to protect especially the poor against wartime inflation by rationing of basic goods and extensive price controls that intensified the government's role in the economy.

After the end of the war in 1989, production of oil recovered and the Iranian government started economic reforms by five-year plans that gradually dismantled rationing and price controls, increased the role of markets in distribution of goods and services, and began the move away from state ownership of productive assets. The reform plans gave priority to growth-based policies creating opportunities for the poor through rising income. In the first five-year plan the average growth of GDP was high, about 7.4% annually, but mainly the result of filling the already existent free capacities of the economy after the war. In the second five-year plan, however, the average growth of GDP decreased to 3.2% annually, primarily because of the decline of oil prices on the world market (Maroofkhani, 2009).

With the oil price increasing again in 1999, Iran's economy experienced a rise in growth of real GDP during almost a decade until 2007. Part of this growth has been due to increases in oil production and in oil prices on the world market improving Iran's terms of trade. Between 1999 and 2006, oil production increased by 13.3 percent, a little more than one-fourth of the increase in GDP. Export prices for Iranian oil have risen much more rapidly, from an average of $16.81 a barrel in 1999 to $59.82 in 2006. As a result, revenues from oil exports more than tripled between 1999 and 2006. According to the IMF report (IMF, 2007), between 1999 and 2006 the average rate of GDP growth was 5.8 percent per year. This economic growth was attributed largely to rising international oil prices, but it was also associated with an agricultural recovery as well as with expansionary monetary and fiscal policy reforms (IMF, 2007). After 2007, however, by the crippling international economic sanctions against Iran, GDP growth became volatile again. Table1 summarizes the GDP growth rate of the economy of Iran during 1992-2012.

Table 2.1. Real GDP Growth of Iran 1992-2012

year	1992	1993	1994	1995	1996	1997	1998
GDP growth rate	-1.9	5.6	-3.7	2.7	-1.4	-5.4	-2.8
year	1999	2000	2001	2002	2003	2004	2005
GDP growth rate	1.9	5.1	3.7	7.5	7.1	5.1	4.6
year	2006	2007	2008	2009	2010	2011	2012
GDP growth rate	5.9	7.8	-3.7	-8	4.5	4.5	-5.7

Source: Central Bank of Iran, 2013

We investigate poverty in Iran for the time-period of 1999-2007, because we intend to study poverty over a time period when Iran's economy experienced a steadily increasing trend of rate of real GDP growth on the one hand, and since we have access to sufficient information for measuring multidimensional poverty over this time-period on the other hand. This study is an attempt to give a new image of poverty in Iran by measuring multidimensional poverty over 8-years of growing economy in rural and urban Iran, and comparing the trend of multidimensional poverty changes to the trend of income poverty changes. Indeed, we try to highlight the importance of poverty measurement for targeting the poverty reduction policies.

The structure of the paper is as follows. Section 2 introduces the methodology of measuring multidimensional poverty, and section 3 gives an overview of selecting dimensions of our poverty indicator. The results from our empirical analysis are presented in section 4. Section 5 offers some concluding remarks.

2.2. Methodology of Measuring Poverty

We develop a measure of multidimensional poverty and compare it with the one-dimensional income poverty measurement. In order to measure income poverty, we follow the appropriate literature and apply the Foster-Greer-Thorbecke (FGT) methodology that also measures how income is distributed below the poverty line and incorporates inequality aspects (breadth of poverty). In order to measure multidimensional poverty, we use the Alkire-Foster method (2011b). This is a well-known method in multidimensional poverty measurement, with the virtues of being intuitive and flexible, as it can be adapted to many contexts. We discuss the two approaches in the following.

2.2.1. One-dimensional Poverty Measurement

In order to measure the traditional one-dimensional income poverty we apply FGT method (Foster et al., 1984). The FGT approach first defines a poverty line z and derives g_i as the relative deviation of individual *i*'s income y_i from that threshold: $g_i \equiv (z-y_i)/z$. We then obtain g_i^{α} as a measure of individual poverty with $\alpha \geq 0$ as a parameter that measures poverty aversion. Aggregating over individuals we get a poverty index P_{α} according to

$$P_{\propto} = \frac{1}{n}\sum\nolimits_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^{\propto}$$

where *n* denotes the total population, and *q* is the number of poor individuals. Obviously, the case $\alpha=0$ yields a distribution of individual poverty levels in which each poor person has poverty level equal to unity; the average across the entire population then is simply the headcount ratio P_0. The case $\alpha=1$ uses the normalized gap g_i as a poor person's poverty level, thereby differentiating among the poor, the average becomes the poverty gap measure P_1. The case $\alpha=2$ squares the normalized gap and thus weights the gap by the gaps, this yields the squared gap measure P_2. As α tends to identify, the condition of the poorest poor is all that matters (Foster et al., 1984). The parameter α has an interpretation as an indicator of "poverty aversion" in that a person whose normalized gap is twice as large has 2α times the level of individual poverty. Alternatively, α is the elasticity of individual poverty with respect to the normalized gap, so that a 1% increase in the gap of a poor person leads to α% increase in the individual's poverty level. The parametric class of measures gave analysts and policymakers an instrument to evaluate poverty under different magnifying glasses with varying sensitivity to distributional issues (Foster et al., 2010).

We use households as the units of measurement in this study, since our data gives the income of families not of individuals. As income poverty line, we use two worldwide income deprivation threshold values of 1,25 $ and 2 $ per day, and apply both of them respectively.

2.2.2. Multidimensional Poverty Measurement

We apply the Alkire-Foster method as the multidimensional poverty measurement. That method encompasses two parts: the process of identifying poor and the aggregation process for measuring poverty. The process of identifying poor involves of two cutoffs: the deprivation cutoff and the poverty cutoff. The method in the first stage defines deprivation cutoffs z_i for j different dimensions of deprivation. A person i with an individual achievement of y_{ij} in dimension j is then characterized as deprived if $y_{ij}<z_j$. Individual i can then be characterized by its total number deprivations c_i diagnosed by that procedure. At the second stage, we identify some individual as

poor if its total number of diagnosed deprivations c_i exceeds some threshold value k. Thus we have $c_i>k$ for the poor, and $c_i<k$ for the non-poor.

In order to implement the aggregation process for measuring poverty, we make use of a set of definitions (cf. Alkire and Foster, 2011b). However, first we present a progression of matrices for transition between the identification step and the aggregation step. The achievement matrix y contains the single achievements y_{ij} of n persons in d dimensions. We then obtain the deprivation matrix g_{ij}^0 by replacing each element of y that is below its respective deprivation cutoff z_j by 1, and each entry that is not below its deprivation cutoff by zero. Therefore, the deprivation matrix censors the value of non-deprived items, i.e. it focuses only on the deprived items. The g_{ij}^0 matrix provides a snapshot of frequency and breadth of deprivation among the population. Obviously, there is no deprivation at all if the g_{ij}^0 matrix contains only zeros. We observe a concentration of deprivation on any of dimensions, if columns of that matrix contain less zeros (frequency of deprivation). On the other hand, we have a concentration of deprivation on specific persons, if rows of that matrix contain rather any zeros (breadth of poverty).

$$\underbrace{\begin{bmatrix} y_{11} & \cdots & y_{1d} \\ \vdots & \vdots & \vdots \\ y_{n1} & \cdots & y_{nd} \end{bmatrix}}_{Y} \rightarrow \underbrace{Min\{0, 1 \times w_i \; if \; y_{ij} < z_j\}}_{g_{ij}^0} \rightarrow \underbrace{Min\left\{0, \left(\frac{y_{ij} - z_j}{z_j}\right) w_i \; if y_{ij} < z_j \right\}}_{g_{ij}^1}$$

The normalized gap matrix g_{ij}^1 replaces each deprived item in Y with the respective normalized gap (i.e. the difference between the deprivation cutoff and the person's achievement divided by the deprivation cutoff) multiplied by the deprivation weight, w_i. And it replaces each item that is not below its deprivation cutoff with zero. The normalized gap is only valid for achievements, which are cardinally measured. The g_{ij}^1 matrix represents a snapshot of the depth of deprivation of each poor person in each deprived dimension, while weighted by its relative importance.

In aggregation process, the AF method uses the so called headcount ratio H to measure frequency of poverty. That variable is defined as the ratio of the number of the poor persons, which are estimated by the dual cutoff method, q, and the number of persons of the complete population, n.

The measure H has the virtue of being easy both to compute and to understand. But the headcount ration H is a purely static concept and does not reflect changes in deprivation over time. Specifically, H does not reflect that some poor persons become deprived in a new dimension, or that a person initially deprived in some dimension now passes that threshold. In addition to that, H cannot be broken down and cannot show the contribution of each dimension to poverty.

In order to overcome those deficits of the headcount ratio, the AF method introduces the adjusted headcount ratio M_0 that reflects the concerns mentioned above. M_0 is obtained by multiplying the headcount ratio by H by the average deprivation share across the poor given by $A=|c_i(k)|/(qd)$. M_0 is sensitive both to the frequency and the breadth of multidimensional poverty. M_0 also is defined as the mean of the censored deprivation matrix;

$$M_0= HA = \mu(g_{ij}^0(k))$$

If a poor person becomes deprived in a new dimension, M_0 reflects that change. Furthermore, M_0 can be broken down to show how much each dimension contributes to poverty. M_0 has also the virtue of using pure ordinal data, which appear frequently in multidimensional approaches based on capabilities.

2.2.3. Data

The data used in this study are taken from the Household Expenditure and Income Surveys (HEIS) conducted annually by the statistical center of Iran (SCI). These surveys are nationally representative household surveys. They consist of separate rural and urban surveys and are stratified at the provincial level. The number of households e surveyed in each province is determined based on the province population and variance of the variables in the province. The number of Primary Sampling Units (PSU) in each province is determined by dividing the sample size for the province by 5. PSUs correspond to census tracts that are chosen randomly, and from each of which five households are randomly selected. Sample sizes vary from 5,759 households in 1986 to 31,283 in 2007.

The survey includes the basic demographic and economic characteristics of the households including self-reported income and expenditures collected for some 600 items (expenditure includes the self-produced and self-consumed items by the households). Similar to most household surveys, expenditures are based on a 30- or 365-days recall period, depending on the frequency of purchase. The recall period for food, fuel, and clothing, for example, is for the last 30 days, while the recall period for expenditures on durables, travel, school tuition, etc., is annual.

2.3. Criteria for Selecting Dimensions

Applying our multidimensional poverty measurement based on the capability approach brings forward the challenge of selecting dimensions. It is important to select dimensions that are convincingly meaningful in the poverty discourse. However, there is not a well-established list of dimensions or capabilities in the literature, nor there is a process to develop such a fixed list meeting Sen's pretentions: "Pure theory cannot freeze a list of capabilities for all societies for all time to come, irrespective of what the citizens come to understand and value. That would be not only a denial of the reach of democracy, but also a misunderstanding of what pure theory can do." (Sen, 2004, p. 78) Or "To insist on a fixed forever list of capabilities would deny the possibility of progress in social understanding and also go against the productive role of public discussion, social agitation, and open debates" (Sen, 2004, p. 80). Indeed, Sen argues that key capabilities must be selected, but argues consistently against the specification of only one authoritative standard list of capabilities with the expectation of applying it at all times and places.

There are different lists of dimensions in the literature. Although the discussion of the basis of choice is rarely explicit, it seems, as Alkire (2008) argues, that most researchers draw implicitly on either one or more of the following five selection procedures: 1. Use existing data; 2. Make assumptions – perhaps based on a theory; 3. Draw on an approved existing list of dimensions; 4. Use an ongoing deliberative participatory process; and 5. Propose dimensions based on empirical studies of people's values and/or behaviors.

An example of multidimensional index of wellbeing in terms of functioning achievements is the Multidimensional Poverty Index (MPI), developed by the Oxford Poverty & Human Development Initiative (OPHI) with the UN Development Programme (UNDP) for inclusion in UNDP's flagship Human Development Report in 2010. The MPI includes ten indicators in three dimensions; Health (nutrition, child mortality), Education (years of schooling, school attendance), Living Standard (cooking fuel, sanitation, water, electricity, floor, assets).

For this study we tried to adopt the MPI list of dimensions and adapt it according to our available data. Since our data does not contain the health information, we tried to find proxies. Eventually, due to the availability of reliable data, in the present study we draw on the following three variables: (1) nutrition, (2) education, (3) living standard. We choose identical weights for all three dimensions.

Nutrition: Regarding the available data we considered two indicators as the proxies for the nutrition: percentage of expenditures on food, and expenditure of daily minimum calorie intake for each individual. The poorest households in the world spend more than 75 percent of their income on food, while households in the richest countries such as the United States and Canada - on average spend less than 15 percent of their expenditures on food (Smith and Subandoro, 2007). Since the households who spend more than 75 percent of their expenditures on food are presumed very vulnerable to food insecurity, we use that threshold value for the indicator of the percentage of expenditures on food.

Expenditure of the minimum of daily required calories is another indicator of dimension of nutrition. For determining the threshold for this indicator we use the estimated nutrition deprivation threshold by Iran Statistical Research Center (Kashi et al. 2003; Bagheri et al. 2005; Haidari et al 2015). In these studies, the minimum daily-required calories for each individual are taken from nutrition experts' opinion. Then the minimum essential amount of (different types of) food and the value of minimum required food (based on the poorest percentile food habitation) for rural and urban household in Iran were estimated.

Education: The literacy situation can be considered as an index that indicates extreme education deprivation. This dimension consists of two indicators: household head literacy situation and school attendance of 6 to 16 years old children. The household head literacy situation is not only important because data about it are available, but also because of a number of other reasons: The head of the household has a very important role in the Iranian culture. She or he typically is the person that not only earns the major part of household income, but that also decides about how income is spent. Moreover, the head of the household also decides about the cultural issues and social issues of the household. Therefore, the household's welfare may be affected significantly, if the head of the household is completely illiterate or if he or she cannot read, write or count.

School attendance of school-aged children is another indicator of this dimension. If in a household there is a child between six to 16 years old that is not attending school, the household is regarded as deprived in the school attendance indicator.

Living standard: We measure the standard of living by five indicators: accessing electricity and safe water (piped water), enough living space for each individual, fuel for cooking and asset ownership. Access to electricity and to safe water, are the primary prerequisite of living standards in most references in the literature (e.g. in the MPI index mentioned above). Another dimension of living standard considered here is sufficient living space for each individual. A low value of living space per person is a sign of overcrowding. Overcrowded housing may have a negative impact on physical and mental health, relations with others as well as children's development. The indicator includes all living space, along with bathrooms, internal corridors and closets. Covered semi-private spaces such as corridors, inner courtyard or verandas should be included in the calculation, if used for cooking, eating, sleeping, or other domestic activities. The living space per person is defined as the median floor area (in square meter) of a housing unit divided by the average household size. This indicator measures the adequacy of living space in dwelling. Living space per person does not by itself give a complete picture of living conditions. Cultural values affect sensitivity to crowding as well. According to UNCHS (1996), however, this indicator is more precise and policy sensitive than related indicators, such as persons per room or households per dwelling unit. Specifying a threshold for the living space per person is not an easy task, because there is no fixed standard and it is also affected by cultural values. Hence, regarding its self-realization of the cultural circumstances of the case, we choose a threshold of $10m^2$ per capita. That means that each household living in a house with a per capita living space of less than $10m^2$ is deprived in the housing dimension.

To implement the AF methodology, tow general forms of cutoffs should be chosen; the deprivation cutoffs z_j and the poverty cutoff k. The deprivation cutoffs z_j have been introduced in the previous section. For the poverty cutoff the study uses the equal weight of the dimensions and k = 0.333.

Table 2.2. Dimensions, Weights and Deprivation Cut-off the Multidimensional Poverty

Dimension Indicator	The deprivation threshold	Relative weight
Nutrition		
Daily required calories	2300 calories per day	16.7%
Percentage of expenditures on food	Spend more than 75% of expenditures on food	16.7%
Education		
Literacy situation of the household head	Illiterate household head	16.7%
School attendance	Household member (6 to 16 years old) out of school	16.7%
Living standard		
Electricity	No access to electricity	6.66%
Safe water	No access to safe water	6.66%
Overcrowding	No enough (10qm) living space of housing per capita	6.66%
Fuel of cooking	Coking fuel is wood, charcoal or dung.	6.66%
Asset ownership	Household does not own more than one of these items (radio, TV, telephone, bike, motorbike or refrigerators) and does not own a car.	6.66%

2.4. Multidimensional Poverty Versus One-dimensional Monetary Poverty

In this section, we provided a comparison between results of the traditional one-dimensional approach and those of the multi-dimensional approach over time that comprise changes of income poverty, frequency of multidimensional poverty and breadth of multidimensional poverty in two four-year periods 1999-2003 and 2003-2007.

Table 2.3 gives the values of one-dimensional poverty headcount, multi-dimensional poverty headcount and adjusted multi-dimensional poverty headcount by region in Iran in the years 2007, 2003 and 1999. As it can be seen, by income poverty measurement more households are identified as poor than by multidimensional poverty measurement, for instance in 1999 75.9% of total population are income poor with applying old poverty line, 1.25$ per day, and 89.7% of the total population are income poor with applying new poverty line, 2$ per day, while only 16.1% of the total population are multidimensional poor. The same trend is also observed in 2003 and 2007, as well as, in in different regional areas. Indeed, multidimensional poverty measurement is a more appropriate approach for measuring extreme poverty, while income poverty measure, particularly with new poverty line, covers more proportion of population as poor people.

The results also show that poverty (both frequency and breadth) has declined in total and in each region over the time period. However, the income-poverty alleviation trend was significantly faster than the multidimensional-poverty alleviation. The trend of poverty reduction is also uneven in different regional areas. The pace of poverty reduction in rural areas is much slower than in urban areas and in the capital city Tehran. It can be seen from the percentage contribution of poverty in different areas that the percentage contribution of rural areas increased over the time, thus confirming the uneven poverty reduction in different regional areas in Iran. This uneven poverty reduction in favor of urban areas amplifies the welfare inequality between rural and urban areas, which causes many social as well as political issues, like growing emigration from rural to urban areas, or fortifies the populist political parties in rural areas.

Table 2.3. Poverty Profile of Iran 1999,2003 and 2007

	Tehran			Urban			Rural			Total		
	1999	**2003**	**2007**	**1999**	**2003**	**2007**	**1999**	**2003**	**2007**	**1999**	**2003**	**2007**
Income poverty 1.25 $	0.289	0.021	0.003	0.596	0.194	0.046	0.874	0.475	0.174	0.759	0.387	0.111
Percentage Contrib.	16%	3%	1.4%	34%	28%	20.6%	50%	69%	78%	100%	100%	100%
Income poverty 2 $	0.571	0.079	0.016	0.819	0.439	0.149	0.956	0.717	0.399	0.897	0.627	0.272
Percentage Contrib.	24%	6%	3%	35%	36%	27%	41%	58%	70%	100%	100%	100%
Multidimensional poverty headcount H	0.033	0.019	0.002	0.187	0.065	0.027	0.192	0.127	0.086	0.161	0.095	0.056
Percentage Contrib.	8%	9%	2 %	45%	31%	23%	47%	60%	75%	100%	100%	100%
Adjusted multidimensional poverty M_0	0.015	0.008	0.0004	0.067	0.030	0.012	0.093	0.061	0.040	0.077	0.045	0.026
Percentage Contrib.	9%	8%	0.8 %	38%	30%	23%	53%	62%	76.2%	100%	100%	100%

Figure 2.1 illustrates the difference between traditional expenditure poverty headcount and the multidimensional measures H and M_0. It shows large inequality between the different areas of Iran, both in traditional expenditure poverty and multidimensional poverty measurements.

Figures 2.1- 2.4 are respectively illustrating estimated multidimensional poverty headcount, adjusted multidimensional poverty, income poverty headcount with old poverty line, and income poverty headcount with new poverty line for different regional areas of the country over the time period 1999-2007. They show that measuring multidimensional poverty produces more inequality between society's subgroups. Figure 5 depicts and compares the poverty alleviation over the particular time period for different poverty measurement in total and in different regional areas. It can be seen that poverty reduction happens much faster when we measure poverty via income poverty than when we measure multidimensional poverty. These results imply that measuring multidimensional poverty is more accurate in identifying the extreme poor people particularly among different subgroups and over time. As a result, the multidimensional approach helps policy makers in a more proper way to target the extreme poor people.

Figure2.1. Multidimensional Poverty Headcount, H

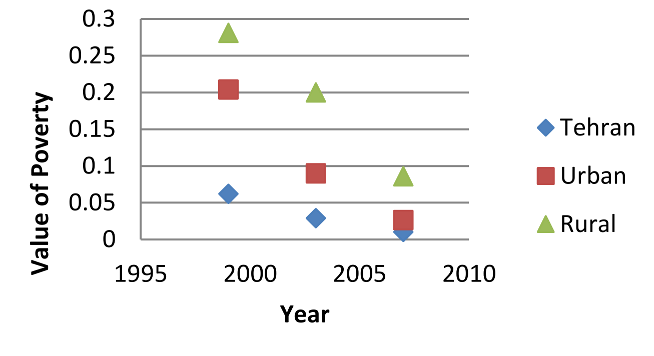

Figure2.2. Adjustment Multidmensional Pverty, M_0

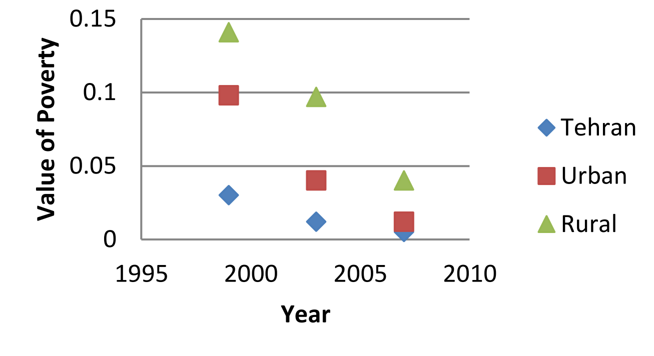

Figure 2.3. Income Poverty Headcount (Z=1,25$)

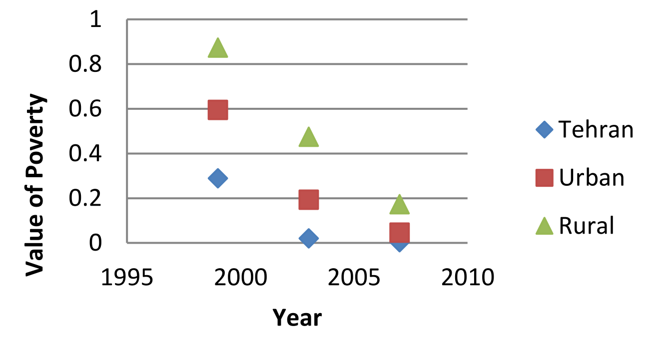

Figure2.4. Income Pverty Headcount (Z=2$)

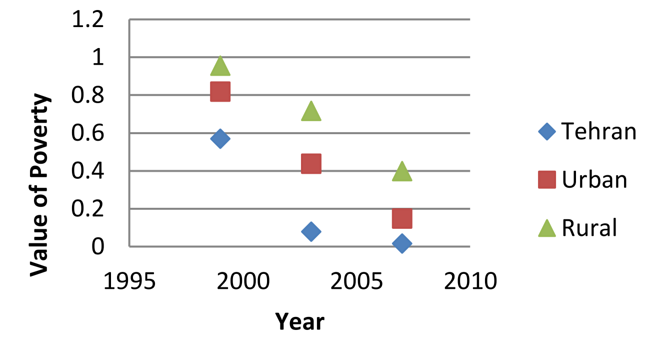

Figure2.5. Poverty Trend over the 1999-2007 Time Period in Iran

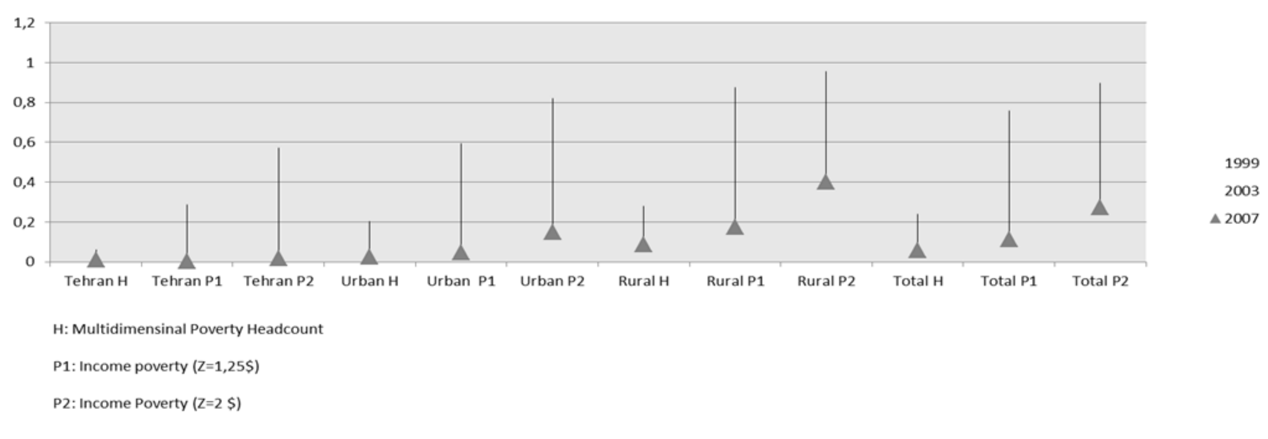

Table 2.4 demonstrates the overlaps between different poverty measurements. As it can be seen, about 30% of income-poor people are multidimensional poor, while the percentage of multidimensional poor people who are also income poor (30% for the lower poverty line and 51% for upper poverty line in 1999) shrinks dramatically over time to 8% for the lower line and 18.5% for the upper line. The results indicate that over the time there are more people who suffer from

multiple deprivations and are not identified as poor by traditional income poverty measurement. Nevertheless, these results again imply that multidimensional poverty is a proper measurement for identifying the extreme poverty, which is also justifiable theoretically, since the multidimensional measurement consider different aspects of welfare. It is also a more accurate measurement to identify the permanent poverty, while measuring income poverty can reflect just a transient situation.

Table 2.4. Profile of Income Deprivation and Non-income Deprivation Overlapping

Year 1999	Income Poor (1,25 $)	Income Poor (2 $)	MD Poor	Non MD Poor	Non Income Poor
Income Poor (1,25 $)	100%	100%	34%	66%	-
Income Poor (2 $)	51%	100%	30%	70%	-
MD Poor	30%	51%	100%	-	49%
Year 2003	**Income Poor (1,25 $)**	**Income Poor (2 $)**	**MD Poor**	**Non MD Poor**	**Non Income Poor**
Income Poor (1,25 $)	100%	100%	28%	72%	-
Income Poor (2 $)	43%	100%	27.5%	71.5%	-
MD Poor	8%	18.5%	100%	-	81.5%
Year 2007	**Income Poor (1,25 $)**	**Income Poor (2 $)**	**MD Poor**	**Non MD Poor**	**Non Income Poor**
Income Poor (1,25 $)	100%	100%	31%	69%	-
Income Poor (2 $)	26%	100%	25%	75%	-
MD Poor	3 %	8.5%	100%	-	91.5%

Table 2.5 shows the relative variation in the income poverty index and multidimensional poverty index in 1999-2003 and 2003-2007. The pace of poverty reduction is different with different poverty measurement. In Tehran income poverty (with both old and new poverty line) in comparison to multidimensional poverty decreases much stronger over 1999-2003. On the contrary over the period 2003-2007 multidimensional poverty decreases more than income poverty. In other urban areas and in rural areas, the pace of poverty reduction with old poverty line is more than the pace of multidimensional poverty reduction, however the pace of adjusted multidimensional poverty (breadth of poverty) reduction is considerable.

The results in table 2.5 also indicate clearly the different pace of poverty alleviation in Tehran, urban areas and rural areas. The rate of poverty reduction in rural areas is much less than the speed of poverty reduction in Tehran and other urban areas thus generating a higher gap between rural areas and urban areas over time. In other words, inequality between regions has become more pronounced. This finding may explain the sensibility of people with respect to inequality and the popularity of pro-poor claims of populists particularly in the rural areas.

Table 2.5. Relative Variation in the Multidimensional Poverty Index, Headcount Ratio and Intensity of Poverty by Division in Iran, 1999-2003, 2003-2007.

Group	1999-2003				2003-2007			
	ΔM_0 %	ΔH %	ΔP_1%	ΔP_2%	ΔM_0 %	ΔH %	ΔP_1%	ΔP_2%
Tehran	-47%	-42 %	- 93 %	- 86 %	-95%	-89%	- 86 %	- 80 %
Urban	-65%	-56 %	- 67 %	- 46 %	-60%	-58%	- 76 %	- 66 %
Rural	-34%	-30%	- 45 %	- 25 %	-34%	-32%	- 63 %	- 44 %
Total	-41%	-41%	- 49 %	- 30 %	-42%	-41%	- 71 %	- 57 %

P_1 denotes income poverty with old poverty line (1,25$ per day) and P2 denotes income poverty line (2$ per day).

Figure 2.2 illustrates table 2.5 via the methodology proposed by Apablaza and Yalonetzky (2011). Basically, it illustrates the changes of adjusted headcount ratio M_0 break down into changes in H, changes in A, and changes in an intersection term, when $\Delta M_0 = \Delta H + \Delta A + \Delta H \times \Delta A$. As can be seen, the most changes in term of poverty alleviation occurred in Tehran 2003-2007 and 1999-2003, while the lowest change related to the rural for both periods. However, it also shows that poverty in rural areas was more alleviated in the period 2003-2007 than in the period 1999-2003.

Fig2.6. Changes of Adjusted Multidimensional Headcount and Its' Components over the Period 1999-2003 and 2003-2007

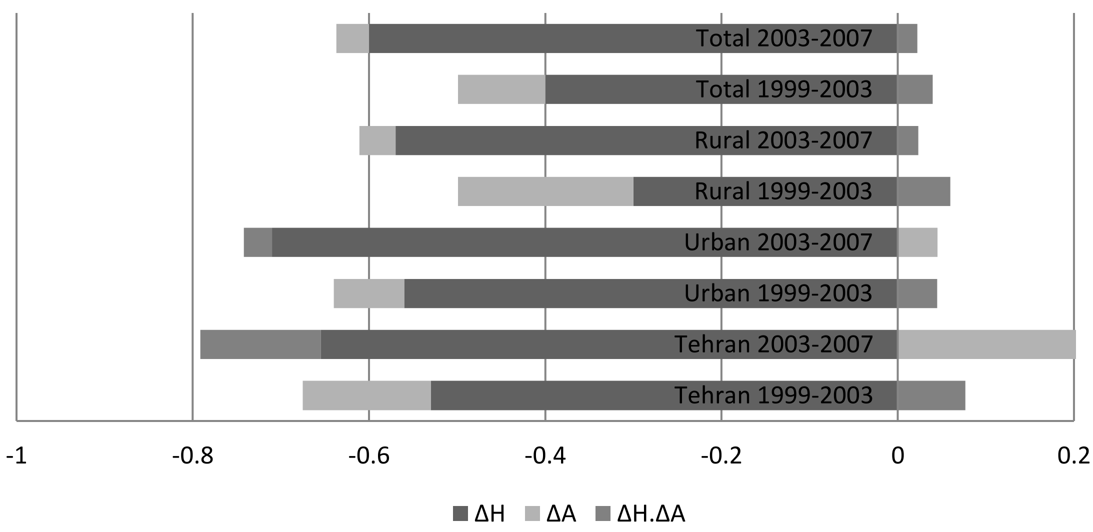

Table 2.6 identifies the percentage contribution of each dimension in adjusted poverty headcount of each region. That is, after identifying the poor, we show which dimensions have more or less contribution in making the poor people to fall in poverty. At first glance, the proceeding may be misunderstood in a way that it first aggregates the indices and then breaks them down again to arrive at the same indices. However, that is just a misunderstanding. Basically, M_0 is obtained after applying a process of identification and its value equals aggregate deprivations experienced by the poor as a share of the maximum possible range of deprivations across society. Hence, the indicators are not independent but rely on the joint distribution through the identification step. Therefore, sub-indices derived from breaking down M_0 are reflecting the share of each dimension in impoverishing the poor population of each group. It helps policymakers to target the contributing dimension of poverty for each subgroup (was mentioned by Alkire and Foster (2011b) as the useful characteristic of the measure for policy discussions).

Finally table 2.6 shows that deprivation in reaching minimum daily food expenditure has the most contribution in poverty, specially, in Tehran and other urban areas, though this contribution decrease over the time. Another contributing factor of poverty in urban areas is the deprivation in the floor area and in the school attendance both which experience an increasing trend of contribution in poverty over the time. In rural areas, contribution of living standard deprivation such as deprivation in accessing safe water is as much as the contribution of education deprivation or nutrition deprivation. It also reflects the breadth of poverty in rural areas, which was indicated before in adjusted multidimensional poverty, M_0.

Table 2.6. Contribution of Dimensions to Multidimensional Poverty.

1	2	3		4		5	6	7	8	9	10
Group	Year	Nutrition Contrib.		Education		Living Standard Percentage Contrib.					M_0
		Daily food expenditure	Percentage of expenditures on food	Illiteracy of the head	No School Attendance	No Electricity	No Tap water	Cooking Fuel	Floor area	Asset	
Tehran	1999	25.8%	0.5%	25.8%	12.9%	0%	0%	0%	23.3%	11.7%	0.03
	2003	27%	0%	23%	12%	0%	1.5%	0%	24.5%	12%	0.012
	2007	25%	0%	50%	0%	0%	0%	0%	25%	0%	0.005
Urban	1999	26.3%	13%	22%	10%	0.2%	1.5%	0%	12%	15%	0.098
	2003	28%	1%	26%	11%	0.5%	2%	0%	145%	17%	0.040
	2007	27%	0.4%	26%	18%	0.1%	3%	0%	20%	5.5%	0.012
Rural	1999	9.3%	4%	22.5%	17%	5.5%	11.5%	0.6%	16%	13.6%	0.174
	2003	15%	2%	23%	16.5%	3.6%	12%	0.4%	16.5%	11%	0.097
	2007	16.5%	2.3%	23.5%	15%	3.2%	11.2%	3.3%	16%	9%	0.040

2.5. Conclusion

We confronted the results of pure income poverty and multidimensional poverty, and we elaborated on the overlap between the results of two different methods. The results of our proceedings display a different picture of multidimensional poverty compared to the traditional one-dimensional poverty in our case study, Iran. While multidimensional poverty measurement is especially sensitive to the extreme poverty of suffering from multiple deprivations, traditional income poverty covers only 30% to 50% of the multidimensional (extreme) poor people in 1999 and even less, 3% to 8% of them, in 2007.

Moreover, a comparison of the results shows that over the time the value of traditionally measured poverty decreased with a more rapid pace than the decrease in value derived by the multidimensional approach. This means that the growth rate of traditional income poverty decreased, while deprivations in other dimensions of poverty were less mitigated.

The results also clearly indicate that the rural population suffers desperately both on income poverty and multidimensional poverty not only in the form of higher frequency of the poverty, but also by deeper breadth of poverty. This implies that welfare tends to concentrate more in urban areas, particularly in Tehran, than in rural areas, and over the time span considered in the study the gap between different regions became even larger. These findings substantiate why fighting poverty remains the top issue in Iran political debates, despite of poverty reduction in general.

Finally, we also benefited the decomposability quality of Alkire-Foster method, which allows the index to be broken down in each population subgroup to show the characteristics of multidimensional poverty for each group, which is a remarkable property for policy-making. It shows that minimum daily food expenditure has the most contribution in poverty, specially, in Tehran and other urban areas. However, the contribution of the expenditure dimension decreased over time. Over time, in Tehran and other urban areas the deprivation in the floor area and in the school attendance both experience an increasing trend of contribution in poverty. In rural areas, contribution of living standard deprivation such as deprivation in accessing safe water and electricity is as much as the contribution of education deprivation or nutrition deprivation. Obviously policymakers could benefit from the information, which is provided by the decomposability feature of the method to target the subgroups in aspects they suffer more.

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Chapter 3

Gender and Spatial Disparity of Multidimensional Poverty in Iran

Abstract

Identifying welfare as a multidimensional concept and demonstrating inequalities in distribution of welfare are two principle issues highlighted in this paper. In order to estimate the frequency and intensity of multidimensional poverty in Iran we applied Alkire-Foster method, while for demonstrating the inequality in distribution of welfare among the Iranian population, based on their spatial, gender, and some other demographic features, we conducted the multilevel regression analysis, with the premise that households are nested in the provinces. Conducting the logit multilevel model, we predicted the possibility of falling in poverty for a typical household with certain circumstances and in each province in Iran. The results show a remarkable disparity among population in Iran in which female-headed households and rural households are heavily disadvantaged compared to their peers in male-headed and urban households.

Keywords: multidimensional poverty; multilevel modeling; welfare inequality.

JEL Classification: I32, D63, O53

3.1. Introduction

Poverty and inequality are two sides of a coin. Whenever discussions about eliminating poverty arise, mitigating inequalities has a large part to play. Therefore, unfolding disparities in welfare among the population is as important as measuring poverty. In this regard, this paper reveals inequalities in well-being across gender and spatial dimensions while measuring poverty in a case study in Iran. This study highlights two principal issues, which in recent decades have been central in the discussion on poverty and inequality: identifying human welfare as a multidimensional phenomenon and inequalities in distribution of welfare among households and specific groups within a population.

Multidimensional measures of poverty have been deployed, particularly during the last three decades, as a complement to traditional one-dimensional measures of poverty or sometimes as a substitute. This discussion has been around in academic circles for many years. The theoretical reasons in economics for measuring welfare as a multidimensional phenomenon were brought forward in the late 1970s and early 1980s by Kolm (1977) and Sen (1984), who criticized one-dimensional monetary measures on a number of points. Kolm argued that the anonymity axiom usually assumed in a welfare analysis is better achieved, as more attributes of the individual are included in the welfare measure. Sen focused on the impact of non-market goods and services and individual heterogeneity on welfare achievement, as the traditional one-dimensional measurements cannot capture these factors. Instead, he recommended a multidimensional assessment of individual welfare in the space of standard of living measures (such as health, nutrition, education, or shelter), quality of life, or subjective well-being. His approach is known as the capability approach (Sen 1984).

Moreover, one-dimensional measures (e.g. income, commodity command) do not constitute or adequately represent human well-being and deprivation. Basically, as Alkire and Foster declare, poor people go beyond income in defining their experience of poverty: "when poor people describe their situation, as has been found repeatedly in participatory discussions, part of their description often narrates the multiplicity of disadvantages that batter their lives at once. Malnutrition is coupled with a lack of work, water has to be fetched from an area with regular violence, or there are poor services and low incomes. In such cases, part of the experience and problem of poverty itself is that several deprivations are coupled – experienced together" (Alkire, and Foster 2011a). There is no one indicator, such as income or consumption, which is able to capture the multiple aspects contributing to poverty.

The discussion also has been reflected in the Millennium Declaration and Millennium Development Goals (MDGs) which have highlighted multiple dimensions of poverty since 2000, as well as in the Human Development Reports of UNDP (United Nations Development Program). Beginning in 1997, the Human Development Reports included the HPI (Human poverty Index), a composite measure of health, education, and standard of living. Then, in 2010, the MPI (Multidimensional Poverty Index) was published for the first time.

The method, which this study also applied, in order to measuring poverty in Iran, while the population segregated by gender and spatial aspect, is the method of MPI for multidimensional poverty measurement (the Alkire-Foster methodology).

In addition to, the study intended to show the inequalities in distribution of welfare among the households with different demographic features in different regions of the country. Hence, after identifying the poor by the Alkire-Foster method, instead of using a counting approach, we applied the poor identification results in multilevel regression models with the premise that households nested within the provinces. The multilevel regressions show how much the inequality in distribution of welfare is related to province level and how much related to the differences in the household level. Besides, these regressions predict the possibility of falling in poverty for a typical household with certain circumstances and in each province in Iran.

There are a few studies on measuring poverty in Iran, mostly focusing on one-dimensional (monetary) poverty. Assadzadeh and Paul (2004) examined changes in income poverty in Iran in the period 1983 to 1993. The analysis is based on household-level data relating to three Household Income and Expenditures Surveys of 1983, 1988, and 1993. Salehi-Isfahani (2009) examined the trends in income poverty and inequality for more than two decades after the revolution (1979-2005) and compared the results with the pre-revolution years. Maasoumi and Mahmoudi (2013) used a nonparametric methodology for the decomposition of the change in poverty into growth and redistribution components. An empirical application is given based on data on real consumption in rural and urban areas of Iran in 2000, 2004 and 2009. The current paper, however, not only focuses on multidimensional poverty in Iran, but also concentrates on the phenomenon of inequality among the households and specific groups within population of Iran.

This paper comprises six sections. After the introduction, it continues with the methodology of measuring poverty. Section 3 introduces the regression analysis and multilevel models. Section 4 presents the results of measuring poverty. Section 5 focuses on the results of multilevel regression models. And the final section offers some concluding remarks.

3.2. Methodology of Measuring Poverty

The general approach of measuring poverty in this study is the capability approach, which was proposed by Sen (1976). In order to estimate multidimensional poverty, the study applies the Alkire-Foster methodology, which detects and counts the individuals (or households) who are suffering multiple deprivations. The method has been used for the MPI in Human Development Reports and has several virtues that make it particularly attractive for the current study. The study enumerates the advantages of this methodology, as the method based on a concept of poverty as multiple deprivations that are simultaneously experienced; it does not have the heterogeneity of the dashboard approaches. In other words, it gives a single indicator, which conveys the concept of poverty as the joint distribution of deprivations and which is particularly useful for reporting the progress of pro-poor policies or comparing socioeconomic performances. It is very flexible and can be adapted to many contexts of data and dimensions.

The Alkire-Foster methodology has three steps. First, it selects the dimensions of poverty (or dimension in the case of one-dimensional poverty), then identifies the poor, and eventually aggregates the results and measures the amount of poverty.

3.2.1. Criteria of Selecting Dimensions

Selecting dimensions and setting the thresholds and weights of dimensions are challenging tasks. It is important to select dimensions that are convincingly meaningful in the poverty discourse. The fact is that there is no fixed list of dimensions in literature. As Alkire argues, "The capability approach can be and, it is expected, will be applied differently depending on the place and situation, the level of analysis, the information available, and the kind of decision involved. The methods will be plural. So if one expects the capability approach to generate one specific and universally relevant set of domains for all evaluative exercises, or to generate a specific and distinctive methodology by which to identify the domains of poverty any particular group values, one may be disappointed" (Alkire 2008, p.2). Although the discussion of the basis of choice is rarely explicit, it seems that most researchers draw implicitly on five selection methods, either alone or in combination. "The five processes are: 1. Use existing data; 2. Make assumptions – perhaps based on a theory; 3. Draw on an existing list that was generated by consensus; 4. Use an ongoing deliberative participatory process; and 5) Propose dimensions based on empirical studies of people's values and/or behaviors" (Alkire 2008, p. 7-8).

There are different lists of dimensions in the literature. An example of a multidimensional index of well-being in terms of functioning achievements is the MPI, which was developed by OPHI (Oxford Poverty & Human Development Initiative) with the UNDP in 2010. The MPI includes ten indicators in three dimensions: health (nutrition, child mortality), education (years of schooling, School attendance), and living standard (cooking fuel, sanitation, water, electricity, floor, assets).

In this study, I modified the list of dimensions of MPI for the case study and designed a set of welfare dimensions regarding the applied source of data. Indeed, the UNDP emphasizes that the MPI methodology can and should be modified to generate national multidimensional poverty measures that reflect local, cultural, economic, climatic, and other factors. As Alkire and Foster declare, their method guides researchers in the creation of a multidimensional poverty measure for a specific society by giving them freedom in the selection of dimensions of disadvantage and in selecting indicators and cut-off points for these dimensions of disadvantage (Alkire and Foster 2011b).

The source of data used in this study is the Household Expenditure and Income Surveys (HEIS) in 2008 which conducted by the Statistical Center of Iran (SCI). The survey includes the basic demographic and economic characteristics of the households including self-reported income and expenditures, which are collected for some 600 food and non-food items (expenditure includes the self-produced items consumed by the households themselves, which is a virtue of this data set). It includes some characteristics of the household's head like gender, age, education and marital situation; and some accommodation characteristics such as floor area and access to electricity and safe water, as well as the household's assets. The survey is composed of separate rural and urban surveys and stratified at the provincial level. The number of households to be surveyed in each province is determined based on the province's population. The number of primary sampling units (PSU) in each province is determined by dividing the sample size for the province by five. PSUs correspond to census tracts, which are chosen randomly, and five households are randomly selected from each. Sampled households are distributed evenly throughout the year with 1/12 of the households surveyed each month, while the interviewee is the head of household.

However, the data has the disadvantage of lacking health dimension information such as child mortality or malnutrition or any other health indicator. Therefore, I consider tow indicators – daily food expenditure and percentage of expenditures on food – as the proxy indicators of nutrition. Finally, this study draws on three variables: (1) nutrition, which consists of two indicators - daily food expenditure and percentage of expenditures on food; (2) education, which consists of two indicators - the literacy situation of the head of the household and the school attendance of children aged 6 to 16 years; (3) living standard, which consists of five indicators – access to electricity, access to safe water, overcrowding, fuel for cooking, and asset ownership.

Table 3.1. Dimensions, Weights and Deprivation Cut-off of the Multidimensional Poverty

Dimension	**Indicator**	**The deprivation cutoff z_j**
Nutrition (1/3)	Daily food expenditure(1/6)	1.08 $ in urban area and 0.69 $ in rural area
	Percentage of expenditures on food (1/6)	Spend more than 75% of expenditures on food
Education (1/3)	Literacy situation of the household head (1/6)	Illiterate household head
	School attendance (1/6)	Household member (6 to 16 years old) out of school
Living standard (1/3)	Electricity (1/15)	No access to electricity
	Safe water (1/15)	No access to safe water
	Overcrowding (1/15)	No enough (10qm) floor area of housing per capita
	Fuel of cooking (1/15)	Coking fuel is wood, charcoal or dung.
	Asset ownership (1/15)	Household does not own more than one of these items (radio, TV, telephone, bike, motorbike or refrigerators) and does not own a car.

Nutrition as a welfare dimension consists of two indicators: percentage of expenditures on food and daily food expenditure for each individual. The poorest households in the world spend more than 75 percent of their income on food, while households in the richest countries such as the United States and Canada on average spend less than 15 percent of their expenditures on food (Smith and Subandoro, 2007). Since the households who spend more than 75 percent of their expenditures on food are presumed very vulnerable to food insecurity, in this study the threshold of the indicator of the percentage of expenditures on food is determined as 75 percent.

Daily food expenditure is another indicator of dimension of nutrition. For determining the threshold for this indicator, I used the estimated nutrition deprivation threshold by Iran Statistical research Center (Haidari et al, 2015). In this method, the minimum required calories daily for each individual was determined based on the nutrition experts' opinion. Then the minimum essential amount of (different type of) food and the value of minimum required food (based on the poorest percentile food habitation) for rural and urban household in Iran were estimated. The threshold of daily food deprivation for urban households is 1.08 $ and for rural households is 0.69 $ (Haidari et al, 2015).

Education consists of two indicators: the household head literacy situation and School attendance of children aged 6 to 16 years old. The household head literacy situation is an important indicator for a number of reasons. In Iranian culture, the head of the household has a very significant role as the person who not only brings in income, but also decides how income can be allocated and spent. Therefore, a head of household who is illiterate and cannot read, write, or count can negatively influence the household welfare. Additionally, as our unit of estimation is the household, the literacy situation of household head is particularly essential with respect to the second part of this study, which examines the disparity of poverty according to some characteristics of the head of household like gender. School attendance of school-aged children is another indicator of this dimension. If in a household, there is a child between 6 to 16 years old who is not attending school, the household deprived in the school attendance indicator.

The Living standard dimension consists of five indicators: accessing electricity and safe water (piped water), sufficient floor area for each individual within the house, cooking fuel, and asset ownership. Access to electricity and safe water and asset ownership are the primary requisites of living standards in most references in the literature, for example the MPI that was mentioned above. Floor area per person is one of the 10 key housing indicators approved by the Commission on Human Settlements (UNCHS, 1996) to measure progress towards meeting the objectives of the Global Strategy for Shelter to the Year 2000. A low value for the floor area per person is a sign of overcrowding. Overcrowded housing may have a negative impact on physical and mental health and relations with others, as well as children's development. Floor area includes all living space, along with bathrooms, internal corridors, and closets. Covered semi-private spaces such as corridors, inner courtyard, or verandas should be included in the calculation, if used by the household for cooking, eating, sleeping, or other domestic activities. The floor area per person is defined as the median floor area (in square meters) of a housing unit divided by the average household size. This indicator measures the adequacy of living space in the dwelling. Cultural values affect sensitivity to crowding as well. According to UNCHS (1996), however, this indicator is more precise and policy sensitive than related indicators, such as persons per room or households per dwelling unit. Hence, in this study floor area with the threshold of 10m2 per capita was considered as one of the indicators of the living standards.

3.2.2. Identification of the Poor

There are two common methods of identifying the poor in a multidimensional approach: the union method, which identifies person i as poor if deprived in at least one indicator, and the intersection approach, which does not recognize person i as poor unless person i is deprived in all dimensions (d). The Alkire-Foster method suggests an alternative approach, called a dual cut-off approach, which defines two kinds of thresholds: the threshold for dimension j, which is denoted by Z_j; and the poverty threshold k, which lies somewhere between the two extremes, $1<k<d$. The current study also followed the dual cut-off approach and when the weight of deprivations for each unit denoted by ci and $0<c_i< 1$, it considered $k = 0.333$.

3.2.3. Measurement of Poverty

Alkire-Foster method was evolved from combining FGT (Foster-Greer-Thorbeck) poverty measurement and counting approach, and like every other poverty measurement, first identifies the poor and then measures the poverty.

In order to measure poverty, Alkire-Foster method introduces a set of definitions based on the FGT approach and can measure the frequency and the breadth of poverty; as well as the depth of poverty if all variables are cardinal. However, the method first presents a progression of matrices for the transition between the identification step and aggregation step.

Y denoted the matrix of achievement when the achievement of a person i in d dimensions was set in a matrix. And, g^0 is the deprivation matrix when each entry in Y that is below its respective deprivation cutoff Z_j is replaced with the deprivation value w_j, and each entry that is not below its deprivation cutoff is substituted with zero. Therefore, the deprivation matrix censors the value of non-deprived items; that is, it focuses only on the deprived items. The g^0 provides a snapshot of frequency and breadth of deprivation among the population. Then, in the aggregation step, the Alkire-Foster method introduces tow definitions; multidimensional poverty headcount ratio denoted by H, and adjusted headcount ratio denoted by M_0.

The multidimensional poverty headcount, which captures the frequency of poverty; estimated as $H=H(y;z)=q/n$, when n is the number of total population, and q is the number of the multidimensional poor people. $q=q(y_i;z)=\Sigma^n_{i-1}\varrho k(y_i;z,)$, when ϱ is an identification function; $\varrho(y_i;z)=1$ if $y_i<z$ means person i is poor; while $\varrho(y_i;z)=0$ if $y_i>z$ means person i is not poor.

Due to a distinction between the groups who endure different levels of multidimensional poverty, the Alkire-Foster method introduces the adjusted headcount ratio M_0, which reflects the breadth of poor people's poverty. And M_0=HA= $\mu(g^0(k))$, when A is the average deprivation share across the poor.

By above-mentioned method, the study estimated the multidimensional poverty of four different groups (rural male-head, rural female-head, urban male-head, and urban female-head) in each of Iran's 30 provinces. The estimated H and M_0 values simply indicate how many percent of households in each province are multidimensionally poor, or how many percent of households in each above-named group, within each province, are poor. Nevertheless, by these aggregated values, it is not clear how much the disparity of poverty, in the whole population, related to the level of provinces and how much related to the household level. It is also not clear which characteristics increase the possibility of falling in poverty, or which type of households are more in danger of falling in poverty. In order to answer these questions, instead of using the counting approach and conducting the aggregation process, we used the poor identification results (by Alkire-Foster method) in the mixed effect regressions and conducted multilevel models.

3.3. Multilevel Regression Models

In order to analyze the disparity of poverty based on spatial, gender, and some other demographic factors, and to estimate the variation in the extent of poverty between the poor (i.e. inequality between the poor) based on spatial and demographic factors, we applied multilevel regression models. Questions explored in this study through multilevel models are the following: What is the extent of between-province variation in poverty incidence? What amount of poverty variation can be attributed to either between-province variation or within-province (among households) variation? To what extent the poverty variation can be explained by the household-level variables (i.e. the demographic features of households). To what extent poverty variation attributes to the province-level variables (e.g. the rural proportion).

Multilevel models are statistical models for analyzing the relationships between variables measured at the different levels of a data structure. These models are suitable for our data structure because in our data households are nested within provinces. Hence, we have two levels of data: households in level 1 and provinces in level 2. Multilevel models allow us to model dependency in hierarchical data, while standard linear regression models (i.e. fixed-effects analysis) assumes that individuals are independent and do not estimate the variance in the group effects. Multilevel models also allow us to analyze the effect of group-level variables (contextual variables) - e.g. the rural proportion of a province- on individual outcomes. Additionally, multilevel models allow us to analyze heterogeneity in the data or the way a first-level outcome varies across groups (Steele, 2008).

The source of data for the multilevel regression models in this study is the same used to estimate that multidimensional poverty headcount H and adjusted headcount ratio M_0. We have two motivations for using multilevel regression analysis. The first is our goal of analyzing the disparity in incidence of poverty among the whole population. Thus, we employ one multilevel regression model (model 1) to estimate the disparity of poverty incidence, which is a multilevel logit regression. The second goal is analyzing the disparity in the intensity of poverty. To accomplish this, we use another multilevel regression model (model 2) to estimate the variation in the intensity of poverty, which is a multilevel linear regression. Since the intensity of poverty is a phenomenon intrinsically demonstrating the intense of poverty among poor people, the multilevel linear regression is conducted to estimate the variation in the intensity of poverty among the poor.

A linear two-level model, where a total of n individuals (at level 1) are nested within j groups (at level 2) with n_j individuals in group j, is:

$$y_{ij} = \beta_0+\beta_1 x_{ij}+u_j+e_{ij}$$

with y_{ij} denote the response for individual i in group j and x_{ij} denoting an individual-level explanatory variable, where the group effects or level 2 residuals u_j and the level 1 residuals e_{ij} are assumed to be independent and to follow normal distributions with zero means:

$$u_j \sim N(0,\sigma_u^2) \text{ and } e_{ij} \sim N(0, \sigma_e^2).$$

The model can also be expressed in terms of the mean or expected value of y_{ij} for an individual in group j and with value x_{ij} on x as

$$E\,(y_{ij} \mid x_{ij}, u_j) = \beta_0+\beta_1 x_{ij}+u_j.$$

For a binary response y_{ij}, we have $E\,(y_{ij} \mid x_{ij}, u_j) = Pr(y_{ij} = 1)$. Hence, a logit tow-level model is written as

$$Pr(y_{ij}=1) = \beta_0+\beta_1 x_{ij}+u_j.$$

In the logit form of the model, the level 1 residual is assumed to follow a logistic distribution, while the level 2 residual is assumed to be normal (Steele, 2009).

We extend these simple models, adding further explanatory variables defined at level 1 or 2, to construct our tow-level logit model (1), as well as tow-level linear model (2).

3.3.1. Multilevel Logit Model

The model (1) is designed to show the disparity in poverty incidence among the population based on their spatial, gender, and some other demographic features. The model is a hierarchical regression model, because the data structure has two levels, where i refers to the unit of level 1, which equals the number of households (=39088) and j refers to level 2 data and equals the number of provinces (=30). In addition, the model is a logit regression model because the response is the probability of poverty incidence ϱ_i, which is binary. The response options are 'poor' and 'non-poor'. The two categories are combined to obtain a binary variable coded '1' for poor and '0' for non-poor.

The level 1 dummy variables are RH (Rural household), FH (Female head of household), NMc (Number of household members, mean centered i.e. four members), YH (Young head household i.e. <25), OH (Old head household i.e. >60), WH (widow head household), DH (Divorced head household), NmH (never married head of household).

The level 2 or province-level Dummy variable is Rp (Rural proportion of the province), Dsc (distance of the province capital to the country's capital, Tehran).

Model (1.1) is a logit tow-level regression model, when all the dummy variables are the level 1 variables.

$$\Pr(\varrho_{ij}=1) = \text{Logit}^{-1}(\beta_0+\beta_1 RH_{ij}+\beta_2 FH_{ij}+ \beta_3 NMc_{ij}+ \beta_4 YH_{ij}+ \beta_5 OH_{ij}+ \beta_6 WH_{ij}+ \beta_7 DH_{ij}+ \beta_8 NmH_{ij}+u_j \quad (1.1)$$

$$\varrho_i \in [0, 1]$$

$$u_j \sim N(0, \sigma_u^2)$$

Model (1.2) is again a logit tow-level regression model like model (1.1), but with an extra dummy variable of level 2 (province variable of rural proportion) which denoted by Rural prop.

$$\Pr(\varrho_{ij}=1) = \text{Logit}^{-1}(\beta_0+\beta_1 RH_{ij}+\beta_2 FH_{ij}+ \beta_3 NMc_{ij}+ \beta_4 YH_{ij}+ \beta_5 OH_{ij}+ \beta_6 WH_{ij}+ \beta_7 DH_{ij}+ \beta_8 NmH_{ij}+ \beta_9 Rp_{.j}+ \beta_{10}\, Dsc_{.j} +u_j) \quad (1.2)$$

$$\varrho_i \in [0, 1]$$

$$u_j \sim N(0, \sigma_u^2)$$

In the logit hierarchical regression model, β_0 is interpreted as the log-odds that $\varrho=1$ when $x_{ij}=0$ and u=0, and is referred to as the ***overall intercept*** in the linear relationship between the log-odds and *x*. By taking the exponential of β_0, we obtain the odds that $\varrho = 1$ for x = 0 and u = 0.

In multilevel model, β_1 is the effect of x after adjusting for (or holding constant) the group effect u. If we are holding u constant, then we are looking at the effect of x for individuals within the same group, so β_1 is referred to as a cluster-specific effect. If we have u=0, β_1 is referred to as the population-average effect.

And u_j is the group (random) effect, group residual, or level 2 residual. The interpretation of residual is the same as the continuous response model; the only difference is that in a logit model they represent group effects on the log-odds scale. While β_0 is the overall intercept in the linear relationship between the log-odds and x, the intercept for a given group j is $\beta_0+ u_j$ which will be higher or lower than the overall intercept depending on whether u_j is greater or less than zero. In analyzing multilevel data, we are also interested for variation that can be attributed to the different levels in the data structure and the extent to which variation at a given level can be explained by explanatory variables. Variance partition coefficient (VPC) measures the proportion of the total variance that is due to differences between groups. For binary data we estimate VPC = $\sigma^2/\sigma^2+3.29$.

3.3.2. Multilevel Linear Model

Model 2 is designed to show the variation in the breadth of poverty among the poor, or, in other words, inequality among the poor based on their spatial, gender, and the other demographic features. In this model, i refers to the multidimensionally poor households because we are interested in estimating inequality among the poor. Hence, the number of observations in level 1 is the number of multidimensionally poor households (=5981). And j refers to level 2 data and equals the number of provinces (=30). Model 2 is a linear multilevel regression model as the response is the average deprivation value for the poor (c_i) and $0<c_i<1$. It also estimates inequality among the poor, based on their characteristics.

Model (2.1) is a linear tow-level regression model, where the dummy variables all are the level 1 variables.

$$C_{ij}=\beta_0+\beta_1RH_{ij}+\beta_2FH_{ij}+\beta_3NMc_{ij}+\beta_4YH_{ij}+\beta_5OH_{ij}+\beta_6WH_{ij}+\beta_7DH_{ij}+\beta_8NmH_{ij}+u_i+\varepsilon_{ij} \quad (2.1)$$

u_j: province-level random effect (or residual)

$u_j \sim N(0, \sigma_u^2)$,

σ_u^2 is the between province variance that measures the variability of the province means.

ε_{ij}: within province random effect (or residual)

$\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$,

σ_ε^2 measures the average variability of H value within provinces.

Model (2.2) is similar to Model (2.1) apart from including an extra dummy of province variable of rural proportion.

$$C_{ij} = \beta_0+\beta_1 RH_{ij}+\beta_2 FH_{ij}+ \beta_3 NMc_{ij}+ \beta_4 YH_{ij}+ \beta_5 OH_{ij}+ \beta_6 WH_{ij}+ \beta_7 DH_{ij}+ \beta_8 NmH_{ij}+ \beta_9 Rp._{ij}+ u_i+ \varepsilon_{ij} \quad (2.2)$$

u_j: province-level random effect (or residual),

$u_j \sim N(0, \sigma_u^2)$

σ_u^2 is the between province variance that measures the variability of the province means.

ε_{ij}: within province random effect (or residual)

$\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$

σ_ε^2 measures the average variability of H value within provinces.

In the linear hierarchical regression model, β_0 is interpreted as the overall intercept or grand mean. In this model, the total residual is decomposed into two error components u_j and ε_{ij}, while u_j is the level 2 random effect or residual, and ε_{ij} is the level 1 random effect or residual error. Where u_j and ε_{ij} are assumed independent, Cov $(u_j, \varepsilon_{ij}) =0$, and the total residual variance is decomposed into two variance components, $Var(Tr_{ij}) = Var(u_j + \varepsilon_{ij}) = Var(u_j) +2 . Cov(u_j , \varepsilon_{ij}) + Var(\varepsilon_{ij}) = \sigma_u^2+ \sigma_\varepsilon^2$. In the linear multilevel regression model, σ_u^2 is the between province variance that measures the variability of the province means, while σ_ε^2 measures the average variability of H values within provinces. The VPC measures the proportion of the total response variance, which lies at a given level. The level 2 or group-level VPC is $VPC_u= \sigma_u^2/ (\sigma_u^2+ \sigma_\varepsilon^2)$. The higher the level-2 VPC, the greater the degree of clustering found in the response variable. VPC_u shows the poverty variation between provinces.

3.4. Results of Measuring Poverty

In this part the multidimensional poverty ratio, H, and the adjusted headcount ratio, M_0, for each of the 30 provinces in Iran is estimated. Table 3.2 sorts the provinces from the poorest to the least poor and demonstrates the amount of incidence and intensity of multidimensional poverty for all 30 provinces in Iran. The poorest provinces respectively are South Khorasan with 44.1% followed by Sistan-Baluchestan with 43.2 %, North Khorasan with 31.7% and Kerman with 29.8% of multidimensional poor households, whereas the provinces with the least poor households are Tehran with 8.4%, Mazandaran with 12.7%, Bushehr with 13% and Semnan 14.1% of multidimensional poor households. It is worth noting that the poorest provinces are located in the far eastern side of the country, while the least poor provinces are mainly located in the central north of the country (capital province and its' neighbor provinces).

Table 3.2. Profile of Regional Multidimensional Poverty in Iran 2008, K= 0.333

Province		**Multidimensional poverty headcount ratio H**	**Adjusted headcount ratio M_0**
1	South Khorasan	0.441	0.164
2	Sistan-Baluchestan	0.432	0.195
3	North Khorasan	0.317	0.12
4	Kerman	0.298	0.117
5	Kohgiluyeh and buyer Ahmad	0.284	0.104
6	Hormozgan	0.256	0.103
7	Golestan	0.246	0.093
8	Zanjan	0.246	0.092
9	Kordestan	0.246	0.093
10	Qom	0.229	0.085
11	Razavi Khorasan	0.244	0.091
12	Ilam	0.243	0.090
13	Khuzestan	0.237	0.094
14	West Azerbaijan	0.235	0.092
15	Kermanshah	0.225	0.086
16	Markazi	0.224	0.08
17	Lorestan	0.204	0.077
18	Hamedan	0.208	0.075
19	Yazd	0.189	0.07
20	East Azerbaijan	0.187	0.069
21	Charmahal and Bakhtiari	0.1795	0.069
22	Ardebil	0.177	0.067
23	Fars	0.1696	0.061
24	Esfahan	0.168	0.059
25	Qazvin	0.167	0.061
26	Gilan	0.156	0.059
27	Semnan	0.141	0.049
28	Bushehr	0.130	0.047
29	Mazandaran	0.127	0.045
30	Tehran	0.084	0.031
Total		**0.224**	**0.085**

Table 3.2 also demonstrates the values of the adjusted headcount ratio, M_0, which indicates the breadth of poverty. A comparison between the values of H and M_0 in table 3.2 shows that generally the provinces with more poor population also tend to have more intensity of poverty, though some exception can be observed e.g. Sistan-Baluchestan has a lower percentage of poor households, but more intensity of poverty comparing to South Khorasan.

The map in figure 3.1 depicts poverty in different provinces in Iran. It can be seen that the southeast and northeast provinces in particular and remote areas near the eastern and western borders have, in general, a higher incidence of poverty, while the provinces in the center and north of Iran suffer less from poverty. It shows that welfare tends to concentrate in capital province (Tehran) and in some of its neighbor provinces. Tehran and Esfahan are also the most industrialized provinces, while Qazvin with a thriving agriculture sector and today as the center of textile trade, in recent decades has become a developing pole of the country, essentially because of its preferable location. And Mazandaran besides the strong agriculture sector is one of the main tourism areas of Iran because of its pleasant climate, beautiful natural landscape, long coastline onto Caspian Sea, and proximity to Tehran.

One of these least poor provinces is Bushehr, located in the south of Iran with a long coastline on the Persian Gulf. Aside from the port city of Bushehr, which is the second main naval port of Iran, the economy of Bushehr province has prospered due to the presence of Kharg island, which is one of the two major petroleum exporting ports of Iran, and the industrial corridor of Assalouyeh, which is the closest land-based point to the South Pars Gas field - the world's largest natural gas field. However, in the neighboring province of Khuzestan, which also has a coastline along the Persian Gulf, is the major oil-producing region of Iran, and one of the most industrialized provinces of Iran, more than 13% of households are multidimensionally poor. It is worth noting that this province was heavily damaged during the Iran-Iraq war (1980-1988). In general, the multidimensional poverty map of Iran shows that the provinces that are endowed with natural resources or located near the capital province experience less poverty.

Unfortunately, there are no official statistics or census figures on the ethnic makeup of Iran. Therefore, there is no data to find out what the contribution of ethnicity to poverty is or how ethnicity correlates with other measured factors relating to multidimensional poverty. We can just by observing the multidimensional map of Iran, make some assumption about the deprivation status of provinces based on their ethnic composition.

In the multidimensional poverty map of Iran, it can be seen that some provinces with large ethnic population in western Iran i.e. Khuzestan (inhabited by a large population of Arabs), Kermanshah, Kordestan (with majority kurdish people), and West Azerbaijan (with majority of Azaries and Kurds) fall into the third category (20% to 25%) of multidimensional poverty. Some others like east Azerbaijan and Ardebil (with a majority of Azaries) rank as less poor provinces that are similar in rank to some other provinces without large ethnic populations. On the other hand, provinces with large ethnic groups on the east side of Iran, i.e. Sistan-Baluchestan (populated mostly by

Baluch people), North Khorasan (populated by a majority of Kurds, Turkamans and Turks) and Golestan (inhabited by a large population of Turkamans) are the most deprived provinces in Iran. Hence, while there are some evidences that provinces with a majority of ethnic inhabitant experience more poverty, because of the limitations in empirical data there is no concrete proof for the role of belonging to particular ethnic group and poverty.

Figure 3.1. Multidimensional Poverty Map of Iran

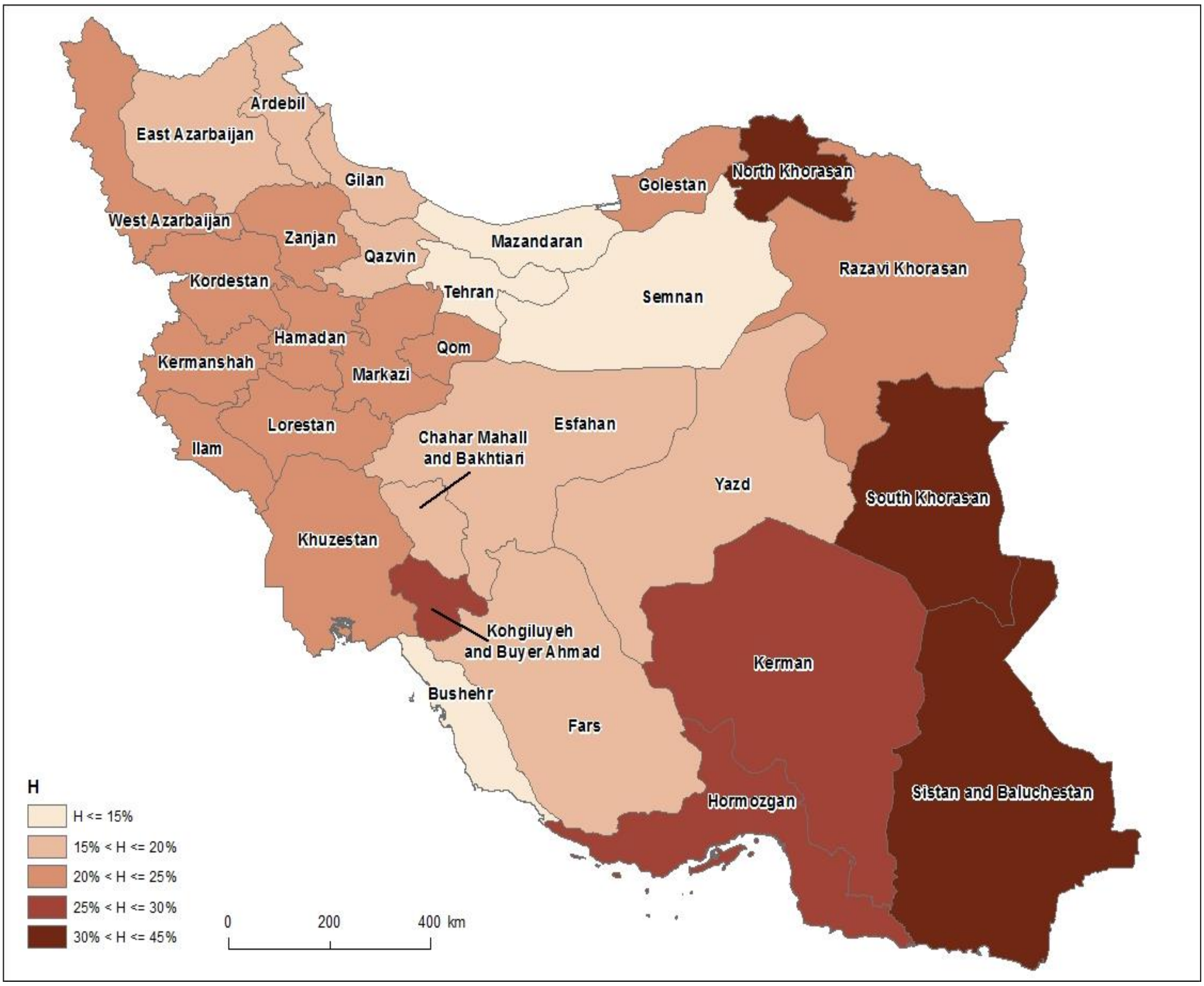


Table 3.3. Profile of Spatial Multidimensional Poverty in Iran 2008 by Distinguishing between Gender of the Head of Households K = 0.333.

Province		H Rural		H Urban		M_0 Rural		M_0 Urban	
		Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
1	South Khorasan	0.550	0.919	0.165	0.649	0.209	0.349	0.057	0.222
2	Sistan-Baluchestan	0.557	0.831	0.280	0.495	0.261	0.372	0.122	0.205
3	North Khorasan	0.549	0.766	0.12	0.2	0.213	0.285	0.043	0.069
4	Kerman	0.327	0.569	0.146	0.253	0.134	0.226	0.052	0.088
5	Kohgiluyeh and buyer Ahmad	0.348	0.762	0.107	0.342	0.128	0.283	0.339	0.122
6	Hormozgan	0.329	0.628	0.104	0.281	0.138	0.245	0.038	0.102
7	Golestan	0.329	0.591	0.103	0.443	0.127	0.219	0.037	0.027
8	Zanjan	0.306	0.673	0.109	0.245	0.117	0.248	0.038	0.087
9	Kordestan	0.283	0.555	0.148	0.441	0.111	0.196	0.054	0.161
10	Qom	0.268	0.563	0.129	0.34	0.102	0.197	0.047	0.116
1	Razavi Khorasan	0.294	0.771	0.106	0.338	0.112	0.292	0.038	0.119
12	Ilam	0.333	0.375	0.134	0.256	0.126	0.145	0.047	0.096
13	Khuzestan	0.32	0.571	0.093	0.25	0.132	0.206	0.033	0.087
14	West Azerbaijan	0.313	0.586	0.124	0.298	0.128	0.240	0.044	0.109
15	Kermanshah	0.282	0.551	0.122	0.326	0.112	0.198	0.044	0.112
16	Markazi	0.260	0.708	0.112	0.370	0.094	0.253	0.038	0.128
17	Lorestan	0.274	0.491	0.083	0.238	0.108	0.186	0.028	0.081
18	Hamedan	0.242	0.682	0.115	0.333	0.089	0.257	0.04	0.117
19	Yazd	0.189	0.663	0.075	0.326	0.072	0.242	0.027	0.326
20	East Azerbaijan	0.22	0.426	0.118	0.295	0.083	0.152	0.042	0.098
21	Charmahal and Bakhtiari	0.219	0.596	0.097	0.344	0.090	0.228	0.033	0.125
22	Ardebil	0.215	0.411	0.097	0.247	0.083	0.154	0.035	0.091
23	Fars	0.188	0.5	0.091	0.25	0.07	0.178	0.031	0.085
24	Esfahan	0.166	0.529	0.103	0.295	0.059	0.183	0.037	0.101
25	Qazvin	0.18	0.558	0.067	0.244	0.067	0.202	0.024	0.084
26	Gilan	0.198	0.564	0.058	0.141	0.077	0.21	0.020	0.049
27	Semnan	0.179	0.446	0.048	0.179	0.063	0.153	0.017	0.058
28	Bushehr	0.148	0.396	0.082	0.186	0.054	0.149	0.03	0.062
29	Mazandaran	0.143	0.492	0.051	0.293	0.052	0.173	0.017	0.102
30	Tehran	0.153	0.283	0.052	0.102	0.059	0.104	0.019	0.037
Total		**0.280**	**0.611**	**0.107**	**0.297**	**0.109**	**0.229**	**0.039**	**0.105**

Nevertheless, table 3.3 depicts another aspect of multidimensional poverty in Iran by displaying the frequency (via H headcount) and breadth (via M_0 headcount) of poverty for four different groups (rural households with a male head, rural households with a female head, urban households with a male head, and urban households with a female head) for each of the 30 provinces in Iran. A glance at the table 3 shows the disparity of poverty within provinces and among different groups in each province. It can be seen by looking carefully at the table that the poorest groups in each province are rural households and mostly the rural female-headed households. However, the bunch of values in table 3.2 and table 3.3 does not reflect the role of each feature of households or region in poverty incidence or intensity of poverty. They also do not make it clear how much poverty variation exists between provinces or how much poverty variation exists within provinces.

A scatterplot of H values in figure 3.2 as well as the scatterplot of M_0 values in figure 3.3 specify poverty variation among different groups of different provinces. They show that some provinces have, on average, more frequency and breadth of poverty than the other provinces, while within-province frequency and breadth of poverty also varies, i.e. in some provinces the variation among households in different groups is less and in the others is more.

Figure 3.2: H Values Scatterplot of 30 Provinces of Iran

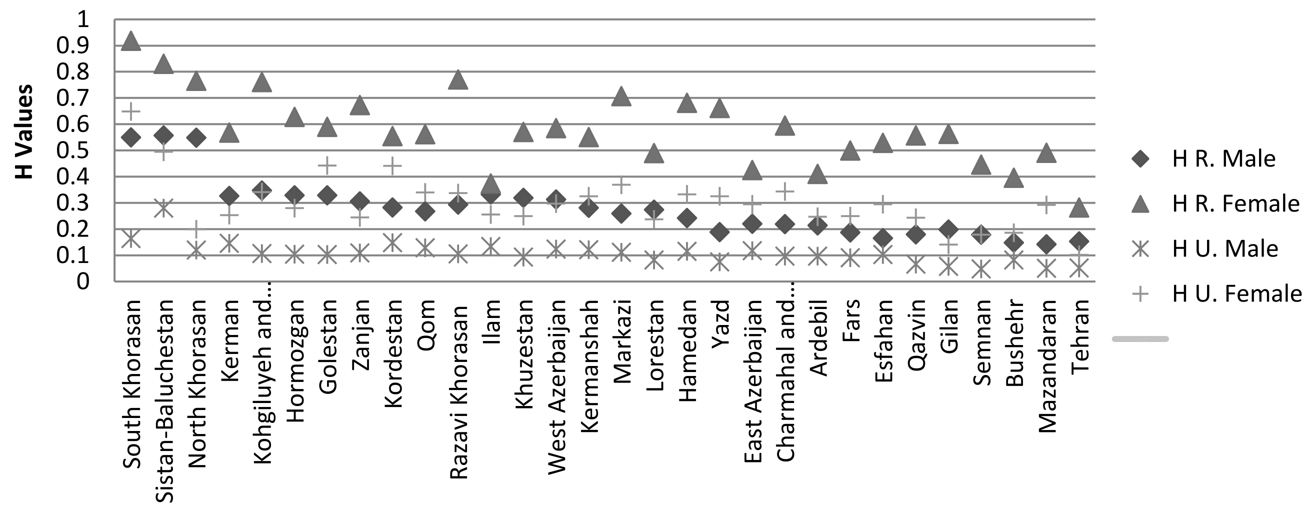
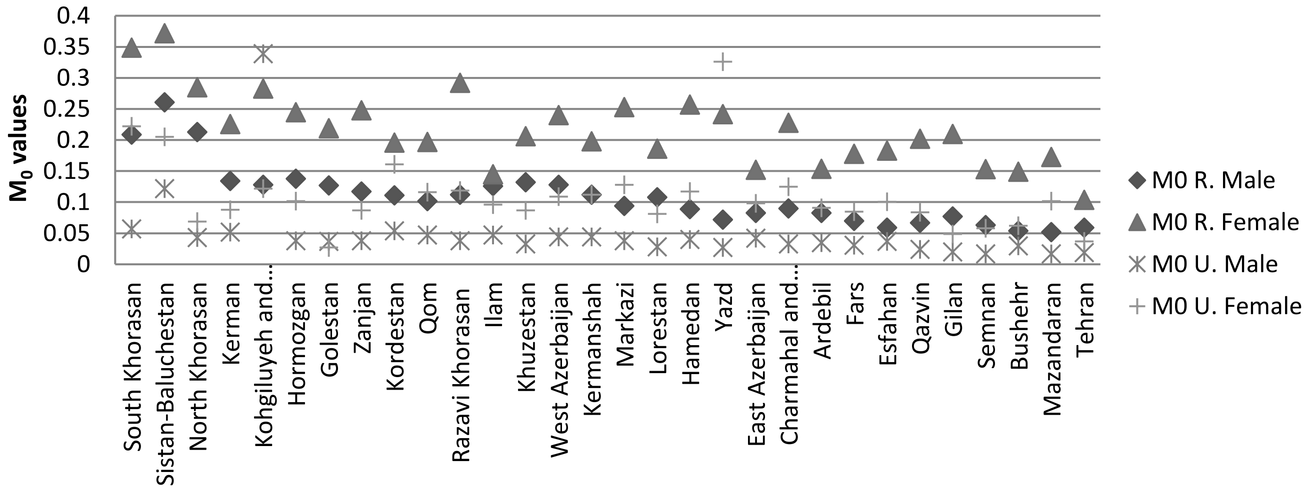


Figure 3.3. M_0 Values Scatterplot of 30 provinces of Iran



3.5. Results of Regressions Analysis

As data are available on two levels, i.e. households are nested within provinces and the response is binary, we applied a multilevel regression model. The model helps to answer questions such as, what is the extent of between-province variation in poverty. What amount of poverty variation can be attributed to either between-province variation or within-province (among households) variation? To what extent the poverty variation can be explained by the household-level variables (i.e. the demographic features of households). Do household-level variables such as age or gender have different effects in different provinces? Can between-province differences in poverty be explained by differences in the province level variables?

Table 3.4 shows the results of multilevel mixed effect regression, when the dependent variable is incidence of poverty and the responses are binary. The results of the empty model, which is sometimes referred to as a variance components model, are shown at the first rows of the table. The empty model helps us to extract the information of how much the variation at the dependent variable is attributable to the second level if none of the household's characteristics is included to the regression. The variance of the intercepts across the groups (provinces) or group-level residual variance in the empty model was estimated as $\sigma^2=0.191$, which is significant by the Wald test in $P<0.001$. The between-group variance helps to estimate the VPC, because in analyzing multilevel data, we are interested for variation that can be attributed to the different levels in the data structure and the extent to which variation at a given level can be explained by explanatory variables. Thus, the VPC for our two-level logit model is VPC= $\sigma^2/\sigma^2+3.29= 0.055$, i.e. 5.5% of variance in the incidence of poverty is due to between-province variation, and 94.5% of variance in the incidence of poverty occurs within provinces or between households.

In model 1.1, we considered hierarchical regression models for the relationship between the binary response variable (ϱ) and a set of explanatory variables of level 1. However, a particular advantage of multilevel modelling is the ability to explore the effects of group-level (level 2) predictors or contextual effects while simultaneously including random effects to allow the effects of unobserved group-level variables. Hence, the model 1.2 is the logit mixed effect model with an added dummy variable for the province level.

In order to prove that the multilevel model provides a significantly better fit to the data than the single-level model, we use a likelihood ratio (LR) test, which is equivalent to the reduction in the deviance. We compare LR to a chi-squared distribution with 1 degree of freedom. The critical value for testing at 5% level is 3.84. The LR test statistic values in all three regressions greatly exceed 3.84 ($p < 0.001$).

β_0 = -3.898 is interpreted as the log-odds that ϱ=1 when x_{ij}=0 and u=0, and is referred to as the overall intercept. The probability of β_0 is estimated by $Logit^{-1}$(-3.898) = 0.0198, that means, when we ignore the state variation, the probability of multidimensional poverty incidence for an urban household with four members and with a married middle-aged male head is 2 %. If we hold u=0, the probability of poverty for a female-headed household with the same circumstances would be $Logit^{-1}$(-3.898 +0.859) = 0.045, i.e. about twice more than the male peer. Furthermore, the probability of poverty incidence for a rural male-headed household with the similar above-mentioned factors is 6%, while the probability of poverty incidence for the peer rural female-headed household is approximately 13%. Controlling for province differences, we would expect the odds of being poor to increase by a factor of exp (0.254) =1.3 for each one-unit increase in the number of household members. The dummies for age (of head of household) show a strong positive and significant correlation between being aged and possibility of falling in poverty. When it comes to marital status variables, the dummy of never married (head of household) is not significant, while there is a positive dummy for divorced (head of household) and a strong positive and significant dummy for the widow (head of household). The results, however, does not demonstrate significant dummy for the province-level variable, rural proportion. The dummy of the other province-level variable, distance to capital city is positive, though it is not strong.

Table 3.4. Mixed Effects REML Regression for the Total Population with Response $\varrho \in [0, 1]$.

Empty Model					
Parameter		Estimate	Std. Err.	Z	P>|Z|
Intercept	β_0	-1.298	0.081	-16.05	0.000
Between state variance	σ^2	0.191	0.050	3.82	0.000
LR test: χ^2 (01) = 1303.92 (p <0.001)					
Individual level Model (1.1)					
Intercept	β_0	-3.57	0.112	-31.70	0.000
Rural HH	β_1	1.167	0.029	39.59	0.000
Female head	β_2	0.861	0.067	12.88	0.000
N of H members c	β_3	0.254	0.008	32.52	0.000
Age Parameters					
Young head H	β_4	-0.771	0.140	-5.49	0.000
Old head H	β_5	1.497	0.32	46.6	0.000
Marital status of household's head H Parameters					
Widow	β_6	0.825	0.068	12.07	0.000
Divorced	β_7	0.583	0.161	3.63	0.000
Never married	β_8	0.167	0.139	1.20	0.229
Random effect Parameters					
Between state variance	σ^2	0.208	0.055	3.78	0.000
LR test: $\chi 2$ (01) = 1124.90 (p <0.001)					
Individual- and Province-level Model (1.2)					
Intercept	β_0	-3.898	0.54	-7.22	0.000
Rural HH	β_1	1.167	0.029	39.57	0.000
Female head	β_2	0.859	0.067	12.86	0.000
N of H members c	β_3	0.254	0.008	32.45	0.000
Age Parameters					
Young head H	β_4	-0.772	0.140	-5.50	0.000
Old head H	β_5	1.497	0.032	46.61	0.000
Marital status of household's head H Parameters					
Widow	β_6	0.825	0.068	12.07	0.000
Divorced	β_7	0.582	0.161	3.62	0.000
Never married	β_8	0.166	0.139	1.19	0.233
Level 2 variables					
Rural prop.	β_9	-0.214	1.058	-0.20	0.840
distance	β_{10}	0.0007	0.0002	3.61	0.000
Random effect Parameters					
Between state variance	σ^2	0.142	0.038	3.74	0.000
LR test: $\chi 2$ (01) = 681.71 (p <0.001)					

Table 3.5. Profile of Residuals for the 30 Provinces.

	State	u_j	$u_j$std. Err.	u_j rank	Random(provincial) intercept	Logit[1](β_0+u_{30})
0	Markazi	0.286	0.071	23	-3.612	0.026
1	Gilan	-0.161	0.083	12	-4.059	0.017
2	Mazandaran	-0.275	0.09	7	-4.173	0.015
3	East Azerbaijan	-0.185	0.077	11	-4.083	0.017
4	West Azerbaijan	-0.006	0.076	18	-3.904	0.020
5	Kermanshah	0.17	0.067	21	-3.728	0.023
6	Khuzestan	-0.283	0.076	5	-4.181	0.015
7	Fars	-0.546	0.08	2	-4.444	0.012
8	Kerman	-0.011	0.063	17	-3.909	0.020
9	Razavi Khorasan	0.047	0.066	19	-3.851	0.021
10	Esfahan	-0.153	0.076	13	-4.051	0.017
11	Sistan-Baluchestan	0.557	0.06	28	-3.341	0.035
12	Kordestan	0.362	0.077	24	-3.536	0.029
13	Hamedan	0.203	0.070	22	-3.695	0.025
14	Charmahal and Bakhtiari	-0.120	0.086	14	-4.018	0.018
15	Lorestan	-0.206	0.081	10	-4.104	0.016
16	Ilam	-0.055	0.081	16	-3.953	0.019
17	Kohgiluyeh and Buyer Ahmad	0.152	0.062	20	-3.746	0.024
18	Bushehr	-0.929	0.091	1	-4.827	0.008
19	Zanjan	0.4	0.073	26	-3.498	0.030
20	Semnan	-0.231	0.097	9	-4.129	0.016
21	Yazd	-0.28	0.075	6	-4.178	0.015
22	Hormozgan	-0.313	0.066	4	-4.211	0.015
23	Tehran	-0.343	0.08	3	-4.241	0.014
24	Ardebil	-0.247	0.082	8	-4.145	0.016
25	Qom	0.385	0.076	25	-3.513	0.03
26	Qazvin	-0.096	0.086	15	-3.994	0.018
27	Golestan	0.442	0.069	27	-3.456	0.031
28	North Korasan	0.709	0.063	29	-3.189	0.041
29	South Khorasan	0.763	0.060	30	-3.135	0.043

However, the advantage of a hierarchical model is that it enables us to look at the effect of variables for units within the same group, which is known as the cluster-specific effect. Hence, β_0 is the overall intercept, the intercept for a given group (state) j is β_0+u_j, which will be higher or lower than the overall intercept depending on whether u_j is greater or less than zero. We can estimate the probability of falling in poverty for any typical household in each province like $Pr(\rho = 1) = logit^{-1}(\beta_0 + \beta_1 x_{ij} + u_j)$, when we estimate uj.

Table 3.5 depicts the estimated u_j and u rank for 30 provinces. As we have already calculated the predicted probability for an average province is u_j=0 and, assuming that u_j follows a normal distribution, we would expect approximately 95% of provinces to have a value of u_j within 2 standard deviations of the mean of zero, i.e. between approximately $-2\sigma_u$=-0.754 and 0.754. Table 3.5 also shows the predicted random intercept for each province, while the column titled by Logit1 (β_0+u_{30}) shows the probability of falling in poverty for a typical urban male headed household (with four members) in each province.

In similar fashion, the probability of poverty for each typical household with certain circumstances can be estimated. As the focus of this study is on the gender and spatial poverty, table 3.6 only categorizes and depicts the probability of poverty for the urban and rural households with a male head or female head in three provinces at the top and three at the bottom, when the other demographic variables are supposed to be constant. The number of household members is assumed four and the age and marital status of the head are considered married and middle-aged.

Table 3.6. Probability of Poverty for Four Typical Households in the Least Poor and the Poorest Provinces.

Provinces	Urban male h.	Urban female h.	Rural male h.	Rural female h.
The least poor				
Tehran	1.4%	3.3%	4.4 %	9.8 %
Bushehr	0.8%	2 %	2.5 %	5.7 %
Mazandaran	1.5%	3.5%	4.7 %	10.5%
The most poor				
South Khorasan	4.3%	9.3%	12.3%	25 %
North Korasan	4.1%	8.8%	11.7%	24 %
Sistan-Baluchestan	3.5%	7.7%	10.2%	21 %
Average in country with controlling states difference	2 %	4.5%	6 %	13 %

The values, which are shown in table 3.6, reflect two main ideas; first, the probability of poverty increases by some household characteristics (Like having female head or being rural), second, the effect of household characteristics are different in different provinces.

Table 3.7. Mixed Effects Regression for the Poor Population with Response c_i.

Fixed effect Model					
Parameter		Estimate	Std. Err.	Z	P>|Z|
Intercept	β_0	0.352	0.004	83.22	0.000
Rural HH	β_1	0.026	0.002	14.48	0.000
Female head	β_2	0.008	0.003	2.19	0.028
N of H members c	β_3	0.008	0.0004	20.74	0.000
Age Parameters					
Young head H	β_4	0.012	0.01	1.22	0.223
Old head H	β_5	-0.013	0.002	-7.10	0.000
Marital status of household’s head Parameters					
Widow	β_6	0.003	0.003	0.85	0.396
Divorced	β_7	0.011	0.01	1.16	0.248
Never married	β_8	0.031	0.01	3.30	0.001
Multilevel Empty Model					
Intercept	β_0	0.376	0.003	104.62	0.000
Between state variance	σ_u^2	0.0003	-	-	-
Within state variance	σ_e^2	0.005	-	-	-
LR test: $\chi2$ (2) = 631.20 ($p < 0.001$)					
Individual level Model					
Intercept	β_0	0.349	0.005	69.06	0.000
Rural HH	β_1	0.029	0.002	16.04	0.000
Female head	β_2	0.006	0.003	1.67	0.095
N of H members c	β_3	0.007	0.0004	18.24	0.000
Age Parameters					
Young head H	β_4	0.003	0.009	0.36	0.721
Old head H	β_5	-0.011	0.002	-5.87	0.000
Marital status of household’s head H Parameters					
Widow	β_6	0.002	0.003	0.69	0.489
Divorced	β_7	0.010	0.009	1.11	0.266
Never married	β_8	0.029	0.009	3.25	0.001
Random effect Parameters					
Between state variance	σ_u^2	0.00025			
Within state variance	σ_e^2	0.005			
LR test: $\chi2$ (2) = 492.60 ($p < 0.001$)					
Individual- and Province-level Model					
Intercept	β_0	0.369	0.02	19.53	0.000
Rural HH	β_1	0.029	0.002	16.06	0.000
Female head	β_2	0.005	0.003	1.65	0.099
N of H members c	β_3	0.007	0.0004	18.17	0.000
Age Parameters					
Young head H	β_4	0.0032	0.01	0.33	0.739
Old head H	β_5	-0.011	0.002	-5.88	0.000
Marital status of household’s head H Parameters					
Widow	β_6	0.002	.003	0.70	0.483
Divorced	β_7	0.010	0.009	1.08	0.278
Never married	β_8	0.029	0.009	3.23	0.001
Level 2 variables					
Rural prop.	β_9	-0.073	0.036	-2.00	0.046
distance	β_{10}	0.00003	6.57e-06	4.16	0.000
Random effect Parameters					
Between state variance	σ_u^2	0.00015			
Within state variance	σ_e^2	0.00069			
LR test: $\chi2$ (2) = 196.69 ($p < 0.001$)					

Table 3.7 shows the results of mixed effect regression when response is ci, when $0<c_i<1$ and the number of observations= the number of poor people (= 8039). We also estimated fixed effect regression to compare it with the results of multilevel models, which show no significant distinction. However, the LR test shows that the mixed effect regression is the preferable regression model to conduct in this case. The empty model again was conducted to show how much the variation at the dependent variable is attributable to the second level if none of the household's characteristics is included to the regression.

The results imply that the average deprivation value for a poor urban male-headed household in the whole country is $\beta_0=0.369$, while the threshold of falling in multidimensional poverty is 0.34. Other factors such as being rural or a female-headed household added only $\beta_1=0.029$ and $\beta_2=0.005$ to the value of poverty intensity, whereas having an old head of household has a negative effect of $\beta_5 = -0.011$on the intensity of poverty. And the marital states parameters and level 2 parameter of rural proportion are insignificant with a p value of <0.001. Therefore, controlling between-provinces variation, the intensity of poverty varies from 0.37 for an urban household with a young male head to 0.445 for a rural household with single female head. On the other hand, as the $VPC_u=\sigma_u^2/\sigma_u^2+\sigma_e^2=0.18$, approximately 18% of the variation in the intensity of poverty lies among provinces variation, and 82 % embedded within provinces variation (or the characteristics of the households).

To sum up, while inequality among the subgroups of the household population of the provinces is significant with respect to the incidence of poverty, the difference in the intensity of poverty among the poor is not remarkable.

To sum up results of the analysis above, we point out the following items. The variance of poverty incidence mostly related to within-province variation (94.5%), while only 5.5% of variance in poverty incidence lays between-province variation. The demographic factors of head of household (gender, age and marital status) have significant correlation with poverty incidence. Female, aged, divorced or widow head of households are significantly disadvantaged to their male, middle age, married counterparts. The other characteristics of household like being rural and the number of members also have positive and significant relation with the incidence of poverty. Being rural puts the household twice more in danger of falling in poverty than their urban counterparts, while each member extra than 4 centric number of members increase 0.5% to the possibility of falling in poverty for a household. And eventually the effect of household characteristics is some provinces are stronger than the others are.

Indeed, the analysis above confirms that certain individuals and groups are marginalized based on their gender and location of residence. In fact, the opportunities that people should have to avoid extreme poverty are vastly different depending on these factors.

3.6. Concluding Remarks

This paper focuses on two phenomena at the same time; multidimensional poverty in different areas in Iran; and inequality in the matter of distribution of welfare among the households and specific groups within the population of Iran.

The study, in the first place expands the monetary concept of poverty, which only captures income or sometimes expenditure, to a more comprehensive concept of multidimensional poverty and applies the Alkire-Foster method to measure the multidimensional poverty of households in 30 provinces of Iran. The results of multidimensional poverty ratio (H) and the adjusted headcount ratio (M_0) estimation show that the southeast and northeast provinces in particular and remote areas near the eastern and western borders in general experience higher incidence of poverty, while welfare tends to concentrate in capital province (Teharan) and in some of its neighbor provinces in the center and north of Iran.

However, measuring multidimensional poverty ratio (H) and the adjusted headcount ratio (M_0) do not reflect the effect of household's characteristics or region's features in incidence or intensity of poverty; also they do not distinct poverty variation between provinces and within provinces. Therefore, to find out the extent of the disparity between subgroups and to measure and compare the likelihood of certain typical units falling into poverty and to capture inequality among the poor, the study employs a multilevel regression analysis.

The results imply that most of the poverty incidence variation related to within-province variation (94.5%), and only 5.5% of the poverty incidence variation related to between-province variation. The results also indicate that having a female, aged, and divorced or widow head, as well as being rural are characteristics, which increase the likelihood of falling in poverty for a household. The probability of poverty for a rural family is, on average, four times greater than an urban family with the same circumstances, while the probability of poverty for a female-headed family is, on average, twice that of a male-headed family with the same circumstances. According to the results, the most disadvantaged households are female-headed rural households in the poorest southeast provinces, while the most fortunate households are male (married, middle aged)-headed urban households in Tehran, Bushehr and Mazandaran. The study concludes that certain households are marginalized based on their demographic and spatial circumstances.

The study focuses on estimating poverty and inequality of welfare in Iran in a way that is beneficial for policy makers, helping them to optimize poverty mitigation policies by targeting the most marginalized communities, as well as addressing inequalities, and social exclusion, which are deeply embedded in the social and economic processes of Iranian society. It is our hope that this study has prepared a base for future projects to design effective policies to alleviate poverty and inequality.

3.7. Appendix: Robustness Analysis

Using a rank robustness analysis, we evaluated how changes in the parameters affect relative multidimensional poverty values. A series of rank robustness tests was applied in order to assess how sensitive the relative values of multidimensional poverty across provinces are to changes in indicators' weights.

To test whether multidimensional poverty results are robust to a plausible range of weights, the multidimensional poverty has been estimated with three other alternative weighting structures - giving 50% of the relative weight to one of three dimensions and 25% to each of the other two in turn. Changing the indicators' weights affects the poverty estimates. However, the provinces rankings are robust to such changes. Table 3.8 presents the correlation between the province rankings obtained with the baseline of equal weights and those obtained with the other three alternatives. The correlation is 0.862 or higher using Kendall Tau and 0.955 or higher with the Spearman correlation. Interestingly, the rank correlation between the three alternative weighting systems is also relatively high – none lower than 0.829 with the Kendall correlation.

Table 3.8. Correlation Coefficients between Multidimensional Poverty Values Using Alternative Weighting Structures (in 30 Provinces of Iran)

		Equal Weights 33% each	50% Expenditure 25% Education 25% LS	50% Education 25% Expenditure 25% LS
50% Expenditure	Spearman	0.968		
25% Education **25% LS**	Kendall	0.956		
50% Education	Spearman	0.966	0.918	
25% Expenditure **25% LS**	Kendall	0.903	0.834	
50% LS	Spearman	0.995	0.971	0.969
25% Expenditure **25% Education**	Kendall	0.981	0.917	0.903

Note: LS: Living Standard. The Spearman rank correlation coefficients are 0.95 and higher

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Chapter 4

Growth Elasticity of Poverty: with Application to Iran Case Study

Abstract

The sensitivity of the frequency of poverty to economic growth is one of the central issues of poverty and development discourse. In this paper, we estimate the income growth elasticity of poverty and income inequality elasticity of poverty for a panel of 28 provinces of Iran from 1998 to 2009. We also, for the first time, estimate the growth elasticity of multidimensional poverty (estimated via Alkire-Foster method). The results demonstrate the low income growth elasticity of poverty while the income inequality elasticity of poverty is stronger and significant. Similar results are obtained for elasticities of multidimensional poverty. The results suggest that changes in inequality are more important for poverty reduction than changes in income growth.

Key words: Growth elasticity of poverty, income inequality, monetary poverty, Multidimensional poverty.

4.1. Introduction

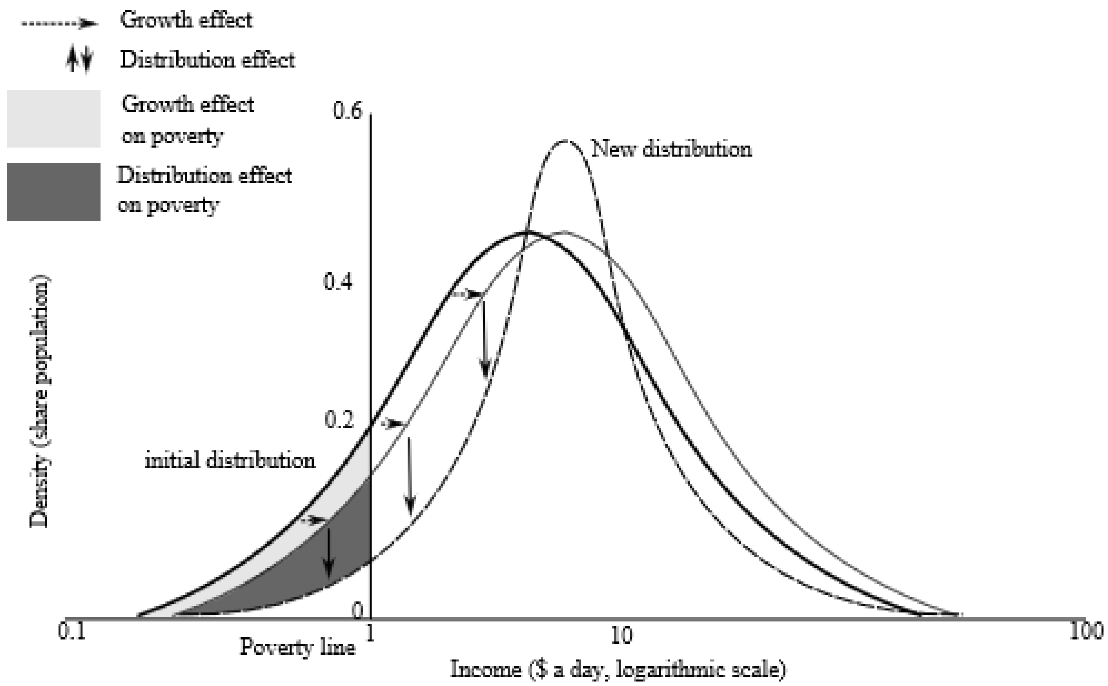
In the welfare-economic discourse there is a strong argument stating that economic growth in terms of increasing per capita incomes or expenditures reduces poverty in the developing world. However, there is no agreement on the exact extent that economic growth reduces poverty. In other words, the growth elasticity of poverty has become a subject of controversy.

The discussion about the sensitivity of the frequency of poverty to economic growth has been going on for about two decades (Ravallion and Chen, 1997; Bruno et al., 1998; Bhalla, 2002; Bourguignon, 2003; Adams, 2004; Kraay, 2006; Bresson, 2009). However, while the extent of poverty reduction by economic growth is a key concept for policy, the size of that sensitivity has been on debate. Whereas Ravallion and Chen (1997), and Bruno et al. (1998) estimated the value of the growth elasticity of poverty for the cross section countries to be between -2.0 and -3.0, Bhalla (2002) calculated the growth elasticity of poverty for a large selection of developing countries to be about -5.0[1]. Richard and Adams (2004) admitted that the growth elasticity of poverty is within the range of -2.0 and -3.0, and argued that Bhalla's suggestion (that the growth elasticity of poverty should be about -5.0) is only correct when the full sample of intervals for a large selection of developing countries is used and growth is defined by changes in the survey mean.

Parallel to the study on the growth-poverty relationship it was also largely debated that the impact of economic growth on poverty can be enforced or reduced by changes in the income distribution over time (Bourguignon, 2003; Datt and Ravallion, 1992). Hence, the changes in poverty headcount can be decomposed into a growth effect and a distributional effect. Figure 4.1 (adapted from Bourguignon 2003, p. 32) qualitatively illustrates the decomposition of change in poverty into a growth and a distributional effect. The initial distribution is taken as given and illustrated by the fat lined density function. The growth effect is illustrated by a pure rightward shift of that distribution without affecting the shape of the curve. The pure growth effect on poverty is illustrated by the light shadowed area. The distribution effect corresponds to a change in the shape of the density function. When the initial distribution transforms to the new distribution as shown in Figure 4.1, we can illustrate the distributional effect on poverty by the dark shadowed area. In contrast to Bourguignon (2003, p. 32) who emphasizes the growth effect on poverty, figure 4.1 emphasizes the inequality effect on poverty, since we find this effect to be stronger in our data. As will be shown, the size of the growth effect relative to the size of the inequality effect depends on particular country circumstances such as initial income inequality or growth scenarios.

[1] An elasticity value of – x means that an income growth of 1% leads to a reduction of poverty of x%.

Figure4.1. Decomposition of Change in Poverty into Growth and Distributional Effects



As mentioned above, many of the former studies estimated the elasticity of poverty for a cross section of countries. However, addressing this issue by regressing the rate of poverty on mean income for a range of countries suffers from numerous shortcomings; cross-country data often have a limited number of data points for each country so that the results are largely driven by cross-country differences (Meng et al., 2005). It could also potentially be misleading due to some conceptual and practical problems arising from currency conversions, different survey-based measures of living standards, different levels of development and omitted country-specific fixed effects correlated with income (Ravallion, 1995; Ravallion and Chen, 1997). Hence assessing growth and inequality elasticities of poverty, depending on particular country circumstances and growth scenarios could improve our insight and prospect about the impact of growth and distributional change on poverty reduction.

In this paper, we study the income growth-poverty-inequality nexus in a particular country – Iran. Therefore, we avoid the conceptual and practical problems of similar studies with cross-country comparisons, such as currency exchange or surveys diversity. In this study, we utilize data from the Household Expenditure and Income Survey (HEIS) for the whole country, i.e. 28 provinces, and for the period 1998 to 2009. These data present a more general picture of the poverty and the changes in inequality about the twelve-year period in Iran.

The main contribution of this study to the literature, however, is that in the current study we measure the growth elasticity of multidimensional poverty as well as growth elasticity of one-dimensional monetary poverty.

The studies on the growth elasticity of poverty have mainly focused on the traditional income poverty. However, considering poverty as a multidimensional concept as Sen (1984) argued in his capability approach leads us to study the relationship of growth and multidimensional poverty. Such a study is also particularly essential, since a reduction in income poverty does not necessarily reduce non-income dimensions of poverty. "Measuring Pro-Poor Growth in Non-Income Dimensions" (Grosse et al., 2008) is one of the few studies on the growth-poverty relationship which extend the toolbox of pro-poor growth measurement to non-income dimensions and composite measures of well-being (using the human development index, HDI, as a composite measure). They applied the growth incidence curve (GIC) of Ravallion and Chen (2003) for the case study of Bolivia during 1989-98 for measuring pro-poor growth. The GIC is a visual tool for the assessment of the distributional pattern of growth, and shows the mean growth rate in achievements (e.g. incomes) at each centile of the distribution between two points in time. Although GIC is a nice visual tool, which shows the absolute changes of achievement for each centile, and successfully was applied by Grosse et al (2008) to investigate pro-poor growth in non-income dimensions, it can barely be considered as a substitute for growth elasticity of poverty for assessing the impact of growth on poverty. The growth elasticity of poverty gives us a digit, which is easier to interpret and does not have the limitation of GIC in the matter of estimating it for each centile separately. Hence, in the current paper we estimate the growth elasticity of (income and non-income) poverty for the case study of Iran over 1998-2009. In order to estimate growth elasticity of poverty, we applied the method of Ravallion and Chen (1997), while for extending the method to estimate growth elasticity of non-income poverty we have been inspired by the way Grosse et al. (2008) in the way they extend the toolbox of pro-poor growth measurement to non-income dimensions and multidimensional poverty measures. Given that we estimate growth and inequality elasticities of non-income deprivation as well as elasticities of multidimensional poverty, our study may also contribute to the understanding of growth, poverty, and inequality beyond Iran.

The paper proceeds as follows. Section 2 reviews the econometric methods for estimating the growth elasticity of poverty. Section 3 describes how we extend the method to estimate the growth and inequality elasticities of poverty for non-income dimensions. Section 4 derives the results for the case study of Iran. Finally, section 5 offers the concluding remarks.

4.2. Econometric Methods for Estimating Growth Elasticity of Poverty

Changing poverty due to income growth and income inequality has been strongly discussed in the literature. Kakwani (1993), Ravallion and Chen (1997), Bourguignon (2003), Klasen and Misselhorn (2008) are some of the most outstanding studies which worked in this area.

Kakwani (1993) estimated the pure growth effect on poverty and the effect of inequality on poverty. Since both mean income and income inequality affects poverty, he argued that proportionate changes in poverty could be decomposed into an effect from mean income on poverty and an effect from a change in the Gini index. Denoting the poverty variable by θ, mean income by μ, and the Gini coefficient by G, this decomposition can be written as:

$$\frac{d\theta}{\theta} = \eta_\theta \frac{d\mu}{\mu} + \varepsilon_\theta \frac{dG}{G} ,$$

Where η_θ denotes the growth elasticity of poverty, while ε_θ is the effect of change in the Gini index on the total poverty. Then he introduced marginal proportional rate of substitution (MPRS) between mean income and income inequality which can be computed for each poverty measure: $= \frac{\partial\mu}{\partial G}\frac{G}{\mu} = -\frac{\varepsilon_\theta}{\eta_\theta}$.

Ravallion and Chen (1997) suggested the following regression to show the relation between poverty, mean income and inequality for a cross-country analysis

$$\text{Log } P_{it} = \alpha_i + \beta \log\mu_{it} + \Upsilon t + \varepsilon_{it} \quad (i=1\ldots N;\ t=1\ldots Ti),$$

Where P is the measure of poverty in country i at time t, α_i is a fixed-effect reflecting time differences between countries in distribution, β is the growth elasticity of poverty with respect to mean expenditure (or mean income) given by μ_{it}. Υ is a trend rate of change over time t, and ε_{it} is a white-noise error term that includes errors in the poverty measure. Taking first differences in the equation above, x_i, the fixed effect term, can be eliminated in order to obtain:

$$\Delta\text{Log } P_{it} = \Upsilon + \beta\Delta \log\mu_{it} + \Delta\varepsilon_{it} - \beta\Delta v_{it}$$

Where v_{it} is a country-specific, time-varying error that is assumed white noise. In this equation, the rate of poverty reduction (P) is regressed on the rate of growth in mean consumption (or income) and the rate of change in income inequality (Gini coefficient). Ravallion and Chen (1997) argue that one can obtain consistent estimates of the growth elasticity by simply applying OLS to this equation.

Another attempt for modelling poverty and elasticities was worked out by Bourguignon (2003), who tried to overcome the limitation of cross-country studies of poverty that generally there is no access to micro data sets of incomes or expenditures for all countries but usually estimate poverty based on grouped data. As a solution to that, Bourguignon suggested to approximate the entire income distribution of each country using a two-parameter log normal distribution. He assumed that income, y_t, is a log normal random variable, such that $\ln y_t \sim N(\mu_t, \sigma_t^2)$, and mean income can be written as $\bar{y}_t = E[y_t] = \exp(\mu_t + \frac{\sigma_t^2}{2})$. He introduced the "improved standard model" that is usually formulated in (annualized) differences:

$$\Delta \ln H_{it} = \alpha + \beta_1 \Delta ln\bar{y}_{it} + \beta_2 \Delta ln\bar{y}_{it} \times \ln\left(\frac{\bar{y}_{i,t-1}}{z}\right) + \beta_3 \Delta ln\bar{y}_{it} \times lnG_{i,t-1} + \gamma_1 \Delta lnG_{it} + \gamma_2 \Delta lnG_{it} \times \ln\left(\frac{\bar{y}_{i,t-1}}{z}\right) + \gamma_3 \Delta lnG_{it} \times lnG_{i,t-1} + \epsilon_{it}.$$

Where Δ is the difference operator and i is considered as the country subscript, α is denoted as the linear time trend and ϵ_{it} is denoted as an error term. The income elasticity is estimated as $\varepsilon_{it}^{Hy} = \beta_1 + \beta_2 \ln\left(\frac{\bar{y}_{i,t-1}}{z}\right) + \beta_3 lnG_{i,t-1}$ and the inequality elasticity is estimated as $\varepsilon_{it}^{HG} = \gamma_1 + \gamma_2 \ln\left(\frac{\bar{y}_{i,t-1}}{z}\right) + \gamma_3 lnG_{i,t-1}$. Clearly, the elasticities depend on the initial levels of income and inequality.

Klasen and Misselhorn (2008) argued that poverty elasticities could give a distorted picture of poverty dynamics. For example, a drop in the poverty headcount from 2% to 1% in a rich developed country is treated just equal as a drop from 20% to 10% in a developing country. In order to overcome this problem, they suggested focusing on absolute poverty changes. Therefore, by substituting absolute changes to the log difference values in the model of Bourguignon (2003), they introduced a model of semi-elasticities of poverty.

In this study, we intend to estimate the growth elasticity of poverty for a specific country case, while we estimate poverty based on micro data. We also want to estimate growth elasticity of poverty for a panel of 28 provinces over time. Hence, the type of the relationship that we want to estimate can be expressed following as an adopted and expanded version of the model suggested by Ravallion and Chen (1997);

$$\text{Log}(P_{it}) = \alpha + \beta \log(Y_{it}) + \delta \log(G_{it}) + \mu_i + \varepsilon_{it}$$

P represents the poverty index, Y is the mean income, G is the Gini coefficient, and μ is a vector of time-invariant provincial dummy variables, while ε_{it} is a random error term. The subscripts t and i index provinces and time.

4.3. Growth Elasticity of Deprivation for Non-Income Dimensions

In addition to measure the growth elasticity of monetary poverty, we are interested to measure the growth elasticity of multidimensional poverty and study the progress in multidimensional achievements. Apart from few attempts of demonstrating the growth-(non-income and multidimensional) poverty relationship such as Grosse et al. (2008), this approach has been rarely applied in the literature. Partly because non-monetary and multidimensional poverty discussion in comparison with income poverty still is young, partly because most of the former studies were cross-countries studies using different surveys, which usually do not contain enough or compatible information of multidimensional poverty. In addition to, some difficulties are brought out and should be dealt with by estimating growth and inequality elasticities of non-monetary and multidimensional poverty, such as compromising on an aggregated digit as the multidimensional poverty index or non-income deprivation, or the way we should choose to demonstrate the inequality.

In order to solve the first difficulty, we decided on measuring multidimensional poverty index by applying Alkire-Foster (2011b) method, which gives us a single digit to signify experiencing multiple deprivations simultaneously. The Alkire-Foster methodology also gives us the facility of decomposing multidimensional poverty index to the dimensions, hence we can estimate the growth and inequality elasticities of (each dimension) deprivation.

Hereupon, we consider poverty as a set of dimensions containing as three main dimensions: nutrition, education and a non-monetary standard of living that is illustrated in detail in table 4.1.

Table 4.1. Dimensions, Weights and Deprivation Cut-off of the Multidimensional Poverty

Dimension	Indicator	The deprivation cutoff z_j
Nutrition (1/3)	Daily food Expenditure (1/6)	1.08 \$ in urban area and 0.69 \$ in rural area
	Percentage of expenditures on food (1/6)	Spend more than 75% of expenditures on food
Education (1/3)	Literacy situation of the household head (1/6)	Illiterate household head
	School attendance (1/6)	Household member (6 to 16 years old) out of school
Living standard (1/3)	Electricity (1/15)	No access to electricity
	Safe water (1/15)	No access to safe water
	Overcrowding (1/15)	No enough (10qm) floor area of housing per capita
	Fuel of cooking (1/15)	Coking fuel is wood, charcoal or dung.
	Asset ownership (1/15)	Household does not own more than one of these items (radio, TV, telephone, bike, motorbike or refrigerators) and does not own a car.

The amount of deprivation is $0 < Ci < 1$, and the poverty cutoff is $Ci > 0.333$.

The second difficulty in estimating the growth elasticity of multidimensional poverty using the conventional regression model is the inequality index. Grosse et al. (2008) tried to solve this problem in two different ways: in the first approach which they rank the individuals by each respective non-income variable and generate the population centiles based on this ranking; in the second approach they rank the individuals by income and calculate the growth of non-income achievements for these income percentiles. The advantage of first approach is that it answers the questions such as how the education poor benefited disproportionately from improvements in education. The advantage of the second way is that it analyzes the impact of income growth on the income poorest centile, while providing an instrument to assess if public social spending programs have reached the targeted income poorest population groups and if the public resources are effectively allocated.

In our case, we apply the second way, rank the individuals by income, and calculate the growth of non-income achievements for these income percentiles. We cannot apply the first approach to index the inequality, because the identity of most of our indicators makes the ranking impossible as the households either deprived in them or not. There is another idea to rank the individuals by the intense of their deprivation C_i. However, the Gini index, which is calculated in this way, suffers from a limitation. Actually, this generates the problem that some households have reached the upper limit and upper level of welfare is not measurable. It generates the further problem that inequality in such indicator is typically low when a significant share of households has reached the upper limit. Hence, by computing the regression model with income Gini index, we estimate the relation of growth in non-income achievements to the distribution of income, while this provides insights about how far the income poor have benefited by improvements in non-income dimensions of well-being.

4.4. Empirical Results

We present the empirical results of the study in three orders in this section. First, we present the trend of mean income, poverty and inequality for our particular time in the case study of Iran, which we estimated from our available survey data. Second, we represent the results of our estimation of growth elasticity of monetary poverty. The third sub-section is dedicated to display the results of the estimation of growth elasticity of multidimensional poverty.

4.4.1. The Case Study of Iran

The period we consider for our study on growth elasticity of poverty in Iran is from 1998 to 2009, concerning we have the survey data available for that particular time. Over the certain time period Iran experienced both a reformist administration and a conservative government, and recorded 4.5 average growth rate of real GDP (Iran Central Bank, 2012), while the population in 1998 to 2009 changed from 62.103 million to 73.196 million people (Iran Statistical center, 2011).

Table 4.2 shows that the mean income per person calculated from the household expenditure and income survey (HEIS) of Iran statistical center (ISC) constantly increased at the rural, urban and national levels over the time span under consideration. The mean income per person at the national level increased from 366.94$ per year in 1998 to 1617.51$ per year in 2009. However, our estimations of income per person in rural and urban areas show a large disparity of income distribution between rural and urban areas that echoes an important feature of Iran's economy. At the same time, the urban population share in Iran changed from 39.06 in 1998 to 51.41 in 2009. This high pace of urbanization is probably the result of migration from rural to urban areas, which does not sound surprising against the background of the large income disparity between rural and urban areas. However, we do not have complete information about how much this development is related to urban expansion into rural areas or to actual migration from rural to urban areas.

Over the period 1998-2009, the expenditure poverty that we estimated from the HEIS data by applying the Foster-Greer-Thorbecke method is summarized in table 4.3 and is illustrated in figure 4.2 and figure 4.3, decreased alongside the mean income increasing, although the progress is not uniform. Table 4.3 shows that monetary poverty with the old poverty line decreased from 0.649 in 1998 to 0.056 in 2009, while the monetary poverty with the new poverty line decreased from 0.829

in 1998 to 0.172 in 2009, which record a noticeable progress in monetary poverty reduction. However, our estimation of Gini indices demonstrated in table 4.4 shows that inequality has been increased over the particular time. As can be seen in table 4.4, the Gini index at the national level increased from 0.441 in 1998 to 0.7 in 2009. The interesting point is that the Gini index over the same period decreased slightly in both rural and urban areas (from 0.463 to 0.402 in rural areas, and from 0.386 to 0.362 in urban areas). This observation suggests that the inequality between rural and urban areas is the main source of inequality at the national level.

Likewise, the one-dimensional monetary poverty as our estimator of multidimensional poverty indicates a decreasing pace during the period 1998-2009, though this progress is uneven. Eventually, table 4.5 shows the multidimensional poverty in Iran from 1998 to 2009, which we estimated by Alkire-Foster method.

The estimated results presented in this subsection can be sum up as follows: over the time period 1998-2009 we observe a steady increasing income per capita trend in Iran, as well as a decreasing poverty (monetary and multidimensional) trend, while the Gini index at national level constantly increases. The results are tempting enough to lead us to the further investigation of the relationship between income growth, poverty and inequality. Hence, we conduct a regression model with poverty as the response and income growth and inequality as the independent variable to show the relationship between poverty, income growth and inequality and demonstrate the growth elasticity of poverty and elasticity of poverty respecting to inequality.

Table 4.2. Summary Statistics: Mean Income per Person in Iran 1998-2009

	Urban pop. Share (%)	Mean income per person ($)		
		Rural	Urban	National
1998	39.1	267.02	495.55	366.94
1999	40.2	284.80	512.01	383.36
2000	41.4	329.98	636.15	458.43
2001	42.5	360.36	681.39	495.62
2002	43.7	454.41	855.57	629.19
2003	44.8	574.97	1026.18	776.04
2004	46.0	640.54	1197.82	887.13
2005	47.1	787.29	1342.25	1036.98
2006	48.3	903.08	1609.62	1205.95
2007	49.3	1069.45	1901.17	1447.45
2008	50.3	1112.47	2021.63	1548.14
2009	51.4	1206.95	2037.30	1617.51

Table 4.3. Monetary Poverty in Iran, 1998-2009

	Poverty measures					
	Old poverty line (1.25 $ per day)			New poverty line (2$ per day)		
	Rural	Urban	National	Rural	Urban	National
1998	0.792	0.491	0.649	0.919	0.729	0.829
1999	0.806	0.549	0.687	0.926	0.777	0.857
2000	0.717	0.416	0.579	0.889	0.671	0.789
2001	0.642	0.311	0.491	0.839	0.572	0.717
2002	0.512	0.217	0.374	0.756	0.452	0.613
2003	0.396	0.142	0.276	0.671	0.358	0.523
2004	0.302	0.100	0.206	0.570	0.273	0.429
2005	0.255	0.078	0.170	0.514	0.228	0.376
2006	0.218	0.065	0.148	0.468	0.197	0.344
2007	0.145	0.042	0.096	0.372	0.131	0.256
2008	0.096	0.024	0.060	0.286	0.085	0.186
2009	0.086	0.027	0.056	0.256	0.091	0.172

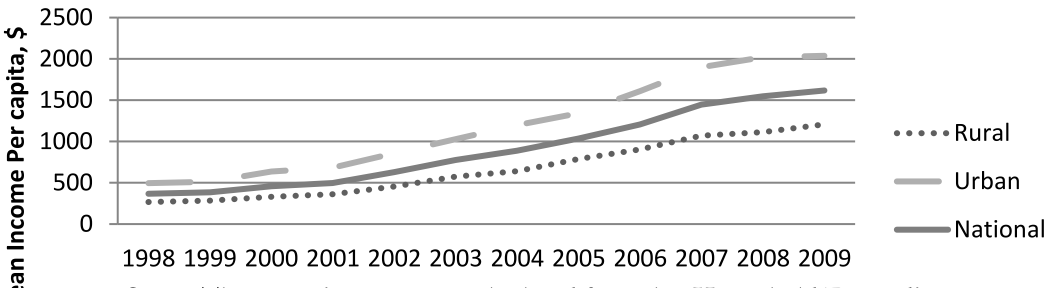
Table 4.4. Gini Indices of Income Inequality

	Rural	Urban	National
1998	0.463	0.386	0.441
1999	0.461	0.405	0.451
2000	0.459	0.402	0.363
2001	0.435	0.389	0.43
2002	0.435	0.396	0.432
2003	0.426	0.383	0.587
2004	0.441	0.345	0.595
2005	0.425	0.376	0.586
2006	0.413	0.389	0.592
2007	0.417	0.381	0.584
2008	0.401	0.37	0.569
2009	0.403	0.362	0.70

Table 4.5. Multidimensional Poverty in Iran, 1999-2009

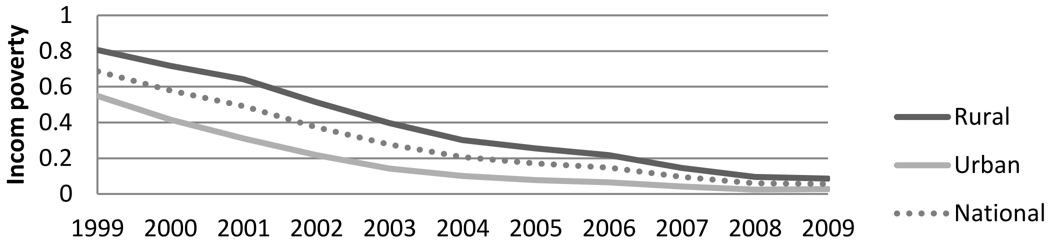
	Poverty measures					
	Rural		Urban		National	
	(MD)H	MD Gini	(MD)H	MD Gini	(MD)H	MD Gini
1998	0. 919	0.178	0.506	0.327	0.724	0.263
1999	0.680	0.228	0.453	0.369	0.575	0.302
2000	0.655	0.248	0.299	0.435	0.492	0.343
2001	0.632	0.255	0.282	0.464	0.472	0.358
2002	0.573	0.299	0.449	0.410	0.515	0.360
2003	0.487	0.363	0.196	0.618	0.349	0.488
2004	0.423	0.417	0.142	0.680	0.289	0.546
2005	0.381	0.447	0.124	0.711	0.257	0.577
2006	0.346	0.469	0.105	0.736	0.236	0.595
2007	0.284	0.523	0.077	0.767	0.185	0.644
2008	0.217	0.565	0.053	0.783	0.136	0.678
2009	0.192	0.575	0.054	0.765	0.122	0.675

Figure 4.2. Mean Income per Person ($) in Iran for 1998-2009



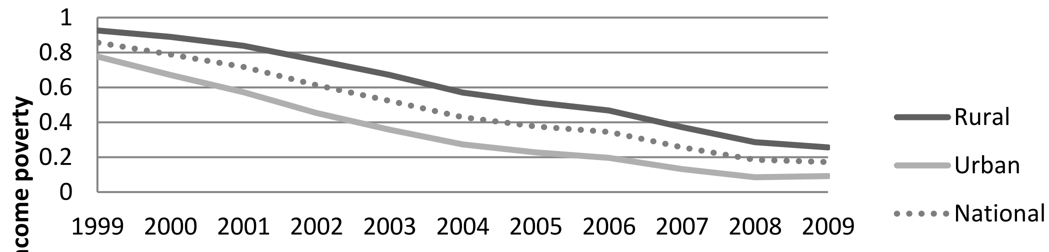
Sorce: The mean income was calculated from the Household Expenditure and Income Survey which eas conducted by Statistical Center of Iran

Figure 4.3. Income Poverty in Iran 1999-2009 (Old Poverty Line 1.25 $ per Day)



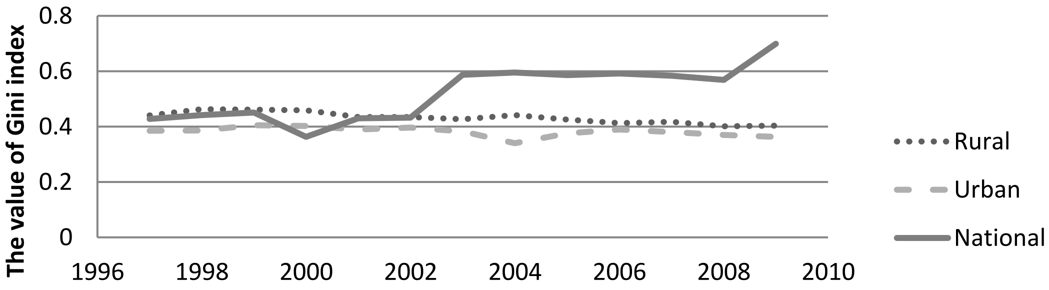
Sorce: The income poverty was calculated from Househlod Expenditre and Income Survey which was conducted by Statistical center of Iran

Figure 4.4. Income Poverty in Iran 1999-2009 (New poverty Line 2$ per Day)



Source: The Income poverty was calculated from Household Expenditure and Income Survey which was conducted by Statistical Center of Iran

Figure 4.5. Gini Index in Iran 1999-2009



Source: The Gini index was calculated from Household Expenditure and Income Survey which was conducted by Statistical Center of Iran

4.4.2. Growth Elasticity of Monetary Poverty

We estimate our regression using a fixed-effects model to control for unobservable time-invariant provincial effects. In order to conduct our regression model, we use a panel data of 28 Provinces in Iran for 12 years from 1998 to 2009 (It is worth noting that the number of provinces in Iran since 2005 changed from 28 to 30 provinces. However, for keeping consistency in our panel we kept on with 28 provinces). Table 4.6 summarizes the result of our estimation of regressions of the log difference of monetary poverty on the log difference of growth rate of income and inequality for the whole country, while table 4.7 and 4.8 show the results of our estimation respectively for the rural areas and for the urban areas.

By a glance on the constant terms, we recognize that the poverty diminishes over the time as a whole, while poverty with the old poverty line (1.25$) reduces much faster than poverty with the new poverty line (2$). Constant terms for the urban areas, however, indicate a different trend. Although poverty with the new poverty line decreases over the time by a faster pace than the country level pace, poverty with the old poverty line increases over the time, which can be rather explained by the expanding slums in urban areas because of rural-urban migration.

The results of our estimation show that the coefficient of mean income or growth elasticity of monetary poverty for old poverty line is -0.011, while for new poverty line is -0.008. In fact, the result shows the stronger reaction of the poverty with threshold of 1.25 $ per day to increase of mean income than the reaction of poverty with threshold of 2 $ per day. It is implying that the smaller the poverty threshold, the more is the sensitivity of poverty for changes in mean income. According to table 4.6, the same rule can be confirmed for the sensitivity of poverty for changes in income inequality. This means that with the lower poverty threshold the sensitivity of poverty for changes in income inequality are stronger and vice versa. However, the main fact we extract from the results in table 4.6 is that it is the Gini coefficient which is the major contributor to the changing the path of poverty over the time. This is apparent from the numerical results on the elasticity of poverty for the Gini index. The effect of the log Gini coefficient on poverty is positive, statistically significant at a p-value of 0.005, while the effect of log mean income is small and not significant at a p-value of 0.005. It seems poverty measures are considerably more elastic for changes in inequality than changes in mean income.

Table 4.6. Regressions of the Rate of Monetary Poverty Reduction on Rate of Growth in Household Mean Income from the Survey (the Whole Country)

Old Poverty line (log difference)	Coef.	Std.Err	t	P>|t|
Constant	-0.2018	0.0142	-14.20	0.000
Mean income (log difference)	-0.0109	0.0259	-0.42	0.674
Gini index (log difference)	0.4253	0.1431	2.97	0.003
R^2	Within	Between	Overall	
	0.0309	0.1442	0.0333	
rho	0.04408			
Corr. error U_i with the regressors	0.0417			
New Poverty line (log difference)	Coef.	Std.Err	t	P>|t|
Constant	-0.1363	0.0111	-12.25	0.000
Mean income (log difference)	-0.0081	0.0203	-0.40	0.690
Gini index (log difference)	0.0593	0.1120	0.53	0.597
R^2	Within	Between	Overall	
	0.0015	0.1442	0.0030	
rho	0.0484			
Corr. error Ui with the regressors	0.0743			

Table 4.7. Regressions of the Rate of Monetary Poverty Reduction on Rate of Growth in Household Mean Income from the Survey (the Rural Areas)

Old Poverty line (log difference)	Coef.	Std.Err	t	P>|t|
Constant	-0.184	0.0208	-8.86	0.000
Mean income (log difference)	-0.0766	0.0813	-0.94	0.347
Gini index (log difference)	-0.954	0.544	-1.75	0.080
R^2	Within	Between	Overall	
	0.0139	0.1951	0.0151	
rho	0.0506			
Corr. error U_i with the regressors	0.0337			
New Poverty line (log difference)	Coef.	Std.Err	t	P>|t|
Constant	-0.1262	0.0126	-10.03	0.000
Mean income (log difference)	0.0079	0.0492	0.16	0.872
Gini index (log difference)	-0.5434	0.3288	-1.65	0.100
R^2	Within	Between	Overall	
	0.0098	0.0571	0.0089	
rho	0.0737			
Corr. error Ui with the regressors	-0.0041			

Table 4.8. Regressions of the Rate of Monetary Poverty Reduction on Rate of Growth in Household Mean Income from the Survey (the Urban Areas)

Old Poverty line (log difference)	Coef.	Std.Err	t	P>|t|
Constant	0.736	0.2442	3.01	0.003
Mean income (log difference)	-2.676	1.051	-2.55	0.011
Gini index (log difference)	-0.0474	0.0463	-1.02	0.307
R^2	Within	Between	Overall	
	0.0252	0.0554	0.0259	
rho	0.0480			
Corr. error U_i with the regressors	0.0201			
New Poverty line (log difference)	Coef.	Std.Err	t	P>|t|
Constant	-0.2878	0.0288	-9.99	0.000
Mean income (log difference)	0.2187	0.1239	1.76	0.079
Gini index (log difference)	0.0077	0.0055	1.40	0.161
R^2	Within	Between	Overall	
	0.0168	0.1665	0.0128	
rho	0.0538			
Corr. error Ui with the regressors	-0.0579			

4.4.3. Growth Elasticity of Multidimensional Poverty

Table 4.7 summarizes the results of our estimations of regressions of the log difference of multidimensional and non-monetary deprivations on the log difference of growth rate of income and inequality. As it can be seen, the sensitivity of multidimensional poverty for changes in mean income is small and insignificant, while the sensitivity of multidimensional poverty for changes in the Gini coefficient is strong and statistically highly significant ($p<0.001$). The same result applies when we conduct the regression for nutrition deprivation, education deprivation and living standard deprivation. In all of these cases, the sensitivity of deprivation for changes in mean income is very small and insignificant. The sensitivities of education and living standard deprivations to income inequality are rather strong but statistically insignificant. The point is that in our case study either non-monetary, multidimensional poverty, or income poverty are considerably more elastic for changes in inequality than changes in mean income.

Table 4.9. Regression of the Rate of Multidimensional Poverty Reduction on Rate of Growth in Household Mean Income from the Survey (the Whole Country)

log difference of multidimensional poverty	Coef.	Std.Err	t	P>|t|
Constant	-0.0643	0.0213	-3.01	0.003
Mean income (log difference)	-0.008	0.039	-0.21	0.832
Gini index (log difference)	1.03	0.215	4.82	0.000
R^2	Within	Between	Overall	
	0.0771	0.2352	0.0805	
rho	0.0401			
Corr. error U_i with the regressors	0.0476			
log difference of nutrition deprivation	Coef.	Std.Err	t	P>|t|
Constant	0.453	0.0976	4.64	0.000
Mean income (log difference)	-0.0016	0.1782	-0.01	0.992
Gini index (log difference)	2.362	0.9827	2.40	0.017
R^2	Within	Between	Overall	
	0.0205	0.0191	0.0182	
rho	0.0367			
Corr. error U_i with the regressors	-0.0356			
log difference of education deprivation	Coef.	Std.Err	t	P>|t|
Constant	-0.738	0.008	-92.92	0.000
Mean income (log difference)	0.0003	0.014	0.02	0.983
Gini index (log difference)	0.141	0.08	1.76	0.079
R^2	Within	Between	Overall	
	0.0112	0.0518	0.0117	
rho	0.2009			
Corr. error U_i with the regressors	0.0291			
log difference of living standard deprivation	Coef.	Std.Err	t	P>|t|
Constant	-0.926	0.003	-273.42	0.000
Mean income (log difference)	0.0037	0.006	0.60	0.546
Gini index (log difference)	0.051	0.034	1.49	0.136
R^2	Within	Between	Overall	
	0.0099	0.0049	0.0070	
rho	0.376			
Corr. error U_i with the regressors	0.0079			

Table 4.10. Regression of the Rate of Multidimensional Poverty Reduction on Rate of Growth in Household Mean Income from the Survey (the Rural Areas)

log difference of multidimensional poverty Rural	Coef.	Std.Err	t	P>|t|
Constant	-0.0213	0.0301	-0.71	0.481
Mean income (log difference)	-0.2455	0.1177	-2.09	0.038
Gini index (log difference)	0.2809	0.7868	0.36	0.721
R^2	Within	Between	Overall	
	0.0159	0.0517	0.0167	
rho	0.027			
Corr. error U_i with the regressors	0.0178			
log difference of nutrition deprivation Rural	Coef.	Std.Err	t	P>|t|
Constant	0.5083	0.1809	2.81	0.005
Mean income (log difference)	-1.39	0.7065	-1.97	0.050
Gini index (log difference)	-5.504	4.725	-1.16	0.245
R^2	Within	Between	Overall	
	0.0183	0.0325	0.0149	
rho	0.0674			
Corr. error U_i with the regressors	-0.0374			
log difference of education deprivation Rural	Coef.	Std.Err	t	P>|t|
Constant	-0.0253	0.0087	-2.91	0.004
Mean income (log difference)	-0.01813	0.0340	-0.53	0.595
Gini index (log difference)	0.4258	0.2278	1.87	0.062
R^2	Within	Between	Overall	
	0.0135	0.0717	0.0136	
rho	0.0216			
Corr. error U_i with the regressors	0.0111			
log difference of living standard deprivation Rural	Coef.	Std.Err	t	P>|t|
Constant	-0.0879	0.050	-1.75	0.081
Mean income (log difference)	-0.0272	0.196	-0.14	0.890
Gini index (log difference)	0.4597	1.311	0.35	0.726
R^2	Within	Between	Overall	
	0.0005	0.0008	0.0005	
rho	0.0672			
Corr. error U_i with the regressors	0.0015			

Table 4.11. Regression of the Rate of Multidimensional Poverty Reduction on Rate of Growth in Household Mean Income from the Survey (the Urban Areas)

log difference of multidimensional poverty Urban	Coef.	Std.Err	t	P>|t|
Constant	0.2796	0.1475	1.90	0.059
Mean income (log difference)	0.4640	0.6350	0.73	0.466
Gini index (log difference)	-0.0302	0.0279	-1.08	0.281
R^2	Within	Between	Overall	
	0.0065	0.0361	0.0058	
rho	0.0355			
Corr. error U_i with the regressors	-0.0187			
log difference of nutrition deprivation Urban	Coef.	Std.Err	t	P>|t|
Constant	1.619	0.9417	1.72	0.086
Mean income (log difference)	1.156	4.053	0.29	0.776
Gini index (log difference)	-0.1786	0.1786	-1.00	0.318
R^2	Within	Between	Overall	
	0.004	0.0051	0.0036	
rho	0.0687			
Corr. error U_i with the regressors	-0.0034			
log difference of education deprivation Urban	Coef.	Std.Err	t	P>|t|
Constant	0.0440	0.0214	2.05	0.041
Mean income (log difference)	-0.2875	0.0923	-3.11	0.002
Gini index (log difference)	-0.0043	0.0041	-1.05	0.295
R^2	Within	Between	Overall	
	0.0360	0.0759	0.0369	
rho	0.0472			
Corr. error U_i with the regressors	0.0233			
log difference of living standard deprivation Urban	Coef.	Std.Err	t	P>|t|
Constant	0.2961	0.4743	0.62	0.533
Mean income (log difference)	3.328	2-041	1.63	0.104
Gini index (log difference)	-0.0522	0.0899	-0.58	0.562
R^2	Within	Between	Overall	
	0.0112	0.0232	0.0094	
rho	0.0518			
Corr. error U_i with the regressors	-0.0302			

Comparing the results of table 4.6 and table 4.7 shows the pace of multidimensional poverty reduction for our panel of provinces during the 12 years is just less than the pace of monetary poverty reduction (with lower poverty threshold). The income growth elasticity of monetary poverty (-0.010) is rather equal to the income growth elasticity of multidimensional poverty (-

0.008). However, the elasticity of multidimensional poverty to income inequality (1.03) is much more than the elasticity of monetary poverty to income inequality (0.425). That implies income inequality changes affected multidimensional poverty even much more than monetary poverty. The strong sensitivity of welfare measures to the income inequality suggests that even by slight diminishing of the percentile's gaps we can expect great improvement of chronic extreme poverty.

4.5. Concluding Remarks

In this paper, we conducted a study to investigate the income growth elasticity of poverty and income inequality elasticity of poverty. We concentrated on a single country and chose Iran as our case study. In order to estimate income growth and income inequality elasticities of poverty, we applied an expanded model of Ravallion and Chen (1997) model for a panel of 28 provinces of Iran from 1998 to 2009. The main contribution of the current study is that we estimated the growth elasticity of non-monetary deprivations and multidimensional poverty (estimated by the Alkire-Foster method) for the first time.

Our estimations of income per capita, Gini index and poverty measures over the time period 1998-2009 show a steady increasing income per capita trend as well as decreasing poverty (monetary and multidimensional) trend, while the Gini index at national level constantly increases. Although we observe a noticeable progress in the matter of (monetary and multidimensional) poverty alleviation at the national level, the progress is uneven between rural and urban areas.

The results of our estimations imply that the income growth elasticity of poverty in Iran is -0.011 for the old poverty line (1.25 $ per day) and -0.008 for the new poverty line (2 $ per day). It indicates a weak income growth elasticity of poverty, which become even weaker by using the 2$ poverty threshold. At the same time the income inequality elasticity of poverty is stronger and statistically significant, which is 0.4253 for the old poverty line (1.25 $ per day) and 0.593 for the new poverty line (2 $ per day). As we mentioned before, Bourguignon (2003) emphasized that the changes in poverty headcount can be decomposed into a growth effect and a distributional effect. That is reflected by our results. Our results confirm that in our case study the inequality elasticity of poverty is stronger than the income growth elasticity of poverty implying that the distribution effect is quantitatively more important than the growth effect (as we assumed in figure 4.1). The size of both effects depends on particular country circumstances, especially the initial income inequality and the growth scenarios. Our case study suggests that in an economy experiencing high inequality and slow economic growth, the elasticity of poverty to income inequality is high and the elasticity of poverty to income growth is low.

The results of our estimation of growth elasticity of non-monetary deprivations and multidimensional poverty indicate are close to growth elasticity of monetary poverty. The sensitivity of multidimensional poverty for changes in mean income and the sensitivity of multidimensional poverty for changes in income inequality are higher than the sensitivities of monetary poverty (with upper threshold) and less than the sensitivities of monetary poverty (with the lower threshold). The results also indicate that the smaller the monetary poverty threshold, the higher is the sensitivity of poverty for changes in mean income and the more sensitivity of poverty for changes in income inequality.

To wrap it up, the high income inequality in Iran as a developing economy diminishes the positive effect of income growth and this effect is even stronger for monetary poverty with a lower poverty line and multidimensional poverty. These results can be relevant to policy making, when we can conclude even by slight diminishing of the percentile's gaps we can expect great improvement of chronic poverty. Therefore, in order to diminish extreme and chronic poverty a policy based on focusing on income growth only has slightly or no effect, while a policy based on diminishing income inequality can make a significant effect on (extreme) poverty reduction.

Acknowledgment

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Conclusion and Thoughts on Future Research

Welfare, poverty and inequality discourse is an important subject in development economics, specially, in developing world studies. Income growth, inequality and poverty nexus is particularly serious in this discourse. This cumulative dissertation contributes to the welfare, poverty and inequality literature by arguing the role of poverty measurement on the welfare assessment, the importance of demographic and spatial circumstances of individual and households to fall in poverty, and the influence of income growth and income inequality on monetary and non-monetary deprivations.

In this work, three well-established welfare-related frameworks are in focus. We started with discussing on poverty measurement. Since measuring individual welfare (or individual deprivation) is the basic input to all inequality and poverty analysis, discussing over the best method of measuring deprivation is an important debate in the welfare, poverty and inequality discourse. We estimated traditional income poverty and multidimensional poverty, compared the results over the time, and demonstrated the advantages of each approach. Then we continued our discussion by focusing on inequalities in welfare distribution. We tried to show how subgroups or individuals are marginalized by their demographic and spatial circumstances. By conducting multilevel regression, we tried to detect extend of the inequality in distribution of welfare, which related to the different level of data. Moreover, we predicted the possibility of falling in poverty for a typical household with certain circumstances and in each spatial situation. Finally, we focused on discussing the sensitivity of monetary and non-monetary deprivations to income growth and income inequality. The discussion over the elasticity of poverty in respect of economic growth is a very important issue in the pro-poor growth discourse and in the welfare, poverty and inequality literature. We made our contribution to the relevant literature by investigating the sensitivity of non-monetary deprivations as well as monetary deprivations to income growth.

Moreover, in this work the empirical results of our case study, Iran, lead us to depict a novel image of welfare and poverty issue in the country. We investigated significant differences in poverty value as well as the pace of poverty reduction between rural and urban areas, which causes an expanding welfare gap between different regions over the time. We also, by decomposing adjusted multidimensional poverty, showed that reaching minimum daily food expenditure has the most contribution in poverty, specially, in Tehran and other urban areas, although the contribution of the expenditure dimension decreased over the time. In rural areas, the contribution of living standard deprivation such as deprivation in accessing safe water and electricity is as important as the contribution of education deprivation or nutrition deprivation.

We also found out the significant disparity between provinces of Iran in respect of welfare distribution, whereas welfare tends to concentrate in capital province (Tehran) and in some of its neighbor provinces in the center and north of Iran. While the most disparity of poverty lied down within provinces, having female, aged, divorced or widow head, as well as being rural are characteristics, which increase the likelihood of falling in poverty for a household.

Finally, we investigated a weak income growth elasticity of poverty that becomes even weaker by upper poverty threshold, while income inequality of poverty is strong and more significant. We found out the similar results for growth elasticity of non-monetary deprivations and multidimensional poverty. In fact, high income inequality diminished the positive effect of income growth and this effect is even stronger for a lower poverty line and for the non-monetary deprivations, as well as multidimensional poverty. That implies the significant effect of changes of income inequality, particularly, on extreme and chronic poverty.

In this dissertation, we have tried to highlight different aspects of welfare, poverty and inequality issue in a way that can be useful for policymaking. In fact, we believe depicting a clear and vast image of welfare, poverty and inequality situation in the country of Iran get clue for tailoring better policies in the matter of poverty diminishing or welfare enhancement.

However, no matter how much I would wish for it, this dissertation is not able to cover all the aspects of welfare, poverty and inequality neither in general, nor in the peculiar case study. Understanding this limitation, the focus has been explicitly set on the poverty measurement, disparity of poverty, and the effect of income growth and income inequality on poverty reduction.

As this part of my academic journey is coming to its end, it is worth discussing the possible directions of a further research that emerge from the presented analysis and seem to be not only highly interesting from an academic perspective, but also relevant for policy-making purposes.

Identifying the welfare dimensions, which causes the poverty trap, is a highly policy-relevant subject. In fact, deprivation in some welfare dimensions not only are known as symptoms of poverty, but also can be identified as the causes of the long-run or chronic poverty. Although we can guess some of these dimensions, like malnutrition or school attendance, exactly identifying these dimensions and assessing their effects would be a great progress in the literature. Such a study obviously would be possible in case that we have the relevant data of certain individual (or families) over the time.

Disparity of welfare dimensions among the whole population (including poor and non-poor) and its effect on migration is another attractive subject in that era. There is no doubt that an important cause of migration (internal and external) is seeking for a better welfare situation. The role of disparity of welfare distribution, and particularly the role of non-monetary dimensions of welfare, would be a potentially interesting subject of study, in case of data availability.

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Declaration

Thereby I declare that this dissertation is a work of my own, written without any illegitimate help by any third party and only with materials indicated in the dissertation. I have indicated in the text where I have used texts from already published sources, either word for word or in substance. At any time during the investigations carried out by me and described in the dissertation, I followed the principles of good scientific practice as defined in the "Statutes of the Justus Liebig University Giessen for the Safeguarding of Good Scientific Practice"

Hosnieh Mahoozi

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