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Poverty and Household Decisions – An Exploration of Possible Interdependence

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Abstract

Household poverty is a multidimensional phenomenon, of which access to income/productive assets/resources, food security and nutrition; education, health, housing and sanitation etc. are regarded as the major dimensions. A priori, one would expect a household's major socio-economic decisions like those relating to production, consumption and factor market participation, to be significantly influenced by whether or not the household is poor in respect of one or several dimensions of poverty. On the other hand, poverty and household decisions may be interrelated such that poverty may be self-reinforcing. This study, which is based on a survey conducted in two districts in Assam, a state in the North Eastern region of India, attempts to identify the sets of poverty dimensions and decisions that mutually reinforce each other, through Structural Equation Modeling (SEM).

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1 Introduction

Eradication of poverty has been and continues to be an important policy issue in the context of developing and underdeveloped countries. Poverty analysis thus plays a major role in formulating developmental policies. The two major components of poverty analysis are the measurement of poverty and understanding the structure and causation of poverty.

Over the last quarter century, there has been a rapid growth of literature on poverty measurement. The literature has developed in two close but distinct branches: (i) construction of indicators of poverty (see Sen, 1976; Foster, 1984; Seidl, 1988; Chakravarty, 1990; Foster and Sen, 1997 and Zheng, 1997 for a survey of literature) and (ii) poverty orderings, the branch of literature concerned with rankings of income distributions based on multiple desiderata on poverty measurement (see Atkinson, 1987; Atkinson, 1992; Jenkins and Lambert, 1993 and Zheng, 1999).

All these contributions, however, regard income as the sole indicator of well-being. But poverty of a person is caused by inadequacy in his/her possession of different attributes of well-being that are necessary to maintain a subsistence level of living. Examples of such attributes are housing, literacy, health, provision of public goods etc. and of course, income. This in turn means that poverty is essentially a multidimensional phenomenon and income is just one indicator. It is certainly true that with a sufficiently high income a person will be able to improve the position of some of his non-income attributes. But, market prices may be too high to afford consumption of some attributes above the corresponding thresholds representing subsistence levels. Therefore, poverty should be viewed multidimensionally as the inability to achieve minimally acceptable or subsistence levels of income as well as non-income indicators of welfare. (See Sen 1985, 1992; Ravallion, 1996 and Bourguignon and Chakravarty, 1999, 2002, for further discussions.)

Clearly, the most important issue in multidimensional poverty analysis is the choice of the poverty dimensions, viz., (i) Which dimensions are relevant? (ii) Should more than one indicator per dimension be used, and if so which ones? (iii) Which kind of interaction between dimensions should one assume? Are Dimensions substitutes or complements? (iv) How to deal with interactions between indicators representing a given dimension? The answers are evidently not obvious because of the fact that poverty is not an objective concept. Rather, it is a complex notion.

While the literature on income poverty is already quite rich, research on multidimensional poverty measurement is fairly recent. The literature on multidimensional poverty has grown in two directions: (i) non-axiomatic approach and (ii) axiomatic and fuzzy approach. Approaches that lead to the derivation of an aggregate indicator on the basis of which a poverty threshold (line) is determined and traditional measures of uni-dimensional poverty are derived belong to the non-axiomatic group. Truly multidimensional approaches, where a poverty threshold is determined for each dimension and which lead to the definition of multidimensional indices of poverty, belong to the second group. The **axiomatic approach** emphasizes the desirable properties (axioms) that a poverty measure must respect (see Tsui, 2002; Chakravarty et. al., 1998; Bourguignon and Chakravarty, 1999, 2003, 2007; D'Ambrosio, Deutsch and Silber, 2007 for detailed discussion on these issues). The **fuzzy approach** is based on the mathematical theory of "Fuzzy Sets" (Zadeh, 1965) where certain classes of objects may not be defined by very precise criteria of membership. Here a 'fuzzy' poverty line rather than a 'crisp' one demarcates the sets of poor and non-poor persons. Such a fuzzy approach to the study of poverty has taken various forms in the literature (see Betti, Cheli, Lemmi and Verma, 2008 for a detailed presentation).

In this study we will confine our attention to the non-axiomatic approach. When more than a single dimension of welfare is considered in the nonaxiomatic approach, poverty comparisons are based either on a combination of indicators that have been previously aggregated over individuals (e.g., the Human Poverty Index (HPI) of the UNDP; Ram, 1982; and Collicelli and Valerii, 2001; where the indicators are combined using certain weighting systems) **or** on individuals' data where indicators are aggregated at the individual level first and across individuals next (Bibi, 2005). Examples of the latter method include Smeeding et. al., 1993; Pradhan and Ravallion, 2000; Van Praag and Ferrer-i-Carbonell, 2004; which are based on *subjective poverty lines* determined by *asking* households how they evaluate their own situation in terms of verbal labels, and Klasen (2000), which is based on assigning *scores* to each attribute.

For cases where dimensions are aggregated first, many techniques of aggregation have been proposed (for more details, see, Kakwani and Silber, 2008).

(1) Approaches based on the idea of *latent variable* (in this case "poverty"):

- Rasch (1960) model: (e.g., Fusco and Dickes, 2008)
- Principal Components Analysis (PCA): (e.g., Ram, 1982)
- Factor Analysis (FA): (e.g., Lelli, 2001; Kuklys and Robeyns, 2004)
- Cluster Analysis: (e.g., Hirschberg, Maasoumi and Slottje, 2001; Ferro Luzzi, Fluckiger and Weber, 2008)

(2) Efficiency Analysis and Multidimensional Poverty: Taking inputs to be the various indicators relating to a given well-being dimension and the outputs to be the *standards* for the corresponding dimension one can measure "efficiency" using

- Data envelopment analysis (DEA): (e.g. Anderson, Crawford and Leicester, 2008)
- Econometric Approaches: (e.g, Ramos, 2008**)**

(3) Information Theory: An 'individual' is represented by a utility-like function of all attributes received. This aggregate or summary attribute is interpreted as the ideal

index or evaluation of individual welfare (e.g., Maasoumi, 1986; Miceli, 1997; Maasoumi and Lugo, 2008).

A poverty profile describes the pattern of poverty, but is not principally concerned with explaining its causes. Yet a satisfactory explanation of why some people are poor is essential if we are to be able to tackle the roots of poverty. Understanding the structure and causation of poverty has also received wide attention in recent years. Among the key causes, or at least correlates, of poverty have generally been taken to be

1. **Regional-level characteristics**: these include vulnerability to flooding or typhoons; remoteness; quality of governance; property rights and their enforcement.
2. **Community level characteristics:** these include the availability of infrastructure (roads, water, electricity) and services (health, education), proximity to markets, and social relationships.
3. **Household and individual characteristics:** Among the most important are:

   Demographic: household size, age structure, dependency ratio, gender of head.

   Economic: employment status, hours worked, property owned.

   Social: health and nutritional status, education, shelter.

There are basically *three* approaches to modelling causation of poverty. *The first approach* works by regressing consumption expenditure (in log terms) on the household, community and common characteristics, which are supposed to determine household welfare (e.g. Glewwe, 1990; Muller, 1999; Canagarajah and Portner, 2003). This approach rests on the assumption that higher expenditure implies higher utility and vice versa. *The second approach* is to directly model poverty by employing a discrete choice model. The practice of discrete choice models in the analysis of determinants of poverty has been a more popular approach[1] (e.g., Gaiha, 1988; Kabubuo-Mariara, 2002;

[1] Another approach is to combine these two approaches by using multinomial logit selection model to analyse the determinants of living standards (see Mckay and Coloube ,1996). This approach is not yet common though.

Amuedo_Dorantes, 2004; Goaed and Ghazouani, 2001). The analysis then proceeds by employing binary logit or probit model to estimate the probability of a household being poor conditional upon some characteristics. In some cases the households are divided into three categories: absolute poor, poor and non poor and then ordered logit or ordered probit model is employed to identify the factors which affect the probability a household being poor conditional upon set of characteristics. The discrete choice model has a number of attractive features in comparison to the expenditure approach. The expenditure approach, unlike the discrete choice models, does not give probabilistic estimates for the classification of the sample into different poverty categories. The consumption approach assumes that consumption expenditures are negatively correlated with absolute poverty at all expenditure levels. By the same logic factors, which increase expenditure, reduce poverty. However, this is not always the case. For instance increasing consumption expenditure for individuals above the poverty line will not affect the poverty level. On the other hand in discrete choice model one may allow the effects of independent variables to vary across poverty categories.

The third approach is the Multiple Cause Multiple Indicator (MIMIC) models (e.g., DiTommaso, Raiser and Weeks, 2007; Kuklys, 2004). The MIMIC model (cf. Joreskog and Goldberger, 1975) assumes that the observed variables are manifestations of an underlying unobserved latent concept (poverty) and that there are other exogenous variables that "cause" and influence the latent factor(s).

It may be pointed out that the important issues underlying these analyses are the choice of the independent variables and the assumption that they are indeed exogenous. Strictly speaking, the statistical relationships should be interpreted as *correlates* and not as *determinants* since causality can run both ways for some variables.

Application of Logit/Probit models has also been extended in the context of multidimensional poverty. Here, the binary dependent variable is based on an individual being classified as poor/non-poor according to the multidimensional index (see for example, D'Ambrosio, Deutsch and Silber, 2007). However, with the wealth of information on the multidimensional aspects of poverty one could ask more probing questions. For instance, we know that poor people tend to have low levels of education;

but are they poor because they have little education, or do they have little education because they are poor? To understand this one could explore the interrelationships amongst the various dimensions/attributes and the direction of causality. Also, to develop an effective strategy to combat poverty a clear understanding of the fundamental causes of poverty is needed. Therefore, a statistical association (correlation analysis) alone is not enough to establish causality and this calls for the methodology of *Structural Equation Modelling* (SEM) (e.g., Krishnakumar, 2004; 2008).

Krishnakumar (2004) formulates the model following Sen's (Sen, 1985, 1999) concept of 'capabilities' and 'functionings'. According to Sen, the basic purpose of development is to enlarge people's choices so that they can lead the life they want to. He also emphasizes that development is a multidimensional concept. In Sen's approach, the *choices* that one has are termed 'capabilities' and the actual levels of *achievement* attained in the various dimensions are called 'functionings'. Thus, while 'capabilities' are the choices, 'functionings' are the outcomes and there could be more than one achievement level for the same capability level. As 'capabilities' by definition cannot be directly measured, Krishnakumar (2004) specifies them as latent unobservable variables. On the other hand, 'functionings' can be measured in terms of the achievements in each dimension both at the individual (household) and at the national levels. These achievements are taken to be indicators reflecting the performance in the associated dimension. There are several types of indicators available in practice. Some of them could be continuous whereas some could be of a qualitative nature. At the individual level one could also have *subjective* assessments such as whether a person considers himself to be poor or not. Qualitative variables can be binary or dichotomous, and polychotomous (more than two outcomes e.g. different levels of education - no formal education, primary, secondary, college...). Note that there is a certain order in the last variable and hence it is termed as an ordinal variable. There could also be polychotomous variables with no order, for example, religion - Hindu, Muslim, Buddhist, Christian etc. Some other indicators could be truncated or censored - truncated when not observed for a particular range of values, censored when observed only if greater than a threshold value. It may be mentioned that the statistical/econometric treatment of these variables differs according to the particular type concerned. Having established the interdependent nature of the underlying latent capabilities and the observable nature of the outcomes or functionings, one may formulate a model through a set of relationships. The formulation of the model thus involves setting up a simultaneous equations system where dependent variables could be discrete. Given the nature of the variables, the estimation calls for the LInear Structural RELationship (LISREL) methodology (see Muthen, 1983, 1984), which is extensively used in psychometric literature. Krishnakumar (2004) proposes a modified version of LISREL, where exogenous variables are taken into account, in estimating the latent variables. However, the model has not been implemented empirically.

The present exercise is an attempt towards understanding the structural relationships amongst the various attributes related to poverty in the above framework. Household poverty, as already mentioned, is understood to be a multidimensional phenomenon, of which access to income/productive assets/resources, food security and nutrition; education, health, housing and sanitation etc. are regarded as the major dimensions. A priori, one would expect a household's major socioeconomic decisions like those relating to production, consumption and factor market participation, to be significantly influenced by whether or not the household is poor in respect of one or several dimensions of poverty. On the other hand, poverty and household decisions may be interrelated such that poverty may be self-reinforcing. For example, an income poor household may decide not to send its children, particularly the girl children, to school for reasons of poverty, even though an opposite decision may be beneficial for the household in the long run. The results of this study should help identify the sets of poverty dimensions and decisions that mutually reinforce each other.

As already pointed out, majority of the poverty studies uses expenditure on different items as one of the principal indicators of welfare. Yet, in many developing countries, income and expenditure data are either of poor quality or completely absent. Thus, reliable data necessary to make poverty comparisons are scarce. In some countries, however, the demographic and health surveys provide micro-level information on education, ownership of assets, access to health services, etc. In India, most of the poverty studies have been based on per capita consumer expenditure data obtained from the household level surveys of the National Sample Survey (NSS) organization and the National Council of Applied economic Research (NCAER) (see Sharma, 2004; Borooah, 2005; Morten, 2006 and the references therein). There has been a handful of studies in the multidimensional context in India (e.g. Rudra, Chakrabarti, Mazumdar and Bhattacharya, 1995; Chakravarty, Mukherjee and Ranade; 1998; Kapur Mehta, 2003). These studies have, however, concentrated mainly on the *measurement* of poverty. Thus, the issue of poverty being self-reinforcing still remains largely unattended.

The present study is an attempt to bridge this gap. It is based on a survey conducted in two districts in Assam, a state in the North Eastern region of India. Data have been collection on various demographic, social and economic attributes and the SEM is estimated using LISREL.

The plan of presentation is as follows: Section 2 describes the data and variables used, Section 3 describes the methodology and estimation procedure; Section 4 presents the results; and finally, Section 5 concludes.

2 Data and Variables

2.1 Data

Data have been collected from Kamrup and Cachar, two districts in the state of Assam, North-East India. The choice of Assam was guided by the perception that the study would be more relevant in a backward area of the North-Eastern region of India, as the Govt. of India has rendered special attention to the North-Eastern States. The two districts were chosen considering proximity, time and the budget constraint.

Kamrup is near the state capital and is comparatively developed. On the other hand, Cachar is a backward district away from the capital. Two adjacent villages from each district, viz, 'Barbari' and 'Keotpara' from Block Ajara of Kamrup and 'Bishambharpur' and 'Gumrah Gram' from Block Hilara of Cachar were selected.

Households were surveyed on a complete enumeration basis, the number of households in Kamrup being 179 and that for Cachar being 229.[2] After scrutiny and cleaning of data the samples sizes for Kamrup and Cachar turned out to be 175 and 221, respectively.

A variety of qualitative and quantitative information relating to various aspects of household level of living focusing on poverty and household decisions were gathered from the households.[3] However, many variables had to be dropped owing to missing and infeasible data. Some of the variables were combined to obtain *composite* and *latent* variables, because it was felt that meaningfully combining some of the individual variables would provide a better understanding of the underlying relationships.

2.2 Variables

The table below gives a description of the variables used in this study.

[2] The sample sizes are: Barbari – 157, Keotpara – 22, Bishambharpur - 193 and Gumrah Gram – 36.

[3] See Appendix for the schedule (questionnaire) that was canvassed.

Variable Name	Description	Value/ range	Expected Direction of Relationship with Poverty
Edu	**Highest education level in the family** 1: < primary; 2: primary, but <secondary; 3: secondary, but <higher secondary; 4: higher secondary, but < graduation; 5 : graduation and above	1 – 5	-ve
Inf	**Access to Information** (constructed from the following variables:) At least one member of the family **(a) reads newspaper, (b) listens to radio,** **(a) watches television.** Each can take one of the following values: 1: regularly; 2: occasionally; 3: no	0 – 6 Composite score constructed from scores of (a), (b) and (c) as [(a)+(b)+(c)-3]	+ve
Veh	**Possession of vehicle** (like cycle, moped, van, scooter etc.) 0 : yes; 1 : no	0 – 1	+ve
Freq	**Frequency of purchase** of grocery items 1: everyday; 2: 2/3 times in a week; 3: 1 time in a week; 4 : 1-3 times in a month; 5 : no fixed time	0-4 Recoded from scores as [5-score]	+ve
Foodgt	**Cooked food as gift or loan** During last 30 days a household (a) has taken from other family (b) has given to other family 1 : no; 2 : 1 / 2 times; 3 : frequently	1 – 5 Composite score constructed from scores as [(a)+3-(b)]	+ve
Mealsp	**Special food in any social / religious function** during last one year: 0 : yes; 1 : no	0 – 1	+ve
Hse	**Housing condition** with respect to **(a) sources of drinking water** : 1 : own & within residence, 2: shared & within residence, 3: outside residence; **(b) lighting:** 1: Electricity, 2: kerosene light, 3: others; **(c) cooking media**: 1: forest collection, cowdung etc., 2: wood, coal, coke, 3: LPG, bio-gas, kerosene; **(d) latrine:** 1: no proper system, 2: Kancha latrine, 3: peat latrine, 4: sanitary latrine.	1-10 Composite score constructed from scores of (a), (b), (c) and (d) as: [(a) + (b) + {3-(c)} + {4-(d)]-1	+ve
Clth	**Purchase of new clothes** during last one year for any (a) adult female member : 1: at the time of any occasion 0:otherwise (none, when required or not applicable); (b) other relative – 1: yes, 0: no	0 – 2 Composite score constructed from scores as [2–(a)– (b)]	+ve
Fmlb	**Female member (15 – 65 years of age) working as a manual labourer:** 1:regularly, 2:occasionaly, 3: no and not applicable.	0 – 2 Recoded from scores as [3 – score]	+ve
Povaid	**Respondent's perception regarding allocation of Govt. fund released for poverty eradication:** 1: most of the poor households receive, adequate 2: most of the poor households receive, inadequate 3: not properly distributed, 4: can not say, 5: does not want to say.	1 – 5	
Hhs	**Household size**	Number of family members	+ve
Depr	**Dependency ratio** = [(Hhs – no. of adult male)/Hhs]	Interval [0,1]	+ve
Rel	**Religion** 1: Hindu, 0: Non-Hindu	0 – 1	

The following 'latent variables' were formed from individual variables.

Latent 1 (*Access*): Edu, Inf, Veh

Latent 2 (*Food*): Freq, Foodgt, Mealsp

The final variables for structural equation modelling are:

Endogeneous: *Hse*, *Clth*, *Fmlb*, *Paid* and *Access*

Exogeneous: *Rel*, *Hhs*, *Depr* and *Food*[4]

3 Methodology and Estimation

3.1 Methodology

The LISREL model is made up of two related submodels:

- A measurement model representing the relationships between the latent variables (exogenous and endogenous) and their observable indicators.

- A structural model representing the relationships among the latent/observable exogenous and endogenous variables.

(i) The measurement model

Let $y = (y_1, y_2, ..., y_p)^T$ and $x = (x_1, x_2, ..., x_q)^T$ be vectors of observable endogenous and exogenous variables, respectively.[5] Furthermore, let $\eta = (\eta_1, \eta_2, ..., \eta_m)^T$ be a vector of latent endogenous variables and $\xi = (\xi_1, \xi_2, ..., \xi_n)^T$ a vector of latent exogenous variables. Finally, $\varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_p)^T$ and $\delta = (\delta_1, \delta_2, ..., \delta_q)^T$ are defined as vectors of measurement errors of *y* and *x*, respectively. The relationships between the observed and latent variables are given in the latent variables measurement models (1) and (2):

$$y = \Lambda_y \eta + \varepsilon \qquad (1)$$

[4] Households live under conditions of food poverty owing to non-availability of food in the area and/or their own inability to secure entitlement to food, which is determined by income. Since both determinants are beyond the purview of our study, the latent variable *'Food'* is taken as an exogenous variable here.

and

$$x = \Lambda_x \xi + \delta \tag{2}$$

where Λ_y and Λ_x are (p×m) and (q×n) matrices of regression coefficients (also called factor loadings).

(ii) The structural model

The structural model consists of a set of relationships among the latent variables:

$$\eta = \tilde{B}\eta + \Gamma\xi + \varsigma \tag{3}$$

or

$$B\eta = \Gamma\xi + \varsigma \tag{4}$$

where $\tilde{B}$ is an (m×m) coefficient matrix with β_{ij} representing the effect of the j-th endogenous variable on the i-th endogenous variables; Γ is a (m×n) coefficient matrix with γ_{ij} representing the effect of the j-th exogenous variable on the i-th endogenous variable; ς is a random vector of residuals; $B = I - \tilde{B}$, where I is the identity matrix.

The covariance matrices of ε and δ will be denoted by $\Theta_\varepsilon(p \times p)$ and $\Theta_\delta(q \times q)$ and the covariance matrices of ξ and ς by $\Phi(n \times n)$ and $\Psi(m \times m)$.

The following remarks are in order here. First, for reasons of simplicity but without loss of generality, it is assumed that B is non-singular. Thus, dependent equations are assumed to have been removed from the system of equations. Second, it is possible to estimate intercept terms of the equations (1) – (4). Such parameters may be of interest in the comparison of different, mutually exclusive, sets of observations. In the present kind of study, however, attention will only be paid to the analyses of a single sample. Therefore, the assumption is made here, that both the observed and the latent variables are centralized. Formally:

$$E(y) = 0; \quad E(x) = 0; \quad E(\eta) = 0; \quad E(\xi) = 0 \tag{5}$$

Third, the following standard assumptions are made:

[5] The superscript ‘T’ denotes the transposed vector of matrix.

$$\left.\begin{array}{l} E(\varepsilon) = 0;\;\; E(\delta) = 0;\;\; E(\varsigma) = 0 \\ E(\eta\varepsilon^T) = 0;\;\; E(\xi\delta^T) = 0;\;\; E(\eta\delta^T) = 0;\;\; E(\xi\varepsilon^T) = 0;\;\; E(\varepsilon\delta^T) = 0 \\ E(\varsigma\xi^T) = 0;\;\; E(\varsigma\delta^T) = 0;\;\; E(\varsigma\varepsilon^T) = 0 \end{array}\right\} \qquad (6)$$

In (5) and (6), "0" denotes a vector or matrix of appropriate order. Fourth, multiple observable variables for a latent variable are often preferable and necessary so as to provide a tool for identification (see, among others, Goldberger 1972, 1973). However, the structural model may include observed variables. In that case an identity relationship is specified between the observed and corresponding latent variable. Fifth, one single observable variable may be an indicator of more than one latent variable. Finally, the LISREL approach makes it possible to reduce the problem of multicollinearity. As described by, among others, Theil (1971), this problem arises as a consequence of the presence of (highly) correlated explanatory variables. It leads to the increase of the estimated variances of the estimators of the coefficients of the collinear explanatory variables, so that one may be led to drop variables incorrectly from an equation. By simultaneously handling observable and latent variables within one model framework, the consequences of multicollinearity can be mitigated. This can be seen as follows. Collinear explanatory variables, which are indicators of a given latent variable, are dependent variables in one of the latent variables measurement models (1) and (2) and therefore would not be removed from one of these models because of their collinear nature. Furthermore, in the structural model the latent variables appear instead of their corresponding observable variables. So, collinear variables would not be removed from the structural model in spite of the fact that they are collinear.

Model (1) to (4) is a general framework in which several specific models are contained. The most common of these models are first- and second- order factor analysis models, structural equation models for directly observable variables, and various types of regression models.

3.1 Estimation

The covariance matrix as implied by the LISREL model is given by

$$\mathrm{cov}(y,x) = \mathrm{cov}(\Lambda_y\eta + \varepsilon, \Lambda_x\xi + \delta) = \mathrm{cov}(\Lambda_y(A\Gamma\xi + A\zeta) + \varepsilon, \Lambda_x\xi + \delta)$$

where $A = B^{-1}$ *and* $\eta = A\Gamma\xi + A\zeta$ *by equation* (4),

$$= \Sigma = \begin{pmatrix} \Lambda_y A(\Gamma\Phi\Gamma' + \Psi)A'\Lambda_y' + \Theta_\varepsilon & \Lambda_y A\Gamma\Phi\Lambda_x' \\ \Lambda_x\Phi\Gamma' A'\Lambda_y' & \Lambda_x\Phi\Lambda_x' + \Theta_\delta \end{pmatrix}$$

Let $S = \hat{\Sigma}$.

The purpose is to estimate the free and constrained parameters by appropriately defining the covariance structure for indentifiability of the parameters.
The most general function to be minimized for fitting covariance structures is:

$$F(\theta) = (s-\sigma)'W^{-1}(s-\sigma),$$

where $s' = (s_{11}, s_{21}, s_{22}, s_{31}, ..., s_{kk})$ is a vector of elements in the lower half, including the diagonal, of the covariance matrix *S* of order $k \times k$, ($k=p+q$), to fit the model to the data. $\sigma' = (\sigma_{11}, \sigma_{21}, \sigma_{22}, \sigma_{31}, ...\sigma_{kk})$ is the vector of corresponding elements of $\Sigma(\theta)$ reproduced from the model parameter θ.

The matrix W^{-1} of order $u \times u$, where $u = k(k+1)/2$ is a positive definite matrix.
The LISREL 8 program (Jöreskog and Sörbom, 2001) has been applied to estimate the free and constrained model parameters from the sample covariance matrix *S* using the Diagonally Weighted Least Squares (DWLS) method. DWLS is an appropriate estimator when there are ordinal or nominal variables among the observables, as in the present

study.[6] The usual way of choosing W in weighted Least Squares is to let the elements be a consistent estimate of the asymptotic covariance between the elements of s'. The above applies to sample covariance matrix for continuous variables. In practice, correlation matrices are often analyzed, i.e., covariance matrix S scaled by stochastic standard deviation. This approach can be used when some or all of the variables are ordinal or censored. PRELIS can compute estimates of the asymptotic variances and covariances of estimated *polychoric*[7] and *polyserial*[8] correlations. The LISREL 8 program provides various statistics to check or test the adequacy of the assumed model.

In terms of equation (1) – (3), the relationships specified in section 3 can be presented as follows.[9]

$$y = \begin{bmatrix} Hse \\ Clth \\ Fmlb \\ Paid \\ \left.\begin{matrix} Edu \\ Inf \\ Veh \end{matrix}\right\} \end{bmatrix}, \quad \Lambda_y = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & \lambda_{65}^{y} \\ 0 & 0 & 0 & 0 & \lambda_{75}^{y} \end{bmatrix}, \quad \eta = \begin{bmatrix} Hse \\ Clth \\ Fmlb \\ Paid \\ Access \end{bmatrix}$$

[6] A prerequisite for estimation is that the hypothesized model is identified. The LISREL 8 program gives hints about identification problems. It calculates an estimate of the matrix of second-order derivatives of the fitting function used to estimate the model. Rothenberg (1971) has shown that under quite weak regularity conditions local identifiability is equivalent to non-singularity of the information matrix. Furthermore, the rank of the matrix indicates which parameters are not identified (Jöreskog and Sörborn, 2001).

[7] Used when an interval variable is correlated with a dichotomous or an ordinal variable, which is assumed to reflect an underlying continuous variable.

[8] Used when both variables are dichotomous or ordinal but both are assumed to reflect underlying continuous variables. That is, polychoric correlation extrapolates what the categorical variables' distributions would be if continuous, adding tails to the distribution.

[9] Observe that, for reasons of identification, one of the coefficients for each latent variable is fixed at 1 so as to fix the measurement scale.

$$x=\begin{bmatrix} Rel \\ Hhs \\ Depr \\ \left.\begin{matrix} Freq \\ Foodgt \\ Mealsp \end{matrix}\right\} \end{bmatrix}, \quad \Lambda_x = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & \lambda_{54}^{x} \\ 0 & 0 & 0 & \lambda_{64}^{x} \end{bmatrix}, \quad \xi = \begin{bmatrix} Rel \\ Hhs \\ Depr \\ Food \end{bmatrix}$$

For goodness of fit statistics we present the values for Goodness of Fit Index (GFI) and Adjusted (for degrees of freedom) *GFI (AGFI).*[10] These are given respectively by

$$GFI = 1 - \frac{Min\,Fit\,Function}{Fit\,Function\ for\ null\ \mathrm{mod}\,el} = 1 - \frac{(s-\hat{\sigma})'W^{-1}(s-\hat{\sigma})}{s'W^{-1}s}$$

$AGFI = 1 - \dfrac{(p+q)(p+q+1)}{2df}(1-GFI)$, where df is the degrees of freedom of the model, given by $\frac{1}{2}(p+q)(p+q+1)-t$, t being the number of independent parameters estimated.

These measures should be between 0 and 1, a value closer to 1 indicating better fit.

4. Results

The measurement and structural models were estimated using data from Kamrup and Cachar separately. The final models were arrived at after several iterations of trial and error considering identification status, plausibility and significance of parameters and values of *AGFI*.

[10] For models with small sample size χ^2 is a reasonable measure of fit. But for large sample size χ^2 is almost always statistically significant. It is also affected by the size of the correlations in the model: the larger the correlations, the poorer the fit. For these reasons alternative measures of fit have been presented.

4.1. Results on Kamrup:

Table 1 presents the results of the measurement model. As already mentioned, two 'latent variables' have been formed. The endogenous latent variable *Access* comprises Edu, Inf and Veh. The coefficient of 'Edu' has been set to 1 in order to fix the measurement scale of the latent variable[11]. The direction of relationship of 'Edu' is expected to be negative with *poverty* and the relationships of 'Inf' and 'Veh' are expected to be positive with *poverty* (owing to the way they have been constructed). Since the coefficient of 'Edu' has been set to 1 the estimated coefficients of 'Inf' and 'Veh' have the desired negative signs. In terms of the values of R^2, the main determinant of *Access* turns out to be 'Edu', followed by 'Inf' and 'Veh' with significant t-ratios. Thus, *Access* is expected to be negatively related to poverty.

The exogenous latent variable *Food* comprises Freq, Foodgt and Mealsp. Here the coefficient of 'Freq' has been set to 1 in order to fix the measurement scale of the latent variable. All three variables are expected to be positively related to *poverty* and the estimated coefficients corroborate this. The main determinant of *Food* turns out to be 'Freq', followed by 'Foodgt' and 'Mealsp' with significant t-ratio for 'Foodgt'. For 'Mealsp' the values of t-ratio and R^2 turn out to be low.

Table 2 presents the results of the structural model. It consists of *five* functional relations corresponding to five endogenous variables. Some observations on the table 2 are in order. It may be noted the 9 out of 12 parameters of the system turn out to be significant. Coming to the individual equations, **first**, *Access* is directly affected by housing condition (*Hse*) in a negative way and by Religion (*Rel*) in a positive way. This means that (i) as a household becomes poorer in terms of housing condition, its access to 'information/ education/ communication' reduces and (ii) the majority of the people who are domiciled Hindus (72%) enjoy higher 'access to information/education/ communication' compared to the minority group. **Second**, *Hse* is directly affected by 'inability to purchase new clothes' (*Clth*), food poverty (represented by the latent variable *Food*) and household size (*Hhs*), which is expected in view of the fact that for all these variables a higher value is

[11] Change in the numeriare will automatically induce a change in the coefficients.

expected to indicate higher poverty. **Third**, 'Inability to purchase new clothes' (*Clth*) is directly (positively) affected by food poverty and negatively by *Fmlb* (the value of which increases as female participation in labour force increases). This means that 'food poverty' induces 'clothing poverty', which in turn affects 'housing condition', thereby affecting 'access to information / education / communication' indirectly. Female labour force participation, on the other hand, enhances 'ability to purchase new clothes'. **Fourth**, the direct relationship of *Fmlb* is negative with *Access* and positive with *Depr* and *Rel* with a high value of R^2. This means that, as a household becomes poorer in terms of *Access* (which in turn is determined by housing poverty) and as the proportion of dependants increases, higher is the labour force participation of the female in the household. Also, Hindu women have higher labour force participation. **Finally**, *Povaid*, which represents the perception on Govt. aid for poverty alleviation, is negatively dependent on *Access* and positively on *Food.* Note that, according to the measurement model the major determinant of *Access* is 'Edu' and *Access* is negatively related to poverty. This means that the educated poor are not happy with the role of the government.

The goodness of fit statistics given by *GFI* and *AGFI* are 0.784 and 0.672, respectively. These indicate a fairly reasonable fit of the model.

4.2 Results on Cachar:

Table 3 presents the results of the measurement model. The directions of relationships for both the endogenous and exogenous latent variables are the same as those observed in case of Kamrup. The overall results are more or less the same with the only difference that the all three determinants of *Access* turn out to be almost equally important in terms of values of R^2.

Table 4 presents the results of the structural model. It consists of *four* functional relations corresponding to four endogenous variables. *Fmlb* fails to play any role for Cachar, because there is no variation in female labour force participation data.

Coming to the equations, **first**, *Access* here is directly affected by housing condition (*Hse*) in a negative way as in the case of Kamrup; but here instead of Religion (*Rel*), *Depr* enters the equation negatively. This means that as a household becomes poorer in terms of housing condition and as its dependency ratio increases, its access to 'information/ education/ communication' reduces. **Second**, *Hse* is directly affected by 'inability to purchase new clothes' (*Clth*) and dependency ratio (*Depr*). **Third**, 'Inability to purchase new clothes' (*Clth*) is directly (positively) affected by food poverty (represented by the latent variable *Food*) and household size (*Hhs*). This means that 'food poverty' and large household size induce 'clothing poverty', which in turn affects *Access* indirectly. **Finally**, *Povaid* is negatively dependent on *Access* and positively on *Food* as in case of Kamrup. However, here according to the measurement model all three determinants (*Edu*, *Inf* and *Veh*) of *Access* play almost equally important roles unlike in the case of Kamrup, where *Edu* plays the most important role. Hence, for Cachar dissatisfaction with poverty eradication measures of the government increases with peoples' potential awareness derived from education, informativeness and mobility.

The goodness of fit statistics given by *GFI* and *AGFI* are 0.843 and 0.742, respectively. These also indicate a fairly reasonable fit of the model.

5. Conclusion

In the present exercise an attempt has been made to explore the structural relationships amongst the various attributes related to poverty, which may be related to the household's decisions such that poverty may be self-reinforcing. Using data from a survey conducted in two villages of Kamrup and two villages in Cachar in Assam, a structural equation model has been fitted using LISREL. The results, using limited number of variables, show that there is indeed a two-way relationship between determinants of poverty and poverty itself, thus establishing the self-reinforcing nature of poverty. The main findings may be summarized as follows:

- Female labour force participation plays no role in modelling poverty in Cachar. This is because of the fact that the ‘Barbari’ and ‘Keotpara’ villages of Kamrup district are more urbanized than the ‘Bishambhapur’ and ‘Gumrah Gram’ villages in Cachar, which is basically an agricultural district and all adult female members of a household generally participate in labour force. For Kamrup, on the other hand, the decision on female labour force participation depends on the level of poverty in terms of education, informativeness and mobility.

- For both districts a hierarchical nature of poverty is evident. As mentioned earlier, poverty in terms of *food* is taken as a basic poverty condition (exogenous). From the analysis it emerges that food poverty is a determinant of clothing poverty, which in turn determines poverty in terms of housing condition, which again induces poverty in terms of access to information / education / communication.

- Large household size and greater dependency ratio play important roles in determination of poverty.

- Finally, both in Kamrup and Cachar dissatisfaction with the role of the government in poverty alleviation increases, higher is the value of *Access,* that is, higher is a person’s education, access to information and mobility.

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Table 1: Results of the measurement models: Kamrup

Observable variable	Coefficient	Standard Error	t - ratio	R^2
Latent Variable (endogenous): *Access*				
Edu	1.000			0.793
Inf	-0.648	0.160	-4.054	0.339
Veh	-0.445	0.136	-3.263	0.161
Latent Variable (exogenous): *Food*				
Freq	1.000			0.338
Foodgt	0.873	0.232	3.763	0.257
Mealsp	0.252	0.195	1.293	0.021

Table 2: Results of the structural model (beta and gamma results): Kamrup

Endogenous variables	Explanatory variables								
	Endogenous variables				Exogenous variables				R^2
	Access	*Hse*	*Clth*	*Fmlb*	*Paid*	*Food*	*Hhs*	*Depr*	*Rel*	
Access		-0.336 (-4.695)*							0.264 (2.677)	0.226
Hse			0.017 (0.139)			1.139 (3.492)	0.146 (1.811)			0.460
Clth				-0.006 (-0.059)		0.815 (3.418)				0.224
Fmlb	-0.344 (-2.650)							0.209 (4.415)	0.950 (10.409)	0.860
Paid	-0.297 (-3.394)					0.819 (4.218)				0.379

* Figures in parentheses are the asymptotic t-ratios.

Table 3: Results of the measurement models: Cachar

Observable variable	Coefficient	Standard Error	t - ratio	R^2
Latent Variable (endogenous): *Access*				
Edu	1.000			0.511
Inf	-1.004	0.126	-7.986	0.515
Veh	-1.035	0.159	-6.509	0.547
Latent Variable (exogenous): *Food*				
Freq	1.000			0.363
Foodgt	0.951	0.184	5.166	0.328
Mealsp	0.206	0.168	1.224	0.015

Table 4: Results of the structural model (beta and gamma results): Cachar

Endogenous variables	Explanatory variables									
	Endogenous variables					Exogenous variables				R^2
	Access	*Hse*	*Clth*	*Fmlb*	*Paid*	*Food*	*Hhs*	*Depr*	*Rel*	
Access		-0.322 (-4.680)						-0.173 (-3.125)		0.297
Hse			0.282 (2.698)					0.166 (1.801)		0.108
Clth						1.104 (4.084)	0.025 (0.366)			0.439
Fmlb										
Paid	-0.356 (-2.801)					0.479 (2.597)				0.170

* Figures in parentheses are the asymptotic t-ratios.