

OPHI WORKING PAPER NO. 95

Gender and Spatial Disparity of Multidimensional Poverty in Iran

Hosnieh Mahoozi*

June 2015

Abstract

Demonstrating the frequency, intensity and disparity of poverty among the various gender and spatial subgroups of Iranian society is the main intention of this paper. Respecting the demands, to the extent allowed by the available data, of Sen's (1987) capabilities approach to the assessment of human well-being, this paper estimates multidimensional poverty in Iran. This study uses the Alkire-Foster method, which is flexible enough to use in various data and dimensional contexts and is able to capture the intensity as well as the incidence of poverty. In order to estimate disparity of poverty, multilevel regression models have been utilized with the premise that households are nested within provinces. Therefore, the disparity in the incidence of poverty -between and within provinces- was estimated using a multilevel logit regression model, while the variation in the intensity of poverty among the poor was estimated by applying a multilevel linear model. The results reveal a remarkable disparity among different subgroups in Iran in which female-headed households and rural households are heavily disadvantaged compared to their peers in male-head and urban households.

Keywords: multidimensional poverty, welfare inequality, multilevel modeling.

JEL classification: I32, D63, O53

* Department of International Development and Environment research, Justus-Liebig University, Senckenbergstrasse 3, 35390 Giessen, Germany. Hosnieh.Mahoozi@zeu.uni-giessen.de.

This study has been prepared within the OPHI theme on multidimensional measurement.

OPHI gratefully acknowledges support from the German Federal Ministry for Economic Cooperation and Development (BMZ), Praus, national offices of the United Nations Development Programme (UNDP), national governments, the International Food Policy Research Institute (IFPRI), and private benefactors. For their past support OPHI acknowledges the UK Economic and Social Research Council (ESRC)/(DFID) Joint Scheme, the Robertson Foundation, the John Fell Oxford University Press (OUP) Research Fund, the Human Development Report Office (HDRO/UNDP), the International Development Research Council (IDRC) of Canada, the Canadian International Development Agency (CIDA), the UK Department of International Development (DFID), and AusAID.

Acknowledgements

I thank Armin Bohnet and Jürgen Meckl for valuable suggestions and comments. I also thank Sabina Alkire and Bouba Housseini for their useful comments. I thank Ali Asgar Salem for his help to find and access complementary data. I am grateful for the support of the department of development and environmental studies of Justus-Liebig University (ZEU). I also appreciate participants in the 2014 MAGKS Doctoral Colloquium for critical comments. Financial support from DAAD (Grant No. 57076385) is gratefully acknowledged.

Citation: Mahoozi, H. (2015). "Gender and Spatial Disparity of Multidimensional Poverty in Iran." *OPHI Working Paper 95*, Oxford University.

The Oxford Poverty and Human Development Initiative (OPHI) is a research centre within the Oxford Department of International Development, Queen Elizabeth House, at the University of Oxford. Led by Sabina Alkire, OPHI aspires to build and advance a more systematic methodological and economic framework for reducing multidimensional poverty, grounded in people's experiences and values.

The copyright holder of this publication is Oxford Poverty and Human Development Initiative (OPHI). This publication will be published on OPHI website and will be archived in Oxford University Research Archive (ORA) as a Green Open Access publication. The author may submit this paper to other journals.

This publication is copyright, however it may be reproduced without fee for teaching or non-profit purposes, but not for resale. Formal permission is required for all such uses, and will normally be granted immediately. For copying in any other circumstances, or for re-use in other publications, or for translation or adaptation, prior written permission must be obtained from OPHI and may be subject to a fee.

Oxford Poverty & Human Development Initiative (OPHI)
Oxford Department of International Development
Queen Elizabeth House (QEH), University of Oxford
3 Mansfield Road, Oxford OX1 3TB, UK
Tel. +44 (0)1865 271915 Fax +44 (0)1865 281801
ophi@qeh.ox.ac.uk <http://www.ophi.org.uk>

The views expressed in this publication are those of the author(s). Publication does not imply endorsement by OPHI or the University of Oxford, nor by the sponsors, of any of the views expressed.

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.

In recent decades, two principal issues have been central to the development of discourse on poverty and inequality: identifying human well-being as a multidimensional phenomenon and how inequalities are distributed among individuals, household, 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 symmetry postulate 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 1985, 1992).

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, and, in 2010, the MPI (Multidimensional Poverty Index) was published for the first time.

This study also applies the core method of multidimensional poverty measurement in the MPI – the Alkire-Foster methodology. However, it modifies the list of dimensions of MPI for the case study. 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).

There are a few studies on measuring poverty in Iran, most of which focus 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. They found that both ‘pure growth’ and ‘redistribution’ components are present in a striking change in poverty, especially among rural households.

In this study, however, multidimensional poverty in Iran is measured while the population segregated by gender and spatial aspect. In addition, the study applied random effect models to compute inequality based on household circumstances: first, inequality among the subgroups in the probability of poverty and, second, inequality in the amount of deprivations among multidimensionally poor people.

This paper comprises seven 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. Section 6 provides a robustness analysis, and the final section offers some concluding remarks.

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

1. It is a method based on a concept of poverty as multiple deprivations that are simultaneously experienced;
2. 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;
3. 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.

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: 2). Although the discussion of the basis of choice is rarely explicit, it seems, as Alkire (2008) argues, 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: 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 and 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). Another example of multidimensional measure of well-being in terms of functioning achievements is the Human Development Index published by the UNDP. It aggregates at the country level functioning achievements in terms of life expectancy, per capita real GDP, and educational attainment rate.

In this study, I expand the concept of wealth to a multidimensional approach. Traditionally in one-dimensional approach, income or expenditure was considered as the indicator of poverty. Expenditure is usually considered a preferable indicator because it is presumed that people are more honest in reporting their expenditures than their income. In this study, however, I add some other indicators to the one traditional indicator. The source of data applied in this study is the Household Expenditure and Income Surveys (HEIS) conducted annually 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); 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 and the variance in the variables of interest in the province. 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. The interviewee is the head of household. However, the data has the disadvantage of lacking health dimension data such as child mortality or malnutrition or any other health indicator. Therefore, because of data constraint, our set of dimensions does not contain health dimension, although it is ideal to draw a set of dimensions including health indicators.

Finally, this study draws on three variables: (1) expenditure; (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 1. Dimensions, Weights and Deprivation Cut-off the Multidimensional Poverty

Dimension	Indicator	The deprivation cutoff z_j
Expenditure (1/3)	Net expenditure	Living with per capita expenditure below 2 \$ per day for every person in the household.
Education (1/3)	Literacy situation of the household head (1/6)	Having an illiterate household head
	School attendance (1/6)	Having a household member between 6 to 16 years old out of school
Living standard (1/3)	Electricity (1/15)	Access to electricity
	Safe water (1/15)	Access to safe water
	Overcrowding (1/15)	Enough (10qm) floor area of housing for each individual
	Fuel of cooking (1/15)	Household cooks with 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.

Expenditure (per capita) is one of the dimensions of poverty that reflects a household's welfare situation. Expenditure of households in our set of data is collected for some 600 food and non-food items. It also includes the self-produced items that are consumed by the households themselves and items that the family receives for free (e.g. as a gift or aid), which is a strong point of our data. The deprivation threshold for income or expenditure was set according to the widely accepted \$2 per day per individual. As our data for expenditure is announced for the households not the individuals, we divided household expenditure by the number of household members. That is a weak point of our data because in many cases the monetary resources of the households are not allocated equally. That is why the study eventually considers the household as the unit of measurement. In this respect, a household is deprived in the expenditure dimension when the expenditure of the household divided by the number of the household members (per capita expenditure) is less than \$2 per day.

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 which 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. Setting the floor area per person is not an easy task because there is no fixed standard and it is also affected by cultural values. Hence, taking into account the cultural circumstances of the case the study chooses the threshold of 10m^2 per capita. That means each household that lives in a house with a per person floor area less than 10m^2 is deprived in the housing dimension.

2.2 Identification of the Poor

Alkire-Foster methodology, like every other poverty measurement, first identifies the poor, afterwards measures the poverty. 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 dimension, 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, $1 < k < d$. Therefore, if y_{ij} denoted the achievement of person i in dimension j , the person i is deprived in dimension j when $y_{ij} < Z_j$. And, if c_i denoted the number of deprivation of person i , person i is identified as poor when $c_i > k$.

2.3 Measurement of Poverty

In order to measure poverty, Alkire-Foster method introduces a set of definitions that are based on the FGT (Foster-Greer-Thorbeck) 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.

The multidimensional poverty headcount ratio is denoted by H ; and $H=H(y; z)=q/n$, when n is the number of total population. The number of the multidimensional poor people is denoted by q . And $q=q(y; z)=\sum n_i \rho(y_i; z)$. when ρ is an identification function; $\rho(y; z)=1$ if $y_i < z$ and person i is poor; while $\rho(y; z)=0$ if $y_i > z$ and person i is not poor.

The poverty headcount ratio, H , is easy to compute and understand. However, it does not distinguish between the persons or the groups who suffer different amounts of deprivation. Due to a distinction between the individuals and 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, and $A=|c(k)|/(qd)$, when $c_i(k)$ is the number of deprivation of person i ; $c_i(k)=\rho(y_i; z)c_i$.

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. Computing multidimensional poverty headcount ratio, H , and adjusted headcount ratio, M_0 , for different groups in each province enables us to compare provinces and groups. The estimated H and M_0 values simply indicate what percent of households in each province are multidimensionally poor, what percent of households in each group are poor, which provinces and which groups within provinces contain more poor households and how much the households are deprived (the breadth of poverty). Nevertheless, it is not clear what the relative importance of states as a component of poverty variation is or how similar the residents of a province are. In order to answer these questions, the study conducts the mixed effect regression using multilevel models.

3 Multilevel Regression Models

In order to analyze the disparity of poverty based on spatial, gender, and some other demographic factors, and also 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? To what extent can variations in poverty be explained by the demographic features of households? To what extent are differences in the incidence of poverty between provinces attributable to between-province differences in rural proportion? What amount of poverty variation can be attributed to either between-province variation or within-province (among households) variation?

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 how a first-level outcome varies across groups.

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 among the poor. To accomplish this, we use another multilevel regression model (model 2) to estimate the variation in the intensity of poverty among the poor, which is a multilevel linear regression.

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

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

For a binary response y_{ij} , we have $E(y_{ij} | x_{ij}, u_j) = Pr(y_{ij} = 1)$. 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.

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).

3.1 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 level 1 units and equals the number of households (=39088) and j refers to level 2 data and equals the number of provinces (=30). Also, the model is a logit regression model because the response is the probability of poverty incidence ρ_{ij} , 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 RuralHH (Rural household), FemaleHH (Female head of household), NHHMembersc (Number of household members, mean centered i.e. four members), YoughHH (Young head household i.e. <25), OldHH (Old head household i.e. >60), WidowHH (widow head household), DivorcedHH (Divorced head household), NevermarriedHH (never married head of household).

The level 2 or province-level Dummy variable is Rural prop. (Rural proportion of the province).

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

$$Pr(\rho_{ij}=1) = \text{Logit}^{-1}(\beta_0 + \beta_1 \text{RuralHH}_{ij} + \beta_2 \text{FemalehHH}_{ij} + \beta_3 \text{NHHMembersc}_{ij} + \beta_4 \text{YounghHH}_{ij} + \beta_5 \text{OldhHH}_{ij} + \beta_6 \text{WidowhHH}_{ij} + \beta_7 \text{DivorcedhHH}_{ij} + \beta_8 \text{NevermarriedhHH}_{ij} + u_j) \quad (1.1)$$

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

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

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.

$$Pr(\rho_{ij}=1) = \text{Logit}^{-1}(\beta_0 + \beta_1 \text{RuralHH}_{ij} + \beta_2 \text{FemalehHH}_{ij} + \beta_3 \text{NHHMembersc}_{ij} + \beta_4 \text{YounghHH}_{ij} + \beta_5 \text{OldhHH}_{ij} + \beta_6 \text{WidowhHH}_{ij} + \beta_7 \text{DivorcedhHH}_{ij} + \beta_8 \text{NevermarriedhHH}_{ij} + \beta_9 \text{Rural prop.}_{ij} + u_j) \quad (1.2)$$

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

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

In the logit hierarchical regression model, β_0 is interpreted as the log-odds that $\rho=1$ when $x_j=0$ 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 $\rho = 1$ 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 in the amount of 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 $VPC = \sigma^2 / (\sigma^2 + 3.29)$.

3.2 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.

$$C_{ij} = \beta_0 + \beta_1 \text{RuralHH}_{ij} + \beta_2 \text{FemalehHH}_{ij} + \beta_3 \text{NHHMembersc}_{ij} + \beta_4 \text{YounghHH}_{ij} + \beta_5 \text{OldhHH}_{ij} + \beta_6 \text{WidowhHH}_{ij} + \beta_7 \text{DivorcedhHH}_{ij} + \beta_8 \text{NevermarriedhHH}_{ij} + u_i + \varepsilon_{ij} \quad (2.1)$$

u_i : province-level random effect (or residual)

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

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.

$$C_{ij} = \beta_0 + \beta_1 \text{RuralHH}_{ij} + \beta_2 \text{FemalehHH}_{ij} + \beta_3 \text{NHHMembersc}_{ij} + \beta_4 \text{YounghHH}_{ij} + \beta_5 \text{OldhHH}_{ij} + \beta_6 \text{WidowhHH}_{ij} + \beta_7 \text{DivorcedhHH}_{ij} + \beta_8 \text{NevermarriedhHH}_{ij} + \beta_9 \text{Rural prop.}_{ij} + u_i + \varepsilon_{ij} \quad (2.2)$$

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

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

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 $\text{Cov}(u_j, \varepsilon_{ij}) = 0$ and the total residual variance is decomposed into two variance

components, $\text{Var}(Tr_{ij}) = \text{Var}(u_j + \varepsilon_{ij}) = \text{Var}(u_j) + 2 \cdot \text{Cov}(u_j, \varepsilon_{ij}) + \text{Var}(\varepsilon_{ij}) = \sigma_u^2 + \sigma_\varepsilon^2$. 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 $\text{VPC}_u = \sigma_u^2 / (\sigma_u^2 + \sigma_\varepsilon^2)$. 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.

4 Results of Measuring Poverty

In this study the multidimensional poverty ratio, H , and the adjusted headcount ratio, M_0 , for each of the 30 provinces in Iran is estimated. Table 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. According to the table, the poorest province is Sistan-Baluchestan (with 46.1% of multidimensional poor households) followed by Kohgiluyeh and Buyer Ahmad (29.2%), South Khorasan (22.8%), Golestan (22.3%), and Hormozgan (21%), whereas the provinces with the least poor households are Tehran (2.8%), Bushehr (4.3%), Mazandaran (4.8%), Esfahan (5.2%), Semnan (5.5%), and Qazvin (5.5%). The values of the M_0 columns, which indicate the breadth of poverty, show that, in total, the provinces with more poor also tend to have more intensity of poverty.

Table 2. Profile of Regional Multidimensional Poverty in Iran 2008

Province	H Total	M_0 Total	
1	Sistan-Baluchestan	0.461	0.261
2	Kohgiluyeh and buyer Ahmad	0.292	0.154
3	South Khorasan	0.228	0.122
4	Golestan	0.223	0.257
5	Hormozgan	0.210	0.117
6	Kerman	0.201	0.108
7	North Khorasan	0.185	0.098
8	Markazi	0.146	0.074
9	Razavi Khorasan	0.145	0.078
10	Qom	0.134	0.071
11	Khuzestan	0.132	0.075
12	Kordestan	0.1317	0.072
13	Kermanshah	0.1315	0.072
14	West Azerbaijan	0.129	0.067
15	Lorestan	0.113	0.060
16	Hamedan	0.108	0.056
17	Ilam	0.105	0.055
18	East Azerbaijan	0.103	0.052
19	Yazd	0.101	0.055
20	Fars	0.088	0.045
21	Ardebil	0.085	0.045
22	Gilan	0.0849	0.046
23	Charmahal and Bakhtiari	0.081	0.044

24	Zanjan	0.075	0.041
25	Qazvin	0.0556	0.028
26	Semnan	0.0554	0.028
27	Esfahan	0.052	0.026
28	Mazandaran	0.048	0.023
29	Bushehr	0.043	0.022
30	Tehran	0.028	0.015
Total		0.136	0.073

The map in figure 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, today a center of [textile](#) trade, has in recent decades become a developing pole of the country, primarily due to its preferable location. And Mazandaran because of its pleasant and moderate climate, beautiful natural landscape, long coastline onto Caspian Sea, and proximity to Tehran has become one of the main recreational and tourism areas of [Iran](#).

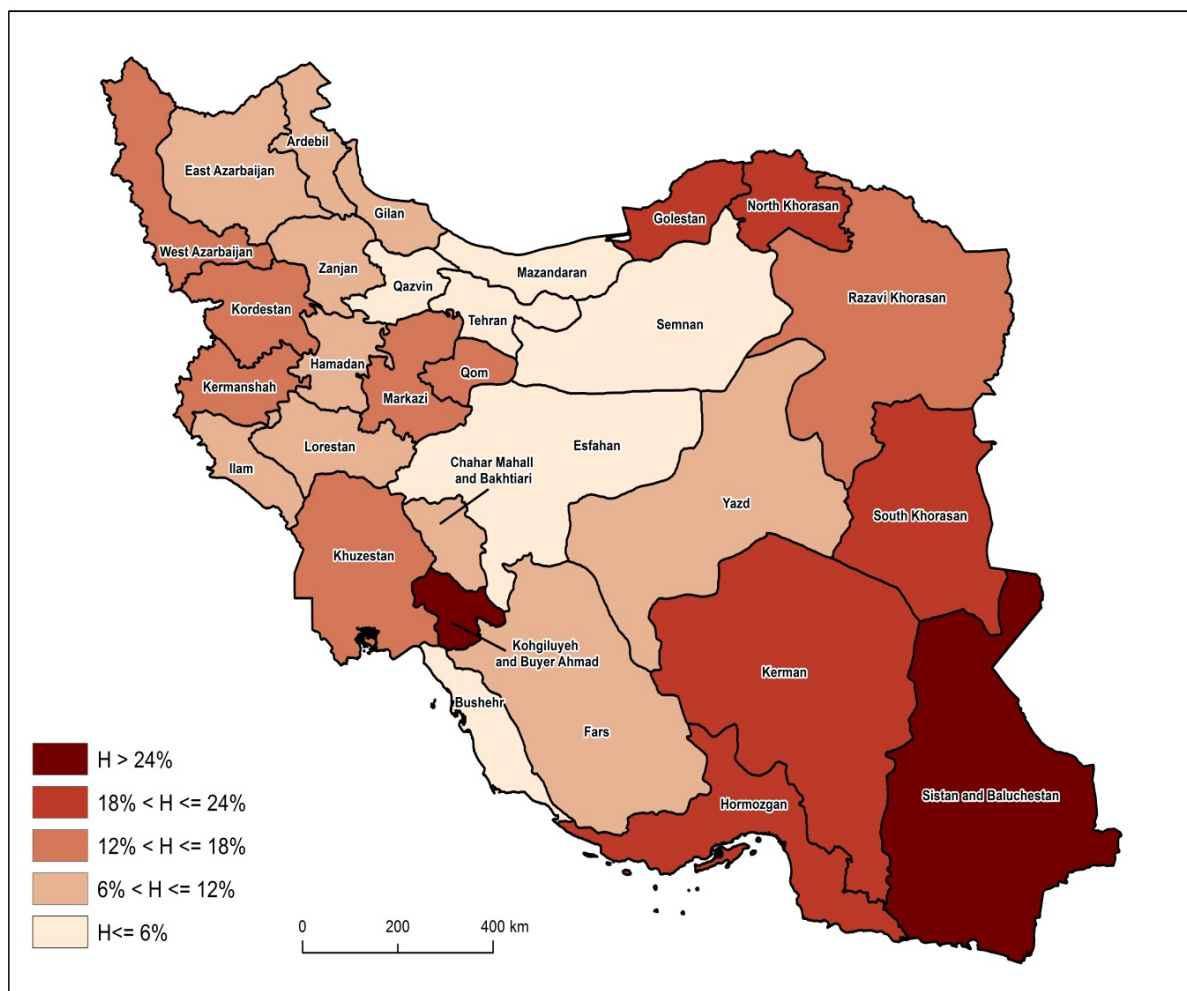
One of these least poor provinces is Bushehr, located in the south of Iran with a long coastline on the [Persian Gulf](#). Aside from the [port city of Bushehr](#), which is the second main naval port of Iran, the economy of Bushehr province has prospered due to the presence of Kharg island, which is 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. But 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 (12% to 18%) of multidimensional poverty, while some others like Ilam (with an absolute majority of Kurds), Lorestan (with a majority of Lurs), and 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 evidence that provinces with a majority of ethnic inhabitants experience more poverty, there is no concrete proof because of the limitations in empirical data.

Figure1. Multidimensional Poverty Map of Iran



Nevertheless, Table 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

shows that the poorest groups in each province are rural households and mostly the rural female-headed households. That is to say, poverty is commonly more prevalent among the rural households compared with urban households of the same region. The reason could be the inequality of welfare distribution in favor of urban areas or could be the immigration of wealthier rural households to urban areas. In the other hand, rather less poverty among the male-headed households (in both urban and rural areas) in comparison to the female-headed household shows the high risk of falling into poverty for female-headed households, particularly in rural areas and the poorest provinces.

Table 3. Profile of Spatial Multidimensional Poverty in Iran 2008 by Distinguishing between Gender of the Head of Households

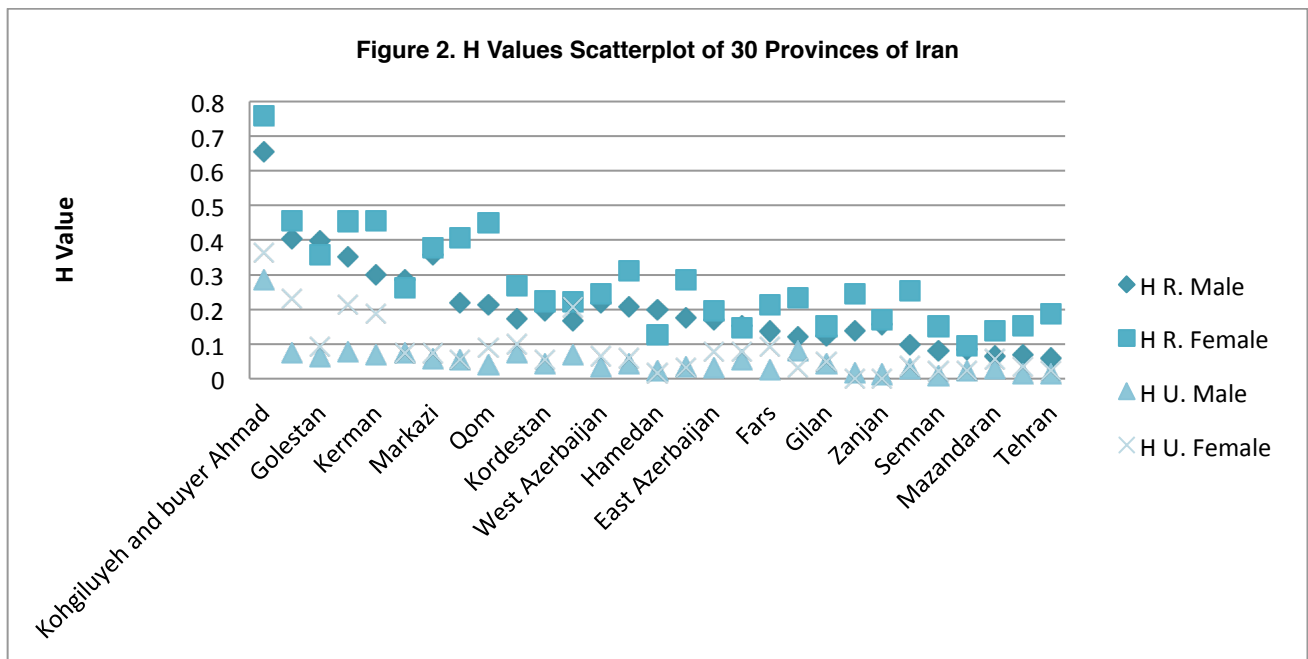
Province		H Rural		H Urban		M ₀ Rural		M ₀ Urban	
		Male	Female	Male	Female	Male	Female	Male	Female
1	Sistan-Baluchestan	0.656	0.760	0.286	0.363	0.379	0.438	0.155	0.207
2	Kohgiluyeh and buyer Ahmad	0.402	0.457	0.076	0.231	0.211	0.248	0.038	0.118
3	South Khorasan	0.398	0.358	0.064	0.092	0.211	0.203	0.032	0.048
4	Golestan	0.350	0.454	0.078	0.214	0.181	0.248	0.038	0.113
5	Hormozgan	0.301	0.457	0.069	0.189	0.171	0.251	0.037	0.105
6	Kerman	0.287	0.263	0.075	0.074	0.157	0.143	0.036	0.042
7	North Khorasan	0.356	0.376	0.058	0.074	0.193	0.209	0.027	0.039
8	Markazi	0.219	0.406	0.054	0.055	0.109	0.214	0.027	0.028
9	Razavi Khorasan	0.212	0.448	0.041	0.090	0.114	0.256	0.021	0.049
10	Qom	0.173	0.267	0.075	0.1	0.093	0.138	0.039	0.05
11	Khuzestan	0.196	0.224	0.043	0.055	0.114	0.122	0.022	0.029
12	Kordestan	0.166	0.222	0.070	0.206	0.093	0.116	0.035	0.112
13	Kermanshah	0.217	0.245	0.035	0.064	0.122	0.129	0.017	0.035
14	West Azerbaijan	0.207	0.310	0.045	0.059	0.109	0.106	0.22	0.036
15	Lorestan	0.198	0.127	0.024	0.016	0.106	0.070	0.011	0.008
16	Hamedan	0.175	0.287	0.033	0.032	0.089	0.161	0.016	0.014
17	Ilam	0.169	0.196	0.031	0.077	0.089	0.109	0.015	0.04
18	East Azerbaijan	0.154	0.147	0.055	0.077	0.076	0.078	0.028	0.038
19	Yazd	0.137	0.215	0.026	0.093	0.076	0.119	0.014	0.046
20	Fars	0.119	0.235	0.079	0.032	0.062	0.125	0.016	0.037
21	Ardebil	0.124	0.151	0.044	0.05	0.065	0.085	0.022	0.027
22	Gilan	0.139	0.244	0.016	0	0.076	0.132	0.008	0
23	Charmahal and Bakhtiari	0.157	0.170	0.013	0	0.087	0.095	0.006	0
24	Zanjan	0.097	0.254	0.027	0.037	0.053	0.141	0.014	0.020
25	Qazvin	0.082	0.151	0.009	0.022	0.042	0.077	0.004	0.014
26	Semnan	0.085	0.094	0.023	0.024	0.043	0.049	0.012	0.009
27	Esfahan	0.064	0.138	0.027	0.057	0.031	0.072	0.014	0.030
28	Mazandaran	0.070	0.154	0.014	0.034	0.033	0.081	0.006	0.023
29	Bushehr	0.059	0.188	0.015	0.023	0.031	0.099	0.007	0.012
30	Tehran	0.064	0.152	0.014	0.018	0.033	0.087	0.007	0.008
Total		0.207	0.287	0.049	0.085	0.112	0.158	0.025	0.045

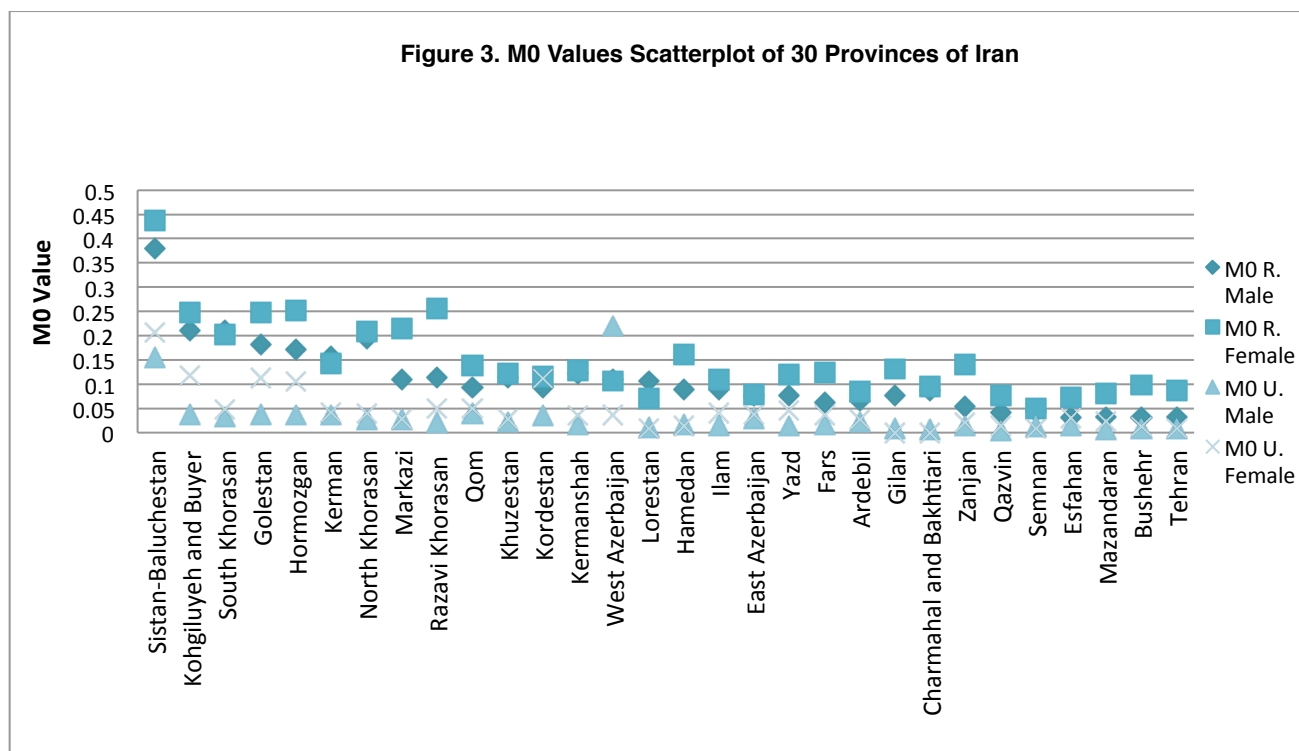
Thus, we can sum up the results of multidimensional poverty estimation in this study as follows:

- Poverty in Iran varies among provinces. The amount and breadth of multidimensional poverty in some provinces is greater than in others.

- There are also variances within provinces and among households based on the gender of the head of household and urban and rural location. However, we do not know how much poverty variation exists between provinces and how much exists within provinces.
- In every province the rural households suffer from more poverty compared to urban households. The same pattern can be seen for the female-headed households in comparison with male-headed households in most regions. However, we do not know to what extent poverty is related to the household's characteristics.

A scatterplot of H values in figure 2 as well as the scatterplot of M_0 values in figure 3 specifies clearly how poverty varies among and within 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.





5 Results of Multilevel Regressions Analysis

In this section, we report the results of multilevel regression models. The results of multilevel logit model (model 1) are demonstrated in sub-section 5.1, and the results of multilevel linear model (model 2) are showed in sub-section 5.2.

5.1 Disparity in the Incidence of Poverty

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 poverty variation among the provinces? How much poverty variation occurs between and how much exists within provinces? What is the probability of poverty for household changes by spatial, gender, and some other demographic factors?

Table 4 shows the results of mixed effect regression for binary responses. 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 state level, i.e. rural proportion in

state. However, as can be seen, the group-level variable (rural proportion) is not statistically significant. And we interpret our results by ignoring this variable.

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 of 1978.68 greatly exceeds 3.84 ($p < 0.001$).

Table 4. Mixed Effects REML Regression for the Total Population with Response $p \in [0, 1]$.

Parameter	Model 1.1					Model 1.2			
		Estimate	Std. Err.	Z	P> Z	Estimate	Std. Err.	Z	P> Z
Intercept	β_0	-4.254	0.160	-26.54	0.000	-4.728	0.985	-4.80	0.000
Rural HH	β_1	1.646	0.039	41.43	0.000	1.646	0.039	41.42	0.000
Female head	β_2	0.686	0.084	8.13	0.000	0.686	0.084	8.13	0.000
N of H members c	β_3	0.314	0.008	35.33	0.000	0.313	0.008	35.33	0.000
Age Parameters									
Young head H	β_4	0.188	0.124	1.51	0.130	0.188	0.124	1.52	0.130
Old head H	β_5	0.703	0.039	17.84	0.000	0.703	0.039	17.84	0.000
Marital status of head H Parameters									
Widow	β_6	0.229	0.088	2.61	0.009	0.229	0.088	2.61	0.009
Divorced	β_7	0.739	0.190	3.88	0.000	0.739	0.190	3.88	0.000
Never married	β_8	-0.202	0.176	-1.14	0.254	-0.202	0.176	-1.14	0.254
Level 2 variable									
Rural prop.	β_9	-	-	-	-	0.929	1.906	0.49	0.626
Random effect P.									
Within state variance	σ^2	0.490	0.129	3.798	0.000	0.486	0.128	3.797	0.000
LR test: $\chi^2(01) = 1978.68$ ($p < 0.001$)					LR test: $\chi^2(01) = 1975.80$ ($p < 0.001$)				

$\beta_0 = -4.254$ is interpreted as the log-odds that $p=1$ when $x_{ij}=0$ and $u=0$, and is referred to as the overall intercept. The probability of β_0 is estimated by $\text{Logit}^{-1}(-4.254) = 0.014$, that means the probability of multidimensional poverty incidence for an urban household with four members and with a married middle-aged male head is 1.4%, when we ignore the state variation. If we hold $u=0$, the probability of poverty for a female-headed household with the same circumstances would be $\text{Logit}^{-1}(-4.254+0.686) = 0.027$, i.e. nearly 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 6.8%, while the probability of poverty incidence for the peer rural female-headed household is approximately 12.7%. Controlling for province differences, we would expect the odds of being poor to increase by a factor of $\exp(0.314) = 1.37$ for each one-unit increase in the number of household members. In this respect, the odds of being poor increase for an old head of household (>60 years old) by $\exp(0.703) = 2.02$, for young head of household by 1.207, and for a divorced head of household by 2.09. Whilst the above-mentioned factors are significant and positive, no significance is perceived for a head of household who is young, widowed, or never married.

However, the advantage of a hierarchical model is that it enables us to look at the effect of x_j 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 $\beta_0 + u_j$, which will be higher or lower than the overall intercept depending on whether u_j is greater or less than zero. We can estimate the probability for ideal or typical individuals with a specific combination of x values for each province like $Pr(\rho = 1) = \frac{\exp(\hat{\beta}_0 + \hat{\beta}_1 x_{ij} + \hat{u}_j)}{1 + \exp(\hat{\beta}_0 + \hat{\beta}_1 x_{ij} + \hat{u}_j)}$, when we estimate u_j . However, the first noteworthy point is the interpretation of $\sigma^2=0.49$, which is the variance of the intercepts across the groups (provinces) or group-level residual variance, and it 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 in the amount of 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 $VPC = \sigma^2 / (\sigma^2 + 3.29) = 0.129$, i.e. 13% of variance in the incidence of poverty is due to between-state variation, and 87% of the variance in the incidence of poverty occurs within provinces and between households.

Table 5 depicts the estimated u_j and u_j rank for 30 provinces. As we have already calculated the predicted probability for an average state is $u_j=0$. Assuming, that u_j follow a normal distribution, the coverage interval (95%) of u_j has a value between $\pm 2\sigma^2 = \pm 0.95$. However, according to the values of Table 5, the residuals of two states from the bottom (11: Sistan Balochestan, 29: South Khorasan), and two states from the top (18: Boshehr) do not overlap the coverage interval.

From these values we can see that state 11 (Sistan Baluchestan) had an estimated residual of 2.056 which was ranked 30. For this state the probability of multidimensional poverty for an urban household with four members and with a married middle-aged male head of household is computed like

$\text{Logit}^{-1}(\beta_0 + u_{11}) = 0.099$, i.e. 9.9%, that is nearly 7 times more than average.

Table 5. Profile of Residuals for the 30 Provinces.

	State	u_j	u_j std. err.	u_j rank
0	Markazi	0.472	0.079	23
1	Gilan	-0.187	0.103	13
2	Mazandaran	-0.754	0.132	4
3	East Azerbaijan	-0.081	0.095	16
4	West Azerbaijan	-0.078	0.096	17
5	Kermanshah	0.102	0.081	19
6	Khuzestan	-0.298	0.094	12
7	Fars	-0.356	0.102	11
8	Kerman	0.502	0.069	24
9	Razavi Khorasan	0.348	0.077	22
10	Esfahan	-0.742	0.119	5
11	Sistan-Baluchestan	2.056	0.060	30

12	Kordestan	0.281	0.091	21
13	Hamedan	-0.029	0.089	18
14	Charmahal and Bakhtiari	-0.406	0.117	8
15	Lorestan	-0.172	0.100	14
16	Ilam	-0.364	0.107	10
17	Kohgiluyeh and Buyer Ahmad	0.928	0.062	28
18	Bushehr	-1.216	0.144	1
19	Zanjan	-0.575	0.112	7
20	Semnan	-0.597	0.137	6
21	Yazd	-0.152	0.094	15
22	Hormozgan	0.689	0.071	25
23	Tehran	-0.899	0.127	2
24	Ardebil	-0.406	0.108	9
25	Qom	0.199	0.089	20
26	Qazvin	-0.855	0.131	3
27	Golestan	0.921	0.071	27
28	North Korasan	0.796	0.074	26
29	South Khorasan	0.975	0.067	29

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 6 only categorized 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, where there a four household members and the head is married and middle-aged.

Table 6. Probability of Poverty for Four Typical Households in the Least Poor and Most Poor Provinces.

Provinces	Urban male h.	Urban female h.	Rural male h.	Rural female h.
The least poor				
Tehran	0.5 %	1.1 %	2.9 %	5.6 %
Qazvin	0.6 %	1.2 %	3 %	5.8 %
Bushehr	0.4 %	0.8 %	2.1 %	4 %
The most poor				
Sistan-Baluchestan	9.9 %	18%	36 %	53 %
Kohgiluyeh and Buyer ahmad	3.5 %	6.6%	15.7 %	27 %
Shouth Khorasan	3.6 %	6.9%	16.3 %	27.9%
Average in country with controlling states difference	1.4 %	2.7%	6.8 %	12.7%

To sum up results of the analysis above, we point out the following items. 13% of variance in the multidimensional poverty incidence is due to between-province variation, and 87% of variance lies within provinces and among households variation. The demographic factors of head of household, being a female head, age (being > 60-year-old and being <25 years old), and being divorced have significant and positive correlations with poverty incidence. Features of households - being rural as well as the number of members in the household - also have a positive and significant relation with the incidence of poverty. 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. The most vulnerable groups in Iran are rural households in Sistan-Baluchestan (Female-headed households have a 53% probability and male-headed households have a 36% probability of falling into multidimensional poverty), followed by rural, female-headed households in South Khorasan and Kohgiluyeh and Buyer Ahmad. The least vulnerable groups are urban, male-headed households in Tehran, Qazvin and Bushehr (with a $\leq 0.6\%$ probability of falling into multidimensional poverty). 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.

5.2 Disparity of Intensity of Poverty among Multidimensionally Poor People

The Alkire-Foster method, however, also gives us the opportunity to consider inequality among the poor. In order to capture inequality (of poverty intensity) among the poor, the study conducts a multilevel linear regression with the continuous response of intensity of poverty.

Table 7. Mixed Effects REML regression for Multidimensional Poor Population (ci)

Parameters	Fixed Effect Model		Mixed Effect Model 1				Mixed Effect Model 2				
	Estimate	Std.Err	Estimate	Std.Err	Z	P> Z	Estimate	Std.Err	Z	P> Z	
Intercept β_0	0.462	0.008	0.458	0.008	54.69	0.000	0.442	0.026	16.57	0.000	
Rural HH β_1	0.028	0.003	0.031	0.003	8.55	0.000	0.031	0.003	8.52	0.000	
Female head β_2	0.029	0.006	0.027	0.006	4.10	0.000	0.027	0.006	4.10	0.000	
N of H members c β_3	0.010	0.0006	0.009	0.0007	13.84	0.000	0.009	0.0006	13.84	0.000	
Age parameters											
Young head β_4	-0.044	0.011	-0.050	0.011	-4.66	0.000	-0.051	0.011	-4.66	0.000	
Old head β_5	0.016	0.003	0.018	0.003	5.26	0.000	0.017	0.003	5.25	0.000	
Marital status of head H Parameters											
Widow β_6	0.004	0.007	0.005	0.007	0.73	0.467	0.005	0.007	0.72	0.469	
Divorced β_7	0.002	0.016	0.0006	0.015	0.04	0.970	0.0005	0.016	0.03	0.976	
Never married β_8	0.024	0.016	0.025	0.016	1.60	0.110	0.026	0.016	1.61	0.108	
Level 2 variable											
Rural prop. β_9	-	-	-	-	-	-	0.0307	0.049	0.62	0.537	
Random effect Parameters											
Between state variance σ_u^2			0.0002				0.0002				
Within state variance σ_e^2			0.009				0.009				
			$\chi^2(2) = 95.73$ (p < 0.001)				$\chi^2 = 93.22$ (p < 0.001)				

Table 7 shows the results of mixed effect regression when the number of observations = the number of poor people (= 8039), and response is c_i , when $0 < c_i < 1$.

The results imply that the average deprivation value for a poor urban male-headed household in the whole country is $\beta_0 = 0.45$, while the threshold of falling in multidimensional poverty is 0.34. Other factors such as being rural or a female-headed household added only $\beta_1 = 0.031$ and $\beta_2 = 0.027$ to the value of poverty intensity, whereas having a young head of household has a negative effect of $\beta_4 = -0.028$ 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 0.4 for an urban household with a young male head to 0.539 for a rural household with old widowed female head. On the other hand, as the $VPC_u = \sigma_u^2 / (\sigma_u^2 + \sigma_e^2) = 0.022$, approximately 2.2% of the variation in the intensity of poverty lies among provinces variation, and 97.8% embedded within provinces variation (or the characteristics of the households). Thus, inequality among the poor is not very considerable.

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

6 Robustness Analysis

Like any poverty measure, when we designed our multidimensional poverty measure, we made some decision regarding the choosing of dimensions, thresholds, and indicators weights. Although we chose our parameters based on available data and some norms in the literature, it raised the question of how robust our measurement is or how authentic our estimations – and how sensitive policy prescriptions based on our estimations – can be with respect to these parameters choices. Hence, using a rank robustness analysis, we evaluated how changes in the parameters affect relative multidimensional poverty values. A group of rank robustness tests was applied in order to assess how sensitive the relative values of multidimensional poverty across provinces are to changes in key indicators, deprivation cutoff, and indicators' weights.

6.1 Robustness to Change in the Indicators and Deprivation Cutoff

One key element of multidimensional poverty robustness is ranking robustness to changes in indicators and deprivation cutoffs. As Alkire and Santos say “There is a legitimate diversity of judgments regarding what would or would not count as a deprivation in a number of indicators. If small changes in any cutoff

would lead to a considerable re-ranking ... , this should be made explicit and the accuracy of that cutoff closely examined” (Alkire and Santos 2013: 31).

In order to test the sensitivity of multidimensional poverty to a deprivation cutoff, we estimated multidimensional poverty using a different cutoff and indicators and computed rank correlation coefficients between the rankings. In particular it was investigated: a) including child school attendance versus using the literacy situation of head of household only, b) excluding expenditure versus including expenditure, and c) using lower deprivation cutoff for expenditure (\$1.25 versus \$2 per day).

After estimating Multidimensional poverty (MP) for each alternative, Spearman and Kendall correlation coefficients between the rankings were estimated. The Spearman rank correlation coefficients between our MP and MP excluding school attendance is 0.937, while the Spearman correlation coefficient between our MP and MP with a lower deprivation cutoff for expenditure is 0.877, both of which suggest that the rankings are highly robust to those changes. Kendall’s Tau correlations for those two above-mentioned items are, respectively, 0.834 and 0.807, which also shows robustness.

The rank correlation coefficient between our MP and MP excluding expenditure by spearman correlation is 0.735 and by Kendall correlation 0.664, which does not show it to be highly robust to that change.

Table 8. Correlation Coefficients between Multidimensional Poverty Values Using Alternative Indicators and Deprivation Cutoff

	Spearman	Kendall
Using head of household literacy situation as the only indicator of education versus including school attendance	0.937	0.834
Excluding expenditure dimension versus including expenditure dimension	0.735	0.664
Using expenditure deprivation cutoff 1.25\$ a day per person versus 2\$ a day per person	0.877	0.807

6.2 Robustness to Changes in the 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 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 9. 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 25% Education 25% LS	Spearman	0.968		
	Kendall	0.956		
50% Education 25% Expenditure 25% LS	Spearman	0.966	0.918	
	Kendall	0.903	0.834	
50% LS 25% Expenditure 25% Education	Spearman	0.995	0.971	0.969
	Kendall	0.981	0.917	0.903

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

7 Concluding Remarks

The study reveals a novel image of the frequency, intensity, and disparity in multidimensional poverty in Iran. First, it expands the monetary phenomenon of poverty, which only captures income or sometimes expenditure, to a more comprehensive concept of multidimensional poverty. Then it applies the Alkire-Foster method to measure the multidimensional poverty of households within location and gender subgroups. Finally, 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 study benefits from the virtue of Alkire-Foster method, which computes the incidence and intensity of poverty for each unit and analyzes the disparity and inequality of multidimensional poverty across subgroups.

The results imply that poverty in Iran varies among provinces and the amount and breadth of multidimensional poverty in some provinces are greater than others. Specifically, the remote areas near the eastern and western borders have, in general, a higher incidence of multidimensional poverty, while the provinces at the center suffer less from poverty. The poverty variation between provinces is 0.49, though only 13% of the variance in the incidence of poverty comes from between-state variation, and 87% of poverty incidence variance occurs within province and between households.

The study also concludes that certain subgroups within provinces are disadvantaged based on their individual circumstances. Indeed, the study found out 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. In fact, the results confirm that the female-headed and rural households are marginalized in welfare matters.

Hence the study highlights three aspects of inequality in Iran: provincial inequality, gender inequality, and regional inequality. The study also clarifies that while the inequality among the subgroups of the household population of Iran is pretty significant with respect to the incidence of poverty, inequality in the intensity of poverty among the poor is not remarkable.

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 prejudice, discrimination, and social exclusion which are deeply embedded in the social, economic, and political 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.

References

- Alkire, S., & Foster, J.E. (2011a). Understandings and misunderstandings of multidimensional poverty measurement. *Journal of Economic Inequality*, 9, 289-314.
- Alkire, S., & Foster, J.E. (2011b). Counting and multidimensional poverty measurement. *Journal of Public Economics*, 95(7), 476-487.
- Assadzadeh, A., & Paul, S. (2004). Poverty, growth, and redistribution: a study of Iran. *Rev. Dev. Econ*, 8(4), 640-53.
- Atkinson, A.B., & Bourguignon, F. (1982). The comparison of multidimensional distributions of economic status. *Review of Economic Studies*, 49, 183-201.
- Bourguignon, F., & Chakravarty, S. (2003). The measurement of multidimensional poverty. *Journal of economic Inequality*, 1, 25-49.
- Cannings, T.I. (2013). Child poverty in an emergency and conflict context: A multidimensional profile and an identification of the poorest children in Western Darfur. *World Development*, 48.48-70.
- Callander, E.J., & Schofield, D.J., & Shrestha, R.N. (2011). Multi-dimensional poverty in Australia and the barriers ill health imposes on the Employment of the disadvantaged. *Journal of Socio-Economic*, 40.736-742.
- Klasen, S. (2000). Measuring poverty and deprivation in South Africa. *Review of Income and Wealth*, 46(1), 33-58.
- Kolm, S. (1977). Multidimensional egalitarianism. *Quarterly Journal of Economics*, 91, 1-13.
- Kuklys, W. (2005). *Amartya Sen's capability approach: Theoretical insights and empirical applications*. Berlin: Springer.
- Maasoumi, E. (1999). Multidimensioned approaches to welfare analysis. In J. Silber, ed. *Handbook of Income Inequality Measurement*. Boston: Kluwer Academics.
- Maasoumi, E., & Mahmoudi, V. (2013). Robust growth-equity decomposition of change in poverty: The case of Iran (2000–2009). *The Quarterly Review of Economics and Finance*, 53(3). 268-276.
- Qizilbash, M., (2002). A Note on the Measurement of Poverty and Vulnerability in the South African Context. *Journal of International Development*, 14,757-772.
- Salehi-Isfahani, D. (2009). Poverty, inequality, and populist politics in Iran. *Journal of Economic Inequal*, 7,5-28.
- Sen, A., (1984). The Living Standard. *Oxford Economic Papers*, 36, 74-90.