Discussion Paper Series

RIEB

Kobe University

DP2012-02

Measuring Households' Vulnerability to Idiosyncratic and Covariate Shocks – the case of Bangladesh *

Md. Shafiul AZAM

Katsushi S. IMAI

January 26, 2012

Research Institute for Economics and Business Administration

Kobe University

2-1 Rokkodai, Nada, Kobe 657-8501 JAPAN

Measuring Households' Vulnerability to Idiosyncratic and Covariate Shocks – the case of Bangladesh

Md. Shafiul Azam

Economics, School of Social Sciences, University of Manchester, UK

&

Katsushi S. Imai *

Economics, School of Social Sciences, University of Manchester, UK and
Research Institute for Economics & Business Administration (RIEB), Kobe University, Japan

This Draft: 16th January 2012

Abstract

The paper examines the level and sources of vulnerability in rural Bangladesh using a household survey. We use a simple two-level random intercept model to estimate expected mean and variance in consumption as well as to decompose the variance into idiosyncratic and covariate components. Our results indicate that both idiosyncratic and covariate shocks have considerable impact on household's vulnerability and idiosyncratic shocks seem to have greater impact on household's consumption vulnerability than the covariate shocks. Furthermore, idiosyncratic shocks appear to have a relatively higher impact on relatively well endowed (i.e. in terms of human capital, land holdings, activity status etc.), well off households and covariate shocks seem to have a relatively higher impact on poorer, less educated, household's vulnerability. Our results also reveal that rural vulnerability in Bangladesh is mainly poverty induced rather than risk induced. Around 78 per cent all who are vulnerable is accounted for by low expected mean consumption and only 22 per cent of them are due to high consumption volatility. Overall vulnerability in rural areas is estimated to be 50 per cent. The categorization of poverty into transient and chronic poverty is even more insightful. The study finds that those without education or agricultural households are likely to be the most vulnerable. The geographical diversity of vulnerability is considerable. It is suggested that *ex ante* measures to prevent households from becoming poor as well as *ex post* measures to alleviate those already in poverty should be combined.

Key words: poverty, vulnerability, risks, poverty dynamics, Bangladesh
JEL codes: C21, C25, I32

* Corresponding Author:
Katsushi Imai (Dr)
Economics, School of Social Sciences
University of Manchester, Arthur Lewis Building,
Oxford Road, Manchester M13 9PL, UK
Phone: +44-(0)161-275-4827
Fax: +44-(0)161-275-4928
E-mail: Katsushi.Imai@manchester.ac.uk

Measuring Households' Vulnerability to Idiosyncratic and Covariate Shocks – the case of Bangladesh

1 Introduction

The concept of risk and its contribution to poverty dynamics is gaining increasing importance in poverty literature. According to Prof. Amartya Sen (Asia Week, October 1999), "… the challenge of development includes not only the elimination of persistent and endemic deprivation, but also the removal of vulnerability to sudden and severe destitution." Similar concerns have also been echoed in a number of World Bank publications (WDR, 2001). It is therefore, important to have an adequate understanding of the risk-poverty nexus and the way resulting vulnerability affects basic dimensions of household's welfare for the design of development policies in general and poverty reduction in particular.

Static measures can provide a 'snap shot' of the poverty situation at a given point in time and these measures differentiate the population of a country between 'the poor' and 'the non-poor' as two relatively separate entities. Poverty in these contexts can seem rather one-dimensional – as a homogenous and relatively static state experienced by a homogenous and discrete group: 'the poor' (Smith and Middleton, 2007). In contrast, recent studies show that there are considerable movements in and out of poverty depending on the natural, social and economic environments of varying degrees of risks and uncertainty households are embedded in. Even if aggregate poverty rates remain constant over time, the share of the population which is vulnerable to poverty might be much higher (i.e. the distribution of vulnerability across different segments of the population might differ significantly from the distribution of poverty). Moreover, these poverty measures cannot assess whether high poverty rates are a cause of structural poverty (i.e., poverty resulting from low endowments, or adverse socio-economic set up) or a cause of poverty risk (i.e. high uninsured income fluctuations), which is important to know from a policy point of view. Static concept of poverty can thus potentially be misleading in these circumstances. In order to understand the effects of economic growth and other policy interventions on poverty rates, it is important to focus not just on static but also on dynamics, i.e., on movements in and out of poverty. According to this dynamic view, poverty is seen not just as a form of deprivation but also as a form of vulnerability.

Vulnerability, on the other hand, may be broadly construed as an *ex-ante* measure of well-being, reflecting not so much on how well off a household currently is, but what their future prospects are (Chaudhuri, 2003). We can understand it as the impact of risk in the "threat of poverty, measured *ex ante*, before 'the veil of uncertainty has been lifted' (Calvo and Dercon, 2005). Risks may emanate from two broad sources: idiosyncratic shocks; or covariate shocks. Household's idiosyncratic shocks, that is, household-specific shocks such as death of the principal income earner, injury, chronic illness or unemployment/underemployment etc, are fairly common in developing countries mainly due to 'the absence of easy access to medical care, drinking water, unhygienic living conditions, and limited opportunities for diversifying income sources. These difficulties are compounded by lack of financial intermediation and formal insurance, credit market imperfections, and weak infrastructure (e.g. physical isolation because of limited transportation facilities) (Gaiha and Imai, 2004). Covariate shocks i.e., community level shocks, are typically natural disasters like floods, cyclones, draughts or epidemics etc. All these can potentially contribute to high income volatility of households. Vulnerability is thus inherently a dynamic concept and could be thought of as a product of poverty, household's potential exposures to risks and their ability to cope with such risks. Proper conceptualisation and characterisation of the underlying dynamic process is thus important from both theoretical and policy perspectives.

Theoretically, the presence of risks can distort household's inter-temporal resource allocation behaviour, not only for those who are currently poor, but also for the non-poor who have a high probability of becoming poor in near future. These distorted behavioural responses can be economically costly and may propel households into persistent poverty (Carter and Barrett, 2006). An adequate understating of risk-poverty linkage is also beneficial in identifying some of the key constraints to poverty reduction binding at micro-level: identifying who are the most vulnerable, as well as what characteristics are correlated with movements in and out of poverty, can yield critical insights for policy makers (Ajay and Rana, 2005). Thus, to address the objective of poverty reduction, policies should not only highlight poverty alleviation interventions to support those who are identified as the poor *ex post*, but also the poverty 'prevention' interventions to help those who are poor *ex ante*, that is, prevent those who are vulnerable to shocks not to fall into poverty. The latter was emphasised by the World Bank's Social Risk Management framework which highlights three types of risk management strategies: prevention, mitigation and coping (Holzmann and Jørgensen, 2000). Similar concerns have also been echoed in several editions of the World Development Report (World Bank, 1998; 2001; 2008). An assessment of household's vulnerability to poverty i.e. to figure out who is likely to be poor, how poor are they likely to be, and why they are vulnerable to poverty, seems to be more than justified.

In addition, an assessment of the relative importance of idiosyncratic and covariate shocks is also important as these are crucial ingredients in the design of public policy, safety nets, and targeting schemes. Households can curb their exposure to idiosyncratic risks through community-based insurance arrangements. They can build informal insurance networks of mutual assistance around family and community relationships as information asymmetries and enforcement limitations are assumed to be smaller within communities than across communities. On the other hand covariate shocks are left uninsured under local risk pooling. Covariate shocks are correlated across households within a community and as such, local risk pooling or mutual insurance mechanism breaks down because of information asymmetry and enforcement limitations across communities. However, covariate shocks are easier to target because they are geographically clustered.

Although the existing poverty literature for Bangladesh is prolific (Khan, 1990; Ravallion, 1991; Ravallion and Sen, 1996; Sen, 2003), a forward looking prospective analysis of poverty dynamics is completely missing. There are a number of studies that examine movements in and out of poverty (Sen, 2003; Quisumbing, 2007; Hossain and Nargis, 2010), but all of them are retrospective in nature. An understanding of the relative impacts of idiosyncratic and covariate shocks is also lacking which is important for a disaster prone, predominantly agrarian economy like Bangladesh. The principal motivation of this paper is to fill the gap and complement the existing empirical literature by undertaking an *ex ante* dynamic analysis of poverty in Bangladesh. Ideally, vulnerability measurement would require the long panel data. But for many developing countries, panel data are rarely available and only cross-sectional survey data are available. Furthermore, most household surveys are not designed to provide a full account of the impact of shocks. Information on idiosyncratic and covariate shocks is therefore either completely missing or very limited in most of the household surveys. Bangladesh is no exception in this regard. Although there have been regular rounds of Household Income and Expenditure surveys in every five year intervals, any nationally representative household panel survey is yet to be available. The absence of nationally representative panel data obliges us, in our assessment of vulnerability to poverty in Bangladesh, to adopt a modelling approach which is spiritually similar to the one proposed by Chaudhuri (2003) particularly designed for cross-section data.

The rest of the paper is structured as follows: the next section will provide a brief overview of the current state of Bangladesh economy along with the poverty situation and discourses. Section 3 reviews the existing approaches and empirical literature on vulnerability to poverty, including its shortcomings. Section 4 lays out the details of the analytical frameworks adopted in this study including the decomposition scheme of poverty and vulnerability status of households. It also gives a brief description of the data. Estimated results and relevant analyses are presented in section 5, followed by concluding remarks in the last section.

2 Overview of the Poverty Situation in Bangladesh

Bangladesh has long been seen as the archetypal theatre of poverty. Although the history of poverty in the region goes back to the British colonial period (Siddiqui, 1982), the actual surge of interests on poverty among academics and researchers began after the independence of the country in 1971 especially against the backdrop of painful and devastating famine of 1974. The following decades saw a stream of studies generating huge literature on poverty issues of Bangladesh. Most of the studies during the 1970s and 80s were *ex post* static analysis and focused mainly on counting the poor. However, the statistics on poverty are generally problematic due mainly to the quality of the data and the use of multiple sources in estimating poverty. The latter half of the 19990s witnessed a shift from static to dynamic analysis of poverty. A number of studies investigating the dynamic aspects of poverty in Bangladesh are available now and notable contributions are made by Rahman (1996) and Sen (2003). A summary of the poverty trends and dynamics in Bangladesh is presented below.

2.1 Poverty Trends

There is little agreement about the poverty figures in Bangladesh due mainly to differing methods and multiple sources of data used in estimating poverty during the 1970s and 80s (different estimates are provided in appendix-1). The official figure for the estimated poverty of the country stood as high as 82.9 per cent in 1973-74. Though the latter half of the 1970s marked the beginning of a rapid decline of poverty followed by a hiatus during the 80s, poverty continued to decline during the 90s. The pace of poverty reduction got even faster during the first half of the 2000s (See table 1)**.** Poverty has declined from over 80 per cent in the early 1970s to around 40 per cent in 2005[1]. People living below the poverty line have declined almost 1.5 percentage points a year since 1990s which is quite impressive. More importantly, the living standards of the poorer section of the population improved substantially during the period 2000-05 as revealed by a greater decline in the depth and severity of poverty in rural areas than in the urban areas.

Nonetheless, the impressive poverty reduction record is of little comfort as the challenges ahead are quite enormous: i) First, poverty still remains at a very high level and the number of people living below poverty line remains almost the same as it was in 1991-92 (about 60 million); ii) faster poverty reduction during the 90s also accompanied by rising inequality measured by private consumption expenditure distribution. During the period 1991/92-2000, the level of consumption inequality increased from 31.9 to 37.9 per cent in urban areas and from 25.5 to 29.7 per cent in rural areas; iii) There are significant regional variations of poverty. Poverty is more pronounced in areas of the country which suffer from flooding, river erosion, mono-cropping and similar disadvantages. Poverty is highest in the western region of the country (Rajshahi Division) followed by Khulna and Chittagong; and iv) Finally, while these static point-in-time poverty estimates are useful to have a snapshot of the poverty situation, they are not quite useful to explain the gross movement of households in and out of poverty. Empirical evidences suggest that the gross movements in and out of poverty are much larger than the net aggregate poverty outcomes indicated by static estimates. To have a proper grip on policy perspectives, it is necessary to understand the underlying dynamism that propels households in and out of poverty.

Table 1 Poverty Trends in Bangladesh 1983-2005

Year	National	Urban	Rural	Poverty Gap	Squared Poverty Gap
1983/84	52.3	40.9	53.8	15.0	5.9
1988/89	47.8	35.9	49.7	13.1	4.8

[1] Overtime comparability of poverty estimates are difficult due mainly to changes in the methodology of data collection and poverty estimation. It is convenient to consider the period between 1995/96 – 2005 when the Household Income and Expenditure Survey (HIES) began to use consistent data collection and poverty estimation methodologies. For details around these issues please see Ahmed (2000).

1991/92	49.7	33.6	52.9	14.6	5.6
1995/96	53.1	35.0	56.7	15.5	5.7
2000	49.8	36.6	53.1	13.8	4.8
2005	40.0	28.4	43.8	9.8	3.1

Source: Sen 2003 and the figure for 2005 is taken from Bangladesh Bureau of statistics 2005

2.2 Poverty Dynamics

Rahman (1996; 2002) and Sen (1996; 2003) have made particular contribution in understanding the dynamics of rural poverty in Bangladesh. The study of 62 villages by BIDS and later Power and Participation Research Centre (PPRC) undertaken periodically have yielded panel data which have been particularly valuable in mapping out the dynamics of poverty over time. This research has found that the poor does not constitute a simple homogenous population that can be neatly categorized into one or two groups, rather there are considerable variations and mobility among the poor. The poor and the vulnerable non-poor are subject to periodic shocks that propel them towards more miserable livelihoods and greater poverty. There are also factors that help them move out of poverty. Rahman (1996) particularly underscored the notion of crisis and vulnerability that continuously plague the rural livelihoods, such as natural disasters, illness and insecurity. The rural households deploy a variety of mechanisms to cope with life course crises and other shock events. Downward mobility occurs as dialectic between the impact of life course events, structural factors and crisis factors, and the failure of coping mechanisms.

Rahman (2002) categorizes the poor in terms of three distinct groups. Tomorrow’s poor: this group is mostly marginal peasants owning up to 1.5 decimals of land and an annual income of Tk. 8368. They comprised 21 per cent of the rural population. The moderate poor: this group is more or less corresponds to the upper poverty line of BBS. It made up 29.2 per cent of villagers. The extreme poor: it corresponds to the lower poverty line of BBS. This category made up 22.7 per cent of rural people. There is considerable upward and downward mobility among these groups. The group called tomorrow’s poor are quite vulnerable and slips down the poverty line as a consequence of different crises that underlie peasant livelihoods in Bangladesh.

Sen (2003) has similarly made an attempt to explore the dynamics of poverty in terms of the panel data of 21 villages, which were part of the IRRI research. The study confirmed that mobility among the poor was considerable, although nearly one-third of the households were entrenched in chronic poverty. In analyzing the upward mobility of the poor, Sen has particularly looked into the increase in asset position of the households or favourable natural conditions or random factors. Thus the analysis is only partial and incomplete. Moreover, they are all *ex-post* retrospective analysis and do not look into poverty in prospect.

2.3 Challenges ahead

The sharp decline in the poverty rate – from an estimated 70 per cent in 1971 to 58 per cent in 1992 and to 40 per cent in 2005 is in large part due to accelerated income growth in the last decade and a half. Advances in health, education, and population growth, and innovative social programmes including micro-credit exemplified by celebrated organizations like – Grameen Bank and Bangladesh Rural Advancement Committee (BRAC) also believed to play a key role in the process.

Despite impressive development records, Bangladesh has still a long way to go to catch up even with its neighbouring South and South-east Asian countries. Sustaining a sound macroeconomic stability with high growth is a major challenge particularly in the face of poor governance. Bangladesh is a tiny land (147,570 sq. km) packed with around 150 million people. Population density is among the highest in the world. Over 2 million people are added to this figure each year. Close to 60 million people are believed to be living with below poverty line income. Moreover, the country has a very adverse and threatening agro-climatic condition. Almost half of the country's population lives near sea level and 40 per cent of its land area are flooded for at least three months every year, making large portion of its population vulnerable to global climate change and the resulting rise in sea levels. In spite of notable social progress in some areas, the level of overall human development remains low. Child malnutrition and maternal mortality rate are only better than Sub-Saharan Africa. So to maintain the tempo of poverty reduction, persistent and judicious growth and poverty reduction strategy based on solid analytical works need to be crafted.

3 Review of Literatures: Poverty and Vulnerability

The increased focus on risk and vulnerability in understanding and designing anti-poverty policies motivated a series of studies aimed at theoretically conceptualizing as well as measuring and addressing household vulnerability empirically. This section begins with a brief review of available approaches to conceptualize and measure vulnerability and then presents majors findings and evidences in brief from relevant empirical literatures.

3.1 An Overview of Existing Approaches

While there is a very rich literature on the appropriate measure of poverty[2] and on methods for creating aggregate summary statistic[3], the literature that intends to present similar summary measures of vulnerability is rather emerging. The current state of the theoretical literature on vulnerability is a bit chaotic and can be described in the words of Hoddinott and Quisumbing (2003) as a "let a hundred flowers bloom" phase of research with numerous definitions and measures and seemingly no consensus on how to estimate vulnerability. A number of competing measures have been proposed and the literature does not seem to be settled yet on a conceptually sound as well as operationally suitable definition. Hoddinott and Quisumbing (2003) and Ligon and Schechter (2004) provided an exhaustive list of methods for estimating vulnerability to poverty surveying all the existing literatures and reviewed strengths and weaknesses of each of them. According to Hoddinott and Quisumbing (2003) measures of vulnerability to poverty can be classified into three broad categories: a) Vulnerability as Expected Poverty (VEP), i.e., the probability that an individual or household will fall below or remain on the poverty line (Chaudhuri, 2002; Christiaensen and Subbarao, 2001; Pritchett, Suryahadi and Sumarto, 2000), b) Vulnerability as Low Expected Utility (VEU), i.e., the distance between the utility that would be achieved by an appropriately chosen level of consumption with certainty and the expected utility of the household given its uncertain prospect (Ligon and Schechter, 2002, 2003), and c) Vulnerability as Uninsured Exposure to Risk (VER), i.e., measures of the cost, in terms of consumption, of exposure to uninsured risk as inferred by the proportion of observed change in consumption attributable to past shocks (Tesliuc and Lindert 2004).

However, the above measures are generally not comparable as noted by Ligon and Schechter (2004; p. 01) – Ligon and Shcechter (2004) then conduct Monte Carlo experiments designed to explore the performance of different vulnerability indicators' proposed in the economic literatures, under different assumptions about the underlying economic environment. They find that when the environment is stationary and consumption is measured without measurement error, the best estimates are the ones proposed by Chaudhuri (2002). If the vulnerability measure is risk-sensitive, but consumption is measured with error the estimates proposed by Ligon and Schechter (2003) generally performs best. However, when the

[2] Deaton (1997); Ravallion (1993)

[3] Atkinson (1987); Foster (1984); Lipton and Ravallion (1995) and for a review of literature, Ravallion (1993)

distribution of consumption is non-stationary and there is measurement error, all estimates perform poorly. But since measurement error is a reality and to assess whether the distribution is non-stationary, relatively long time series are needed, which is a rarity in practice, particularly for most of the developing countries.

Another problem with the above measures is the conceptual inadequacy. As Hoogeveen (2004) noted, there are conceptual problems, using a measure based on the variability of consumption (or another outcome indicator), rather than an *ex-ante* measure that takes into account the cost of taking risk reducing measures. They suggested that using a measure of consumption variability still depends exclusively of past observation and to avoid such problem some kind of *ex-ante* augmented poverty line can be used that is based of *ex-ante* monetary cost of risks or uncertainty. Gunning and Elbers (2003) attempt to deal with this aspect by constructing a stochastic, structural dynamic model of a household's inter-temporal consumption and saving's decisions. In the process, they present yet another measure of vulnerability that is theoretically well defined, but practically hard to implement. What all these imply is that a methodologically sound and practically applicable measure of vulnerability may still be some way away even though literature in this field is growing very fast.

3.2 Empirics on Vulnerability

Regardless of how vulnerability is perceived, it has always been a dynamic concept where one needs to estimate *ex-ante* what happens in the future. While calibrating individual's (household's) poverty level is relatively straight forward, measuring an individual's vulnerability requires information on the possible states of the world in the future and the probability distribution of their occurrences. Information on different future states of the world becomes more complicated as we move further away from the present. Clearly these depend on the quality and nature of data that are available and accordingly most of the empirical literatures are crafted to the strengths of the available data. The part of literature on vulnerability which estimates impacts of shocks on household welfare has also data-driven limitations. Available data, particularly the household surveys (or even most of the panels), have either limited information on idiosyncratic or covariate shocks or no information at all (Gunther and Harttgen, 2009). As a consequence, most of these studies have only been able to focus on the impact of selected shocks on household's wellbeing (Dercon and Krishnan, 2000a; Gertler and Gruber, 2002; Glewwe and Hall, 1998; Kocher, 1995; Paxson, 1992; Nielson 2008; Sen, 2003; Gaiha and Imai, 2004; Quisumbing, 2007).

The early strands of literature defines vulnerability as the ability and the extent to which consumption is protected against income fluctuation due to idiosyncratic or covariate shocks and measured by the observed changes in consumption over time (e.g. Townsend, 1994; Udry, 1995; Glewwe and Hall, 1998; Dercon and Krishnan, 2000a; Jalan and Ravallion, 1998; Morduch, 2003). Their particular interest was not to identify who are vulnerable and correlates of vulnerable; nonetheless, these studies do provide valuable insights about households' behavioural responses in the face of adversaries and complement overall understanding of poverty dynamics and vulnerability. A brief review of these literatures would not be out of context in this sense and is in order.

The general conclusions emerging from this strand of the literature are: First, households are partially able to smooth their consumption. Second, given that there are considerable market failures (e.g., limited enforcement, costly monitoring, and market size) hindering formal credit and insurance market development, informal mechanisms seem to play a significant role in protecting rural household's consumption. However, one of the practical problems with these studies is that they all require representative lengthy panel data. Reliable and representative panel data are still scarce in developing countries and vulnerability analysis mostly relies on more readily available cross-sectional household surveys. Other notable drawbacks of the 'ability to smooth consumption/income' approach are: i) future consumption is measured using an internal rather than an exogenously determined socially accepted threshold. Such a definition is not particularly useful for practical purposes and "most strands of literature agree that vulnerability is a useful concept only if it is defined as vulnerability to a measurable loss (the metric) below a minimum level (the benchmark). Without use of a benchmark, the term 'vulnerability' becomes too imprecise for practical use" (Alwang, Seigel, and Jorgensen 2002, p.5); ii) variation around a given consumption path may not be a good indicator of vulnerability that individuals or households face with uncertain future income (Christianensen and Subbarao, 2005).

Another strand of the literature attempted to overcome the deficiencies of traditional point-in-time welfare measurement by decomposing poverty into those who are chronically poor (structural poverty) and those who are transient poor (temporary) (Ravallion, 1988; Morduch, 1994; Hulme, 2003; Duclos, Araar and Giles, 2006; Jalan and Ravallion, 1998, 2000). Jalan and Ravallion (1998, 2000) defined transient poverty as the poverty that can be attributed to inter-temporal variability in consumption, and distinguished transient from chronic poverty using data from rural china. Using robust semi-parametric methods, they found that household's average wealth holding is an important determinant for both transient and chronic poverty. However, household demographics, education levels and health status of the household members - while important for chronic poverty - were not significant determinant for transient poverty.

There are a number of studies that explored poverty dynamics in Bangladesh, that fall into this category of *ex-post* dynamic analysis. Some of them are purely qualitative in nature. For example, Baulch and Davis (2007) in an interim findings from an integrated qual-quant study[4] of poverty dynamics and life trajectories of 1787 households in 15 (out of 64) districts in rural Bangladesh spanning a twelve year period. They find that: a) a substantial proportion of households move in and out of poverty over time; b) that many more households moved out of poverty than into poverty over two time periods covered; and, c) there still remain a substantial proportion of households who remain poor in all of the survey years. Rahman (1996) using a panel of 1200 rural households in 1987, 1990, and 1994 also revealed that there is considerable movements in and out of income poverty. They suggest that during 1990-94 period about 38 per cent of households stayed in poverty while about 27 per cent stayed above the poverty line. The other 35 per cent cases, however, involved movements in and out. Around 17 per cent became new poor and nearly 18 per cent escaped poverty.

While the distinction between transient and chronic poverty and the underlying dynamics of movement in and out of poverty have significant policy implications, there are important conceptual and practical differences between identifying vulnerability and poor. The transient-chronic poverty approach reflects the ex-post poverty dynamics while vulnerability literature focuses on ex-ante measurement of poverty i.e., distribution of future welfare measures. There has been increasing recognition that exploring vulnerability is very important for understanding *ex-ante* poverty dynamics and policy interventions.

The strand of literature on vulnerability that attempts to define and measure vulnerability as expected poverty is rather a recent phenomena. Chaudhury, Jalan and Suryahadi (2002), and Chaudhury (2003) made the initial contributions by developing a methodology which

[4] This is a combination of qualitative and quantitative approach associated with the q-squared research programmes: see http://www.q-squared.ca

estimates vulnerability as probabilities that are computed as the expected value of a poverty score in the future, conditional on a bundle of covariates. This poverty score takes the form of the Foster, Greer and Thorbecke (1984) FGT measures, specifically the head count index. While panel data of sufficient length would provide a better source for vulnerability estimates – the availability of repeated observations adds a crucial dimension (variability) to the measurement of household welfare, in practice these are scarce in developing countries. Given the scarcity of longitudinal data in developing countries, they resorted to some assumptions under which cross-sectional or relatively short panel of two or three rounds could be used to estimate vulnerability. This triggered an influx of methodological and conceptual innovations and the body of literature along this line is growing.

Chaudhury (2002) applied his methodology to cross-sectional data for Indonesia. The results show that the vulnerable population is generally larger than the fraction observed as poor at a given point in time, implying that true poverty cost of risk is higher than the observed outcome (Dercon, 2005). The author also found differences between the distribution of vulnerability and poverty across different population characteristics (i.e. regions, educational levels, etc.). Chaudhury (2003) applied these methods to cross-section data from the Philippines and Indonesia, finding similar patterns. Suryahadi and Sumarto (2003) estimated household poverty and vulnerability in Indonesia before and after the economic crisis of the late 1990s using cross section data from household surveys. They found the level of vulnerability to poverty among Indonesians after the crisis increased significantly and the number of high vulnerability to poverty households has tripled because of the crisis.

Ligon and Schetcher (2003) took a utilitarian approach to define vulnerability in a risky environment and construct a measure of vulnerability. Applying their measure to a panel data set from Bulgaria in 1994, they found that poverty and risk play roughly equal roles in reducing welfare. McCulloch and Calandrino (2003) estimated the determinants of chronic poverty and vulnerability using the data from rural Sichuan and found that the determinants of chronic poverty and vulnerability appear to be similar, suggesting that policies to reduce chronic poverty will also reduce vulnerability. Zhang and Wan (2006) explored whether diversification and education affect vulnerability in southeast coastal rural China. Imai, Gaiha and Kang (2007) in a similar vein but with data for Vietnam estimate *ex-anti* measures of vulnerability. Comparing static measures with their estimates, they find that vulnerability in

2002 generally translates into poverty in 2004 and also vulnerability of the poor causes persistent poverty.

A number of these studies attempted to estimate the relative impacts of idiosyncratic and covariate shocks while estimating vulnerability scores (Christiaensen and Subbararao, 2005; Ligion and Schechter, 2003; Gunther and Harttgen, 2009). Christiaensen and Subbararao (2005) develop a general framework to estimate household vulnerability to poverty using a pseudo-panel constructed from Kenyan household surveys. Their results indicate that idiosyncratic shocks substantially affect the volatility of consumption. Gunther and Harttgen (2009) developed an approach to empirically assess the impact of idiosyncratic and covariate shocks on household vulnerability which could be applied with cross-sectional or relatively short panel. This is an extension of the approach suggested by Chaudhuri (2002 and 2003). Using cross- sectional household data from Madagascar, their results show that covariate shocks have a relatively higher impact on rural households where as idiosyncratic shocks have a relatively higher impact on urban households' vulnerability. Gaiha and Imai (2004) using a panel on 183 household from five villages in India during 1975-84 to assess the impact of crop failure. Their results indicate that a large number of rural households experienced a long spell of poverty (over three years) even without a crop shock. Crop shocks led to an increased proportion of households experiencing short spell of poverty (one to two years). Small farmers are found to be more vulnerable to long spells of poverty after a large or severe crop shock. Quisumbing (2007) using a multinomial logit model for Bangladesh, shows that the illness and death of a household member, crop loss and livestock death affected the probability of both being chronically poor and escaping poverty. Dercon (2005) analyse the impact of shocks on per capita consumption in rural Ethiopia and find that only experiencing drought reduced per capita consumption; the impact of illness was found to be statistically significant at 10 per cent. This seems inconsistent with Dercon and Khrisnan (2000a) where they found that consumption was significantly affected by both idiosyncratic and covariate shocks, such as crop failure or rainfall.

The impact analyses of shocks undertaken by the above mentioned studies are problematic on a number of counts. Households' vulnerability to shocks is not only a function of the impact of shocks, but also of the frequency distribution of these shocks. In addition, there are substantial econometric problems related to these works, which usually rely on standard regression analysis to study the impact of shocks on households' consumption. First, many of these studies estimate the impact of certain shocks and focusing on certain shocks might introduce omitted variable bias as various shocks are often highly correlated (Tesliuc and Lindert, 2004). Furthermore, a priori categorization of shocks as idiosyncratic or covariate is problematic. The distinction between covariant and idiosyncratic shocks is not always clear-cut. A drought in only one locality might result in poor, rainfall-dependent households selling assets to richer, non-rainfall dependent households so, although the event was common to both, it adversely affected only the poor (Hoddinott and Quisumbing, 2008). The impact of selected shocks on households' consumption is therefore likely to be overestimated. Second, it is often assumed that the impact of shocks on consumption is the same across all households, which is a rather strong assumption to make. Shocks are not expected to affect all households in the same manner. The effect of a shock on a household's consumption will vary by earnings structure and its capacity to smooth consumption. For example, the effect of a drought on farmer's consumption clearly depends on the extent to which his fields are irrigated and the amount of assets he has at his disposal. Third, in modelling the impact of shocks on household welfare, it is generally assumed that shocks are exogenous, unanticipated events. However, the exposure of households to several types of shocks may be endogenous by nature. For example, the risk of malnutrition can be the result of food rationing during a drought; deforestation can be the result of a response to risk realisation; individuals can engage in crime in times of stress, but also can be victims of it, making this particular category both a source of risk as well as a response to it. The problem of endogeneity might exist as households' welfare has presumably also an impact on the occurrence of certain shocks, that is, poorer households are normally found to face higher mortality risks (because, for example, limited access to healthcare, and poor nutritional status etc.).

Studies relating to Bangladesh are mostly retrospective in nature. To the best our knowledge, none of the studies so far attempted to estimate *ex-ante* poverty and the relative impacts of idiosyncratic and covariate sources of vulnerability. This distinction is important for designing anti-poverty policies, particularly policies relating to poverty prevention and promotion of those who are structurally poor. The present study will contribute to fill the gap by empirically estimating *ex-ante* poverty as well as assessing the relative importance of idiosyncratic and covariate shocks in the dynamics and causes poverty and vulnerability in rural Bangladesh using the record level Household Income and Expenditure survey (HIES-2005) data. We use a multilevel modelling framework that would circumvent some of the problems mentioned above; whilst at the same time apply the method to estimate vulnerability from cross section data without detailed information on idiosyncratic and covariate shocks. As a result, the problem of missing lengthy panel will also be resolved.

4 Analytical Framework

Cognizant of the fact that long enough panel with detailed information on shocks at various levels are not available in developing countries; many of the vulnerability assessments rely on the most readily available cross-sectional household surveys. The methodology proposed by Chaudhuri (2003) allows for vulnerability assessment using a single cross section under certain assumptions. We start from this benchmark model and then build on Gunther and Harttgen (2009) to develop our analytical framework to assess vulnerability as well as decomposition of idiosyncratic and covariate variances.

4.1 The Basic Model

The focus of a forward looking vulnerability to poverty estimation is to have an estimate of household's over time mean and variance of some welfare measure. Following Chaudhuri (2003), for a given household i, the vulnerability at time t is defined as the probability of its welfare measure being below poverty line at time $t+1$:

$$V_{it} = Pr(lnc_{it+1} < ln\overline{c}) \qquad (2.1)$$

where V_{it} is vulnerability of household i at time t, lnc_{it+1} is a measure of household welfare at time $t+1$, *and* $\overline{c}$ is an exogenous poverty threshold. To obtain estimates for vulnerability, it is thus necessary to define the level of minimum acceptable welfare and the level of future welfare. Under the assumptions: first, future levels of welfare are relatively stationary from one period to the next; and second, welfare is determined by observable factors as well as the unexpected shocks (i.e. vulnerability may be due to lower expected welfare or higher volatility of wellbeing). The specification of the welfare generating process implies that both the mean and variance of its distribution need to be taken into account. Consistent estimation of vulnerability scores thus involves a three step procedure: i) deciding on welfare measure and its distributional assumption; ii) specification of welfare generating process and estimation of relevant parameters from data; and iii) obtain the probability of being poor in future.

Like poverty, vulnerability is also a multidimensional construct. A number of welfare indicators could be thought off, including income, consumption expenditure, educational outcomes, health or nutritional outcomes. However, the notion of vulnerability is made concrete in the literature due to limited data application in the empirical assessment of the extent to which various characteristics of households make them more or less vulnerable (Chaudhuri, 2002). Hence the most applied indicator of welfare in empirical estimation of vulnerability is per capita consumption expenditure[5]. Household's welfare in this paper is measured by per capita consumption expenditure and is assumed to be distributed log normally. Assuming that for household i, the data generation process for consumption is captured by the following equation:

$$lnc_i = X_i\beta + e_i \qquad (2.2)$$

where c_i stands for per capita consumption expenditure for household i, X_i represents a vector of observable household characteristics, β is a vector of parameters, and e_i is a mean-zero disturbance term that captures all other unobservable effects. For estimation of the variance of expected consumption, Chaudhuri (2003) assumes that the disturbance term e_i captures both community specific as well as idiosyncratic shocks on household consumption and that its variance correlated with observable household and community characteristics. This explicitly assumes that expected consumption variance is heteroscedastic. A simple parametric way to express this characteristic is to model the variance using the following linear functional form:

$$\sigma_{e,i}^2 = X_i\theta \qquad (2.3)$$

Standard regression analysis based on ordinary least squares (OLS) assumes homoscedasticity, and estimates of β and Θ will be unbiased but inefficient if this assumption does not hold. To deal with this problem, Chaudhuri (2003) applies a three-step Feasible Generalized Least Squares (FGLS) method to obtain consistent estimates of β and Θ. Using consistent and asymptotically efficient estimators $\hat{\beta}$ and $\hat{\theta}$ obtained by FGLS, the expected log consumption and variance may be estimated for each household:

$$\hat{E}[ln\hat{c}_i|X_i] = X_i\hat{\beta}_{FGLS} \qquad (2.4)$$

[5] For a good discussion about the choice of welfare indicator for poverty analysis please see Litchfield and McGregor (2008).

$$\hat{V}[ln\hat{c}_i|X_i] = \hat{\sigma}^2_{e,i} = X_i\hat{\theta}_{FGLS} \tag{2.5}$$

Estimates of the above two are then used to compute the probability that a household will be poor in the future. Since consumption is assumed to be log normal, the estimated conditional probability is given by:

$$\hat{V}_i = Pr(lnc_i < \bar{c}|X_i) = \Phi\left(\frac{ln\bar{c} - X_i\hat{\beta}}{\sqrt{X_i\hat{\theta}}}\right) \tag{2.6}$$

where Φ denotes the cumulative density of the standard normal distribution.

4.2 Two-Level Linear Random Intercept Model

This class of models has been designed specifically to analyse relationships between variables measured at different hierarchical levels. Hierarchical data structure refers to the data where variables are collected at different levels with lower level units (i.e. individuals or households) are nested within higher levels units (i.e. clusters or communities). This is usually the case with most of the LSMS type of household surveys where a multi-stage sampling procedure is followed.

To explain the essence of multilevel models with hierarchical data structure, consider a survey data collected across communities where individual households are nested within respective communities. Running a standard regression between a response variable and household level covariates in this case is tantamount to explicitly pooling the data across the two levels. If the data were cross sectional, this modelling strategy is equivalent to stacking each group of community level data. To the extent this modelling strategy is problematic hinges on heterogeneity associated across communities and this may induce non-spherical disturbances. Heteroscedasticity may arise because households nested in particular communities are subject to different agro-climatic conditions or simply because the measurement errors in household level covariates vary across communities. In either case, the usual assumption of zero covariance between disturbances, conditional on the covariates, may not hold. Since the assumption of spherical disturbances is a conditional one, one way of circumventing these problems could be by better specification i.e. including covariates thought to explain or account for level/unit wise heterogeneity. Otherwise, standard OLS estimation commonly yields inefficient and inconsistent standard errors. This in turn, renders the usual hypothesis tests invalid. Moreover, because the intra-class correlation will usually be positive (Hox, 2002), standard errors will usually be attenuated, thus increasing the chances for a Type-I error. Thus, pooling of multilevel data can result in non-spherical disturbances. However, well-understood solutions[6] to this problem are widely available. Therefore, if the sole concern with pooling data lies with the inducement of non-spherical errors, then the correctives are available to remedy the problem. Yet these correctives do little to exploit information found in multilevel data. Commonly, researchers will be interested in features of the data not easily modelled through pooling strategy. This leads to the consideration of multilevel models.

In light of the preceding discussion, it is clear that there are a number of advantages of using multilevel modelling approach over standard regression analysis with hierarchical data: First, both individual as well as group-level observations could be used in the same model without violating the assumption of independent observations while at the same time providing correct standard errors and significant tests (Goldstein, 1999). Another major advantage of using multi-level modelling approach in vulnerability analysis may lie in its ability to control for possible downward bias of localized shocks on estimated mean consumption. Finally, multilevel models decompose the unexplained variance of dependent variable (in our case, consumption per capita) into different levels (i.e. households, communities). This feature of multilevel modelling is exploited here to decompose and characterize relative impact of idiosyncratic household-specific and community-specific shocks on households' vulnerability.

To formally illustrate the basic idea of multilevel modelling suppose$= 1, \ldots, n$, units (e.g., households) at level one and $j = 1, \ldots, j$ units (e.g., communities) at level two and that household i is nested in community$j$. If lnc_{ij} is log of per capita household consumption and X_{ij} is a set of household characteristics of household i in community , the following regression equations can be set up:

$$lnc_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij} \qquad (2.7)$$

[6] A wide variety of solutions have been proposed to fix-up the problems posed by heteroscedastic errors. Heuber-White variance estimator is robust to the presence of heteroscedasticity. The general form of extended Heuber-White sandwich estimator for clustered data is given by –

$\widehat{V_c} = (X'X)^{-1}\left[\sum_{j=1}^{n_c}\left\{\left(\sum_{i=1}^{n_j} e_i\, x_i\right)'\left(\sum_{i=1}^{n_j} e_i\, x_i\right)\right\}\right](X'X)^{-1}$, where $n_c$corresponds to the number of clusters and n_j corresponds to the number of i - cases within unit.

where β_{1j} is the slope coefficient for variables X_{ij} , the level one covariates. Let's further suppose the constant term β_{0j} as well as slope β_{1j} randomly varies across levels as a function of some level two covariates Z_j. Accounting for these, the following equations are in order:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j} \tag{2.8}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}Z_j + u_{1j} \tag{2.9}$$

The reduced form model is given by -

$$lnc_{ij} = \gamma_{00} + \gamma_{01}Z_j + (\gamma_{10} + \gamma_{11}Z_j)X_{ij} + u_{0j} + u_{1j}X_{ij} + e_{ij} \tag{2.10}$$

where, γ_{00} corresponds to the intercept estimate; γ_{10} corresponds to the slope coefficient for the relationship between lnc_{ij} and X_{ij} when Z_j=0; γ_{01} corresponds to the slope coefficient for the relationship between lnc_{ij} and Z_j when X_{ij} =0; γ_{11} corresponds to the interaction between X_{ij} and Z_j; u_{1j} corresponds to the disturbance term for the randomly varying slope coefficient γ_{01}; u_{0j} corresponds to the disturbance term for the random intercept term; and e_{ij} corresponds to the level one disturbance term. To complete the model, we will typically assume the following (Goldstein 1995, p. 17) –

$$e_{ij} \sim N(0, \sigma_e^2)$$

$$u_{0j} \sim N(0, \sigma_{u0}^2)$$

$$u_{1j} \sim N(0, \sigma_{u1}^2)$$

More generally, if we have p explanatory variables X at the household level (lowest level), indicated by the subscript p ($p = 1, \dots, P$). Likewise, if we have Q explanatory variables Z at the community level (e.g., at the highest level) indicated by the subscript q ($q = 1, \dots, Q$). Then the above equation becomes:

$$lnc_{ij} = \gamma_{00} + \gamma_{0q}Z_{qj} + (\gamma_{p0} + \gamma_{pq}Z_{qj})X_{pij} + u_{0j} + u_{pj}X_{pij} + e_{ij} \tag{2.11}$$

Using summation notation, we can express the same equation as:

$$lnc_{ij} = \gamma_{00} + \sum_q \gamma_{0q}Z_{qj} + \sum_p \gamma_{p0} X_{pij} + \sum_p \sum_q \gamma_{pq} X_{pij}Z_{qj} + \sum_p u_{pj}X_{pij} + u_{0j} + e_{ij} \tag{2.12}$$

The first four terms in Equation (2.12) constitute the deterministic part and the last three terms account for the stochastic part of the model. Unlike standard regression analysis, the error term in Equation (2.12) contains a community component along with the usual individual or household component$\sum_p u_{pj} X_{pij} + u_{0j}$. The error component u_{0j} represents the unexplained variance across communities of the intercept β_{0j} and the rest, that is, $\sum_p u_{pj} X_{pij}$ captures the unexplained variances across communities of the slopeβ_{1j}. The individual or household component e_{ij} accounts for the unexplained variance in household's consumption within communities. One of the critical assumption that we need to make for vulnerability analysis is that error terms are dependent i.e. heteroscadastic and multilevel modelling easily accommodate heteroscedasticity at community and household level. The household level error component e_{ij} is assumed to be independent across households within a community, while the community level errors are independent across communities but dependent, that is equal for each one of the household i belonging to community j . This embeds heteroscedasticity within the model as one of the key assumptions that is needed to estimate vulnerability with cross sectional data.

4.3 Some Caveats

While the information provided by this framework may serve as a basis for policy and can be interpreted as a compliment to traditional static poverty assessments, the estimates presented in this study cannot be validated. The interpretation of these results as stemming from variability in future consumption levels hinges crucially on the methodology's identifying assumptions. The crucial assumption behind the method is that inter-temporal variance in consumption can be proxied by the cross-sectional variance- a rather strong assumption. This essentially implies that household's over time consumption variance is stationary and does not allow any unobserved heterogeneity either across households or periods. Nonetheless, the cross-sectional variance can explain inter-temporal variance which is mainly due to idiosyncratic or community-specific shocks. Hence, this model is likely to produce reliable estimates of vulnerability for situations where the distribution of risk and the risk management mechanisms remain similar in all periods (Tesliuc and Lindert, 2004). However, it is unlikely to capture the effect of large and unexpected shocks like the Asian financial crisis during the late 1990s, if the data are collected in a normal year (Gaiha and Imai, 2008). Second, there might be systematic measurement error in the observed welfare outcome. Consumption may be measured with errors which may in turn lead to overestimation of its variance. This consequently biases the vulnerability estimates downward. A suggested solution is to rescale the variance to account for this measurement error. However, given that the measurement error generating process is unknown, this study makes no attempt to adjust variances to avoid imposing further assumptions. Therefore, if measurement error implies an overestimation of consumption variance, the estimates presented here may be regarded as an upper bound of the probability of future poverty.

In view of the above mentioned limitations, the results presented in this paper must be interpreted with caution. However, the major advantage of this extension of Chaudhuri (2003) with multilevel modelling is that in addition to vulnerability estimates, it provides estimates of household's consumption variance due to idiosyncratic and covariate shocks. This could provide useful insights about the relative impacts of these shocks on household's welfare dynamics and vulnerability. More importantly, the estimation can be done with only a single cross-section data (or short panel) without any information on shocks and their distribution.

4.4 Decomposing Poverty and Vulnerability

While knowing the probability of falling into poverty may be preferable to a static assessment of poverty, it is arguably also important that a vulnerability measure come up with a clearer picture to discern between those facing the risk of falling into poverty, those with the ability to move out of poverty, and the ones with bleak prospect of getting out of it. One of the objectives of this study is to create household's current poverty and vulnerability to poverty profiles and thereby figuring out prospective course of poverty in Bangladesh. In what follows, we outline a detailed taxonomy of vulnerability profile of rural households.

Head Count Poverty index is calculated using the poverty lines suggested by the Bangladesh Bureau of Statistics (BBS). BBS used two poverty lines for its poverty estimates. One is called the lower poverty line which is equal to only the food poverty line and households whose total expenditures are equal to or less than the food poverty line are called the extreme poor. The second one is the upper poverty line which is equal to food plus non-food poverty line and the corresponding households are labelled as moderately poor households. These two poverty lines – lower and upper – are available for the entire 16 stratum of the HIES 2005. However, in this study we have used only the upper poverty lines for the rural areas.

Any operationally useful assessment of households' vulnerability status depends essentially on two important factors: first, the choice of a vulnerability threshold, that is, a minimum level of vulnerability above which all households are defined to be vulnerable and second, specifying the time horizon over which households' vulnerability is to be assessed. There is, however, a certain degree of arbitrariness involved in making such decisions.

The most preferred and natural candidate for the vulnerability threshold is 0.5. This midway dividing point has three attractive features (Suryahadi and Sumarto, 2003). First, this is the point where the estimated expected log consumption coincides with the log of the poverty line. Second, it makes intuitive sense to say a household is 'vulnerable' if it faces a 50 per cent or higher probability of falling into poverty in the near future. Third, if a household is just at the poverty line and faces a mean zero shock, then this household has a one period ahead vulnerability of 0.5. This implies that, in the limit, as the time horizon goes to zero, then being 'currently in poverty' and being 'currently vulnerable to poverty' coincide (Pritchett, Suryahai and Sumarto, 2000). Another threshold that makes sense is the observed headcount ratio. The underlying logic is that "because the observed poverty rate represents the mean vulnerability level in the population, anyone whose vulnerability level lies above this threshold faces a risk of poverty that is greater than the average risk in the population and hence can be legitimately included among the vulnerable" Chaudhuri (2003, p.11). In practice, therefore, most of the empirical studies adopted the vulnerability threshold of 0.5.

The other aspect of an operationally useful vulnerability index is to decide on a time horizon over which households' vulnerability is to be assessed. The existing literature again is of little help in this regard. In most of the cases, the time horizon is defined through some arbitrary expression like 'probability of falling into poverty in the near future' indicating that there is no obvious choice. Recognising that a certain degree of arbitrariness is needed, Chaudhuri (2003) proposed two possible cases - a time horizon of one year, which can be thought of in terms of the likelihood of poverty in the short run, and a time horizon of three years which roughly corresponds to the likelihood of poverty in the medium-term. In the later case all households experience poverty spell at least once in the next three years are categorised as vulnerable. Following Chaudhuri (2003) this paper adopts a vulnerability threshold of 0.5 and a time horizon of 2 years. Households are considered to be vulnerable if they have a 0.5 or higher probability of falling into poverty at least once in the next two years. This corresponds to a 0.29 or higher probability to fall below poverty line in any given year over the next two years (calculation of various thresholds is given in Appendix 2.3).

With this vulnerability threshold and time horizon, using a combination of household poverty, the estimated vulnerability to poverty, expected consumption, and variance of consumption, households can now be grouped into several poverty and vulnerability categories as illustrated in figure 1[7].

Figure 1: Poverty and Vulnerability Categories

		Current Consumption (c)			
		$c < \bar{c}$	$c \geq \bar{c}$		
Vulnerability to poverty	$v \geq 0.5$	**A**	**D**	$E[c] < \bar{c}$	Expected consumption
		B	**E**	$E[c] \geq \bar{c}$	
	$v < 0.5$	**C**	**F**		

Poor = A + B + C

- Chronic Poor = A
- Transient Poor = B + C

Non-poor = D + E + F

- High Vulnerability Non-poor = D + E
- Low Vulnerability Non-poor = F

High Vulnerability Group = A + B + D + E

- Low Level of Consumption = A + D
- High Variability of Consumption = B + E

Low Vulnerability Group = C + F

Total Vulnerable Group = A + B + D + E

Here, $\bar{c}$ is the consumption at poverty line.

The above categorization process results in a number of overlapping groups of households. First, the population is divided into two distinct groups using the consumption threshold: the

[7] The categorization of poverty and vulnerability to poverty of households is drawn on Suryahadi and Sumarto, 2003.

‘poor’ and the ‘non-poor’. Those who have average consumption equal to or below the poverty lines are generally termed as the ‘poor’ and the rest are ‘non-poor’. The poor then are decomposed into two distinct groups: the ‘chronic poor’ and the ‘transient poor’. The chronic poor are the ones who are currently poor and also have expected consumption levels below the poverty lines. These household are most likely to remain poor in future. The transient poor, on the other hand, are those who are also currently poor but their expected consumption levels are above the poverty line. Some of the transient poor have low vulnerability, but some of them have high vulnerability. As a result of this process, a total of five groups of households will emerge: the ‘poor’, the ‘non-poor’, the ‘high vulnerability group’, the ‘low vulnerability group’, and the ‘total vulnerable group’.

The high vulnerable group is differentiated into two sub-groups based on the causes of high vulnerability, which is ‘low level of expected consumption’ and ‘high-variability of consumption’. The non-poor can be disaggregated into the ‘high vulnerable non-poor’ and the ‘low-vulnerable non-poor’. Meanwhile, the ‘total vulnerable group’ is defined as a combination of the high vulnerability group and those who are currently poor. This means that the total vulnerable group includes all those who are currently poor plus those people who are currently non-poor but who have a relatively strong chance of falling into poverty in the near future. Hence, while vulnerability to poverty is defined as the risk or probability of falling below the poverty line, the definition of the total vulnerability group is based on both this risk as well as initial poverty status. This is entirely in line with the argument put forward by Glewwe and Hall (1998), to categorize a household as vulnerable it is necessary to combine the probability of bad outcomes as well as some measure of their ‘badness’ according to a given social welfare function.

There are obvious advantages in further disaggregation of poverty categories such as those depicted in figure 1, rather than simply dividing households into the poor and the non-poor. This disaggregation clearly demonstrates that the poor and the vulnerable are heterogeneous rather than static homogenous groups. It will facilitate advocacy, allow monitoring of progress in reducing vulnerability. In addition, each one of these groups is likely to respond differently to particular policies aimed at reducing poverty and vulnerability and as such, it might be necessary to devise different policies for different groups (Jalan and Ravallion, 2000).

5 Empirical Strategy

5.1 The Empirical Model

The empirical model we estimate is developed in line with Gunther and Harttgen (2009) which is an extension of Chaudhuri (2003), described in Eq. (2.1) through (2.5). The consumption generating process is posited by the two level random intercept model described in equation (2.12)**:**

$$lnc_{ij} = \gamma_{00} + \gamma_{01}Z_j + (\gamma_{10} + \gamma_{11}Z_j)X_{ij} + u_{0j} + u_{1j}X_{ij} + e_{ij} \qquad (2.13)$$

where, lnc_{ij} represents log of per capita consumption of household i in community$j$, X_{ij} is a bundle of household characteristics, and Z_j corresponds to a set of community covariates. Only those cross-level interactions $X_{ij}Z_j$ were included in Eqn. (2.13), where the estimated coefficients, γ_{11}on the interaction term were significant. Otherwise the interaction term (as well as the corresponding error term) was set to zero[8]. Out of three error terms, it is assumed that household level error e_{ij} captures the impacts of idiosyncratic shocks where as the remaining two community level errors, $u_{0j} + u_{1j}X_{ij}$ capture the effects of covariate shocks.

Again following Chaudhuri (2003), we assume that the unexplained variance of consumption at the household as well as at the community level depends on a set of household and community characteristics. Accordingly, the squared residuals of Eqn. (2.13) are regressed on a set of household X_{ij} and community Z_j Characteristics:

$$e_{ij}^2 = \Theta_0 + \Theta_1 X_{ij} + \Theta_2 Z_j + \Theta_3 X_{ij}Z_j \qquad (2.14)$$

$$u_{0j}^2 = \tau_0 + \tau_1 Z_j \qquad (2.15)$$

$$\left(e_{ij}{}^2 + u_{0j}{}^2\right) = \Theta_0 + \Theta_1 X_{ij} + \Theta_2 Z_j + \Theta_3 X_{ij}Z_j \qquad (2.16)$$

Finally, the expected mean as well as the expected idiosyncratic σ_{eij}^2, covariate σ_{u0j}^2, and total $\sigma_{eij+u0j}^2$ variance of households' consumption are estimated with the coefficients of Eqn. (2.13) to (2.16). These estimates are used to assess the impact of idiosyncratic, covariate and overall shocks on households' vulnerability, applying the FGT measure of poverty.

[8] Interaction terms should only be incorporated in multilevel models if they show significant results (Hox 2002).

$$\hat{V}_{ij} = \hat{P}\left(lnc_{ij} < ln\overline{c}|X,Z\right) = \emptyset\left(\frac{ln\overline{c} - ln\hat{c}_{ij}}{\sqrt{\hat{\sigma}_{ij}^2}}\right) \quad (2.17)$$

where $\emptyset(.)$ denotes the cumulative density of the standard normal distribution function; $\overline{c}$ stands for the poverty line; $ln\hat{c}_{ij}$ is the expected mean of per capita log consumption. $\hat{V}_{ij}$ is the estimated vulnerability or probability to fall below the poverty line. The estimation is conducted separately for the estimated idiosyncratic variance and covariate variance as well as jointly for the overall variance in consumption.

The model could be estimated either by Maximum Likelihood (ML) or Restricted Maximum Likelihood (REML) technique. ML parameter estimates are thought to be consistent and asymptotically unbiased. Although, the consistency and asymptotic unbiasedness of ML estimates are large sample properties. ML estimates are therefore likely to fail to comply with such properties when the number of higher level units are small (Raudenbush and Bryk, 2002 p.13-14). REML estimates the random intercepts variance accounting for the loss of degrees of freedom from the estimation of the mean while ML does not (Rabe-Hesketh and Skondral, 2005, p.16). In addition, when the data design is unbalanced (i.e. uneven distribution of lower level observations nested into higher level units) REML estimates are more trustworthy. We estimated the model using REML technique, because the distribution of households nested into clusters are in many cases not the same in our sample.

5.2 Data and Specification of the Model

5.2.1 Data

This study employs rural data from the 'Household Income and Expenditure Survey' (HIES) - 2005 conducted by the Bangladesh Bureau of Statistics (BBS). The actual data collection period span from January 2005 to December 2005. HIES-2005 is a nationally representative household survey, covering all areas of the country. A total of 10080 household were interviewed of which 6400 are rural and the remaining 3680 are urban. A two stage stratified random sampling technique was followed in drawing sample for HIES-2005 under the framework of Integrated Multipurpose Sample (IMPS) design developed on the basis of Population and Housing Census 2001. There are 320 rural and 184 urban Primary Sampling Units (PSU) in the sample. This means that households are nested into clusters, where clusters in this study are used synonymously with communities.

Data on daily consumption of food items were collected on a day to day basis by the same enumerators and recorded into (laptops) at the field level same day. The interviewers regularly entered all the information collected during the interview into the laptop computers at the end each day. If they found any inconsistency in the data they were asked to go back to the relevant households and made required changes to remove the discrepancy. Once they had completed and checked the information, they must also validate the data entered through data entry programme that checked the information for accuracy. Thus data entry, cleaning and validation were completed simultaneously with the survey works. Moreover, food consumption data were collected during a period of 20 days. During this period, for collecting information on food consumption, the households were divided into two groups each consisting of 10 households. Each enumerator collected information on food consumption of the households for 14 days by paying 7 visits. In each visit information on food consumption of previous two days was collected. Along with amount of each items consumed, unit prices were also recorded. Estimation of consumption expenditure is relatively straight forward. As data were collected year round, it is not necessary to adjust for within year inflation or seasonal biases.

The data is rich in providing general information required for an assessment of vulnerability to poverty and decomposing the sources of vulnerability i.e. idiosyncratic and covariate shocks. In addition to providing information on the structure and composition of households, it also contains information on physical and socio-economic infrastructures available to the households. In fact, there are 10 different modules containing wide ranges of individual and household level information. It has specific modules for general household characteristics as well as modules on health, education, activities, employment and labour force participation, assets and income, prices, consumption expenditures of all kinds, social safety net programmes etc.

HIES-2005 collected some selected community/village level information as well. However, community information was collected only from the rural areas and are available only for 302 rural primary sampling units (PSUs). This is the main reason for us to restrict our analysis only to the rural areas. The community level information includes principal economic activities of the village, physical and other social infrastructure, availability of other facilities like marketing, banks, etc.

5.2.2 Model Specification

To estimate the household's expected mean and variance of consumption, we estimate the consumption generating model described in equation (2.13) through (2.16). A summary statistics of variables included in the model is given in table 3. The variables 'size of the households', 'age of head of the households' and the 'size of land holding' by households along with their squares are included in the model because of the possible non-linearity of the relationship between log consumption per capita and these variables.

Other variables reflecting household's idiosyncratic characteristics are; dependency ratio, hygienic conditions, whether a household has electricity, telephone connection or not, and whether households do participate in social safety net programmes or not. Household's hygienic condition is defined as bad if a household does not have sanitary latrine and safe drinking water. Other important inclusions are housing condition, educational level achieved by the head of the household, activity status of the head of the household, and whether head of the household suffered any chronic or serious illness over the past twelve months. While the variables other than the housing condition seem to be natural candidates for inclusion in the regression (Suryahadi and Sumarto, 2003; Imai, and Gaiha, 2007), housing condition defined by the type of the construction materials used, is included in the model as this is thought to be a major and quite regular source of shocks for Bangladeshi households. Even with moderate rainfall and normal flooding conditions, which is fairly common in Bangladesh, households particularly in rural areas need to spend significant amount resources for repairing and reconstruction of their houses. So houses constructed by mud brick, hemp/hay/bamboo are considered to be poor while brick/tiles/wood houses are considered to be good houses.

Variables for regional characteristics are also included in the model to reflect geographical heterogeneity which has been recognized in many poverty studies (Justino and Litchfield, 2003; Imai and Gaiha, 2007). Accordingly, six regional dummy variables are incorporated in the model. Remittances are another important determinant of household wellbeing in Bangladesh and supposed to reflect some measure of diversification of earning sources. Remittances are also considered to be one of the important consumption smoothing instruments.

A range of community level variables like community level median rice yield per acre, percentage of agricultural land irrigated are also included to capture the community level heterogeneity. These variables are also expected to capture some measure of technology use and intensification of agriculture within the communities. Furthermore, instead of using community level physical and economic infrastructure variables separately, we construct an infrastructure index based on principal component analysis (Filmer and Pritchett, 2001), using fourteen characteristics reflecting the infrastructure of the community. The use of an aggregate index in place of individual variables has a number of advantages, particularly in the context of multilevel modelling framework: first, the chosen index represents state of physical and economic infrastructure within communities. Second, multilevel models require considerable computational power. It is therefore, recommended to be parsimonious on the number of parameters if possible (Hox, 2002).

Table 2 Household Characteristics included in the Model

Variable Name	Definition Of Variables	Mean	Standard Deviation	Minimum	Maximum
Age of the Head of Household		46.078	13.912	15	99
Age Squared		2316.756	1399.907	225	9801
Household Size		4.914	2.108	1	19
Household Size Squared		28.594	27.252	1	361
Total land holding of the household		.945	1.702	0	34.8
Land holding squared		3.790	28.178	0	1211.04
Dependency ratio	Dependency Ratio is defined to be the proportion of the total number of household members who are 15 years of age or younger	.368	.218	0	1
Educational level achieved by the Head of the household					
Illiterate	No formal Education attained by the head of the Household	.619	.528	0	1
Primary Completed	Head of the household completed primary education	.334	.471	0	1
Higher secondary level completed	Head of the household completed secondary education	.025	.155	0	1
Tertiary and above	Head of the household with higher secondary and above	.022	.146	0	1
Remittances	Whether received any remittances or not. 0=no,1=yes	.303	.459	0	1
Illness over the last one year by the head of the household	0=no, 1=yes	.259	.438	0	1
Housing condition	0=bad, 1=good	.664	.472	0	1
Hygienic condition	0=bad, 1=good,	.406	.491	0	1
Whether household has electricity connection or not	0=no, 1=yes	.298	.457	0	1
Whether household has telephone connection or not	0=no, 1=yes	.059	.236	0	1
Whether household has participated in safety net programme or not	0=no, 1=yes	.144	.351	0	1
Activity Status of the Head of the Household					

Variable Name	Definition Of Variables	Mean	Standard Deviation	Minimum	Maximum
No job	Head of the household does not have any major activity	.141	.349	0	1
Agricultural Household	Head of the household engaged in agricultural activity	.480	.499	0	1
Non-agricultural household	Head of the household engaged in non-agricultural activity	.377	.484	0	1
Region of Residence					
Barishal region	Household located in Barishal region	.094	.292	0	1
Chittagoan region	Household located in Chittagoan region	.171	.376	0	1
Dhaka region	Household located in Dhaka region	.275	.447	0	1
Khulna region	Household located in Khulna region	.143	.350	0	1
Rajshahi region	Household located in Rajshahi region	.262	.439	0	1
Community level Variables					
Infrastructure Index	Infrastructure index computed using principal component analysis	-.096	2.058	-3.420294	3.439686
Percentage of land Irrigated	Percentage of land irrigated	60.388	33.143	0	100
Median paddy yield (mt/acre)	Median paddy yield in metric ton per acre	29.104	10.142	0	83.33334
Interaction term paddy yield*age of the HHH	Interaction term between paddy yield and age of the head of the household	1339.088	629.352	0	5440
Interaction term paddy yield*land holding of the HH	Interaction term between paddy yield and land holding of the household	26.760	47.645	0	904.8
Number of Observations		5714			

5.3 Econometric Results and Discussion

5.3.1 The Model Estimates

The regression results are presented in table 4. The likelihood ratio test comparing the model to ordinary linear regression model without Random Effects is provided and is highly significant, meaning that this model offers significant improvement over a linear regression model with Fixed Effects only. Lagrange multiplier test strongly supports the presence of heteroscedasticity in household level variance ($\chi^2_{28} = n.\bar{R}^2 = 198, Pr > \chi^2 = 0.000$). Correlation between household and community level error terms is negligible (0.01), enabling us to separate the household and community level variances.

Table 3 Regression Results of REML. Dependent Variable: Log of Consumption per capita

Independent Variables	Coefficients	Z
Age of the HH	0.0161***	(8.07)
Age squared	-0.000131***	(-7.16)
Size of the household	-0.115***	(-15.92)
Size squared	0.00397***	(7.64)
Land holding of the household	0.0839***	(9.67)
Land holding squared	-0.00260***	(-10.21)
Dependency ratio	-0.330***	(-13.28)
Ref: Illiterate		
Primary education completed	0.133***	(13.75)
Secondary education completed	0.282***	(9.96)
Higher secondary and above	0.319***	(10.69)
Whether received remittances (0=no, 1=yes)	0.101***	(9.16)
Whether HH suffered illness (0=no, 1=yes)	-0.030**	(-2.96)
Housing condition (0=bad, 1=good)	0.119***	(11.19)
Hygienic condition (0=bad, 1=good)	0.126***	(11.30)
Whether HH has electricity (0=no, 1=yes)	0.159***	(13.78)
Whether HH has telephone (0=no, 1=yes)	0.333***	(17.28)
Whether in Safety net (0=no, 1=yes)	0.138***	(10.60)
Ref: Unemployed		
Head of households agricultural	-0.063***	(-4.37)
Head of household in non-agricultural	-0.014	(-0.94)
Ref: Sylhet		
Barishal region	-0.271***	(-4.63)
Chittagoan region	-0.00981	(-0.18)
Dhaka region	-0.0664	(-1.25)
Khulna region	-0.321***	(-5.75)
Rajshahi region	-0.298***	(-5.63)
Community level covariates		
Infrastructure index	-0.0113*	(-2.11)
Land irrigated (%)	-0.000554	(-1.43)
Paddy Yield (mt/acre)	0.00371*	(2.15)

Paddy yield*age of HH	-0.0000558	(-1.80)
Paddy yield*land_tot	0.000564*	(2.24)
Constant	6.816	(85.80)

Random Effect Parameters	Estimates	No. of Obs.
Community	.1642826 (.0084062)	279
Household	.305628 (.0029387)	5714

Z -statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The assumed non-linearity of the relationship between log consumption per capita and the size of the household, age of household head, and size of total land holding and their squared terms is confirmed by the relevant coefficients of these variables. This also justifies the inclusion of their squared terms in the model. The coefficient for 'age of household head' is positive and highly significant. Its square is then negative and statistically significant. Similarly, size of the total land holding seems to affect consumption positively but its square is negative and highly significant. Similarly, the size of households has a negative influence on consumption, that is, the larger the households the lower tends to be the per capita consumption. Its' square again is of opposite sign indicating the non-linearity of relationship with log of consumption per capita. However, this negative effect weakens with the household size because the coefficient on household size squared is positive and highly significant. Many factors may be responsible for this result: for example, more family members (generous labour supply) contributes to greater flexibility and time savings in times of high economic activity; or during times of consumption stress children may be drafted to contribute to income earnings activities.

The variables – housing condition, electricity connection, telephone connection, and hygienic condition all have sizeable positive effect on per capita consumption and the coefficients are also statistically significant. Compared to the base category 'illiterate head of household', the rest of dummies on education are found to affect consumption per capita positively. The relevant coefficients are all statistically significant as well. This basically conforms to similar studies concluding that literacy and education attainment decrease poverty (World Bank, 2002). Imai and Gaiha (2007) also observe similar pattern of relationship between log consumption per capita and education of head of household for Vietnam. They find that consumption tends to increase as the household head's educational attainment rises. The coefficient for 'dependency ratio' is negative and statistically significant indicating that households with larger number of younger people tend to have lower level of per capita consumption. The relatively larger coefficient for non-agricultural activity dummy indicates that in terms of per capita consumption, the non-agricultural activity is more rewarding than agricultural activities.

Controlling for all other determinants, the Rajshahi, Khulna, and Barishal regions have significantly lower expected consumption compared to the Sylhet region. These regions are mostly disaster prone and historically underdeveloped in terms physical and socio-economic infrastructure. The regression results are probably a mere reflection of these facts. The coefficients for two other regions i.e. Dhaka and Chittagoan, are very small and statistically insignificant. Remittance appears to have significant positive effect on household's consumption implying that households receiving remittances are less likely to be vulnerable to poverty. Remittances enhance household welfare through provision of investment as well as smooth consumption (Hossain and Nargis, 2010).

The coefficients for infrastructure variables and irrigation are negative and in case of irrigation, it is statistically insignificant. This is somewhat counterintuitive. However, similar results have also been observed in other studies (Hossain and Nargis, 2010). This could be explained by adverse terms of trade of paddy production during the period. The coefficient of paddy yield is negligible, but positive and significant at the 10% level.

5.3.2 The Vulnerability Profiles

The estimates of vulnerability to poverty for rural Bangladesh are summarized in table 5. The estimates are shown for different vulnerability cut off points and time horizons. The resulting incidence of vulnerability ranges from 43 per cent, for $V^* = 0.43$ and $t = 1$, to 55 per cent of total rural population for $V^* = 0.5$ and $t = 3$. Taking a medium-term perspective ($V^* = 0.5$, $t = 2$ years), the estimates in table 5 show that around half the rural population of Bangladesh is expected to experience poverty at least once in the next two years.

Table 4 Estimates for Rural poverty and vulnerability to poverty categories.

	Vulnerability Threshold and Time Horizon		
	$\boldsymbol{V^* = 0.5}$		$\boldsymbol{V^* = 0.43}$
	2-year	**3-year**	**1-year**
Mean Vulnerability	**0.41**		
Chronically Poor	0.31	0.31	0.31
Transient Poor	0.12	0.12	0.12
Poverty Incidence	**0.43**	**0.43**	**0.43**
Low Mean Consumption	0.39	0.39	0.39
High Variability of Consumption	0.11	0.16	0.04
Total Vulnerability Group	**0.50**	**0.55**	**0.43**
High Vulnerable Non-poor	0.14	0.17	0.10

Low Vulnerable Non-poor	0.43	0.40	0.47
Idiosyncratic Vulnerable	0.402		
Covariate Vulnerable	0.394		
Idiosyncratic to Covariate Ratio	**1.02**		

It further shows that total vulnerability to poverty in rural Bangladesh is much higher than the point-in-time estimates of poverty, signifying the importance of forward looking poverty analysis. Arguably, this indicates that the current poverty estimates might be underestimated. The transient poor is estimated to be 12 per cent as opposed to the 14 per cent 'high vulnerable non-poor' group - people who are currently non-poor but have the potential to become poor at some point during the next two years. The high percentage (e.g. 31) of chronic poverty, which is also referred to as structural poverty, is in line with BBS's official estimates for extreme poverty rate of around 25 per cent in 2005. Low level of endowments, poor economic infrastructure, and limited opportunities for employment, among others, might explain the prevalence of such huge numbers of chronic poor in rural Bangladesh.

The fraction of the low expected consumption group, which remains constant regardless of the threshold of vulnerability selected, is equal to almost 40 per cent of the rural population. Thus low mean consumption accounts for a large part of the overall vulnerability, ranging from 78 per cent when the threshold of vulnerability is 0.5 and the time horizon is 3 years, to 90 per cent in the short-term (1 year ahead) with a lower value of the threshold of vulnerability ($V^* = 0.43$). The remaining 22 to 10 per cent is attributable to variation in mean consumption levels.

The impacts of idiosyncratic shocks have a slightly higher influence than the covariate shocks on consumption among the rural households. Around 40 per cent households are vulnerable to idiosyncratic shocks where as 39 per cent are vulnerable to covariate shocks. This result is largely in line with the findings of most of the empirical literature available that a large part of shocks/risks in rural settings is household specific (Gunther and Harttgen, 2009; Morduch, 1993; Alderman and Garcia, 1993; Townsend, 1994 and 1995). The implication is – ultimately what matters is the household's ability to cope with risks.

Table 5 Poverty and Vulnerability Categories for Region of Residence

	Sylhet	*Chittagoan*	*Dhaka*	*Rajshahi*	*Barishal*	*Khulna*
Mean Vulnerability	**0.38**	**0.35**	**0.32**	**0.49**	**0.51**	**0.42**
Chronically Poor	0.27	0.25	0.24	0.39	0.43	0.32
Transient Poor	0.11	0.10	0.13	0.11	0.10	0.13
Poverty Incident	**0.38**	**0.35**	**0.37**	**0.50**	**0.53**	**0.45**

Low Mean Consumption	0.36	0.33	0.30	0.48	0.52	0.41
High Variability of Consumption	0.11	0.09	0.10	0.11	0.13	0.12
Total Vulnerable Group	**0.47**	**0.42**	**0.40**	**0.59**	**0.65**	**0.53**
High Vulnerable Non-poor	0.15	0.13	0.11	0.15	0.17	0.16
Low Vulnerable Non-poor	0.46	0.52	0.52	0.35	0.30	0.39
Vulnerable to Poor Ratio	1.24	1.20	1.08	1.18	1.23	1.18
Idiosyncratic Vulnerable	0.373	0.345	0.314	0.488	0.513	0.420
Covariate Vulnerable	0.360	0.337	0.302	0.485	0.505	0.412
Idiosyncratic to Covariate ratio	**1.036**	**1.024**	**1.040**	**1.006**	**1.016**	**1.019**

Table 6 presents the vulnerability estimates by region of residence. There is considerable variation in the poverty and vulnerability to poverty rates among the six administrative divisions of the country. Poverty is highest in the southern and northern part of the country while the central part has the lowest poverty rate. In Barishal Division poverty is as high as 53 per cent and the total vulnerability figure is above 65 per cent. While chronic poverty is highest in Barishal closely followed by Rajshahi and Khulna; Dhaka has the lowest rate of chronic poverty followed by Chittagoan and Sylhet Division. Nonetheless, Dhaka shares the highest rate of transient poverty. Chittagaon and Sylhet Division have the highest share of high vulnerable-non-poor population. All these figures again justify the forward looking poverty analysis as it unveils different dimensions of poverty prevalence enabling policy makers to have a deeper understanding of poverty dynamics in different regions of the country. Structural vulnerability or poverty induced vulnerability is very high in Barishal and Rajshahi while risk induced vulnerability (or high income variability) shows a similar pattern across all six regions of residence; whereas idiosyncratic vulnerability is higher in all cases compared to the covariate; however, this is more pronounced for Dhaka and Sylhet region.

Table 6 Vulnerability and Poverty Categories by Educational Level of the Head of the Household

	Illiterate	Primary Completed	Secondary Completed	Higher Secondary and above
Mean Vulnerability	**0.52**	**0.25**	**0.08**	**0.06**
Chronically Poor	0.41	0.16	0.05	0.03
Transient Poor	0.12	0.13	0.06	0.05
Poverty Incident	**0.53**	**0.30**	**0.11**	**0.08**
Low Mean Consumption	0.51	0.21	0.05	0.02
High Variability of Consumption	0.11	0.11	0.03	0.04
Total Vulnerable Group	**0.62**	**0.32**	**0.08**	**0.06**
High Vulnerable Non-poor	0.16	0.10	0.01	0.03
Low Vulnerable Non-poor	0.31	0.60	0.87	0.88

Vulnerable to Poor Ratio	**1.17**	**1.06**	**0.72**	**0.75**
Idiosyncratic Vulnerable	0.515	0.238	0.061	0.053
Covariate Vulnerable	0.513	0.220	0.048	0.038
Idiosyncratic to Covariate ratio	**1.00**	**1.08**	**1.27**	**1.40**

Table 7 represents poverty and vulnerability categories differentiated by educational level achieved by the head of the households. The highest concentration of poverty and vulnerability is in households headed by illiterates. It is however worthy to note that while poverty and vulnerability diminishes as we move up the education ladder; its effect on poverty and vulnerability propagates mainly through the mean enhancing channel rather than through the variance of consumption. While 51 per cent households headed by illiterates are poverty-induced vulnerable (low expected mean consumption), the figure for the higher education group is only 2 per cent. Education can affect people's standard of living through a number of channels: it helps skill formation resulting in higher marginal productivity of labour that eventually enables people to engage in more remunerative jobs. Hence it is expected that education is positively correlated with consumption levels of households. This group of people have better coping abilities against future odds as revealed by the absence of future threat of becoming poor. A meagre 4.24 per cent of highly educated people are transient poor. Indeed, educated people can adapt more easily to changing circumstances, therefore showing greater ex post coping capacity (Christiansen and Subbarao, 2005).

Regarding the relative impacts of shocks, idiosyncratic shocks clearly play much more pronounced role for households headed by more literate persons. For households with illiterate heads, the impacts of idiosyncratic and covariate shocks on vulnerability are almost the same. For households headed by highly educated person, idiosyncratic shocks seem to have 40 per cent higher influence than the covariate shocks, indicating that community level informal insurance mechanisms do not work well for this group of households and they probably are less integrated within the community.

Table 7 Poverty and Vulnerability to Poverty by Activity of Head of Households

	No Activity	Non-agricultural	Agricultural
Mean Vulnerability	**0.24**	**0.41**	**0.45**
Chronically Poor	0.16	0.31	0.35
Transient Poor	0.12	0.11	0.12
Poverty Incident	**0.29**	**0.42**	**0.47**
Low Mean Consumption	0.21	0.39	0.44
High Variability of Consumption	0.10	0.11	0.12
Total Vulnerable Group	**0.31**	**0.50**	**0.56**

High Vulnerable Non-poor	0.10	0.15	0.14
Low Vulnerable Non-poor	0.61	0.43	0.38
Vulnerable to Poor Ratio	**1.07**	**1.19**	**1.19**
Idiosyncratic Vulnerable	0.235	0.405	0.448
Covariate Vulnerable	0.221	0.398	0.441
Idiosyncratic/Covariate	**1.06**	**1.02**	**1.01**

Table 8 presents the incidence of poverty and vulnerability across broad sectors: agricultural and non-agricultural. However, there seems to be a group of households belonging to neither of the above two groups. These are probably the household where head of the household either retired from jobs or households receiving remittances and not involved in any economic activity. They are possibly unemployed by choice, especially with family members working abroad (Kakwani and Pernia, 2000). Poverty is less prevalent in this group while households with heads engaged in agriculture share the majority of poor. Chronic poverty in households with heads working in agriculture is widespread. The high vulnerable non-poor population also constitutes a significant proportion of these households. On the other hand, non-agricultural activities appear to be more remunerative in terms of reducing poverty as is the case with most other developing countries. Nonetheless, more than 35 per cent of non-agricultural households are chronically poor while almost 9 per cent of the non-poor non-agricultural household are at risk of poverty.

Table 8 Poverty and Vulnerability to Poverty by Sex of Head of Household

	Head of the Household -Male	**Head of the Household -Female**
Mean Vulnerability	**0.42**	**0.26**
Chronically Poor	0.33	0.18
Transient Poor	0.12	0.15
Poverty Incident	**0.45**	**0.33**
Low Mean Consumption	0.41	0.23
High Variability of Consumption	0.11	0.09
Total Vulnerable Group	**0.52**	**0.32**
High Vulnerable Non-poor	0.14	0.10
Low Vulnerable Non-poor	0.41	0.57
Vulnerable to Poor Ratio	**1.16**	**0.97**
Idiosyncratic Vulnerable	0.42	0.26
Covariate Vulnerable	0.41	0.24
Idiosyncratic to Covariate ratio	**1.02**	**1.08**

Male headed households appear to be poorer and more vulnerable than their female headed counterparts. Around 33 per cent of the male-headed households are chronically poor as opposed to only 18 per cent female-headed households. The estimated figures for vulnerability are quite similar. Among the male-headed households 52 per cent are tagged as vulnerable, whereas the estimated figure for the female-headed households is 32 per cent. This result is somewhat counterintuitive, but may be explained by a number of factors, including the lack of a adequate operational definition of household leadership. In fact, as Chant (2003) points out, there are mixed results on the relationship between household headship and poverty status across countries, and this issue ought to be the subject of further research given the clear relationship between poverty and gender issues.

Table 9 Poverty and Vulnerability to Poverty by Size of Land holdings

	Landless (0.00)	Small Holders (0- 0.5) acres	Medium Holders (0.5<-1.5) acres	Large Holders (1.5 +) acres
Mean Vulnerability	**0.51**	**0.39**	**0.24**	**0.12**
Chronically Poor	0.42	0.29	0.14	0.06
Transient Poor	0.14	0.11	0.10	0.05
Poverty Incident	**0.56**	**0.40**	**0.24**	**0.11**
Low Mean Consumption	0.51	0.37	0.21	0.09
High Variability of Consumption	0.12	0.11	0.10	0.07
Total Vulnerable Group	**0.63**	**0.48**	**0.31**	**0.16**
High Vulnerable Non-poor	0.14	0.15	0.12	0.10
Low Vulnerable Non-poor	0.30	0.45	0.64	0.79
Vulnerable to Poor Ratio	**1.13**	**1.20**	**1.29**	**1.45**
Idiosyncratic Vulnerable	0.51	0.39	0.223	0.11
Covariate Vulnerable	0.505	0.38	0.21	0.10
Idiosyncratic to Covariate ratio	**1.01**	**1.03**	**1.06**	**1.10**

The decrease in the risk of becoming poor in future that comes with the increase in the size of the land possession is pretty steep. Poverty and vulnerability is widespread among the landless and small holders. As revealed by the figures in table 10, vulnerability manifests mainly through structural causes i.e. low expected mean consumption for the landless and small holder's groups as opposed to high variability of consumption. This probably indicates the low endowments, risk-averse subsistence nature of livelihood strategy by these two groups of households. For these groups idiosyncratic and covariate shocks weigh equally where as for medium and large holders idiosyncratic shocks play much more pronounced role than covariate shocks.

Table 10 Poverty and Vulnerability to Poverty of households classified on the basis of remittance

	No Remittances	Remittances from Bangladesh	Remittances from Abroad

Mean Vulnerability	**0.46**	**0.31**	**0.18**
Chronically Poor	0.38	0.22	0.10
Transient Poor	0.11	0.16	0.07
Poverty Incident	**0.48**	**0.38**	**0.17**
Low Mean Consumption	0.46	0.28	0.15
High Variability of Consumption	0.11	0.12	0.08
Total Vulnerable Group	**0.57**	**0.40**	**0.23**
High Vulnerable Non-poor	0.15	0.11	0.10
Low Vulnerable Non-poor	0.37	0.51	0.72
Vulnerable to Poor Ratio	**1.19**	**1.05**	**1.35**
Idiosyncratic Vulnerable	0.462	0.302	0.174
Covariate Vulnerable	0.457	0.286	0.158
Idiosyncratic to Covariate ratio	**1.01**	**1.06**	**1.10**

Remittances appear to make a difference in household’s living standards in rural Bangladesh. Households receiving remittances fare much better all across the board than the ones that do not receive any remittance. A breakdown by domestic and external sources further reveal that remittances from abroad has far more poverty and vulnerability reducing effect than remittances from domestic sources. However, idiosyncratic shocks are far more important for households receiving remittance from abroad than the covariate shocks. For the group that does not receive any remittances, both idiosyncratic and covariate shocks weigh equally in terms of vulnerability to poverty.

2.1 Concluding Observations

This paper examines the level and sources of vulnerability in rural Bangladesh using a standard cross-sectional household survey without explicit information on idiosyncratic and covariate shocks. Cognizant of the fact that shocks at various levels affect households differently and calls for differentiated policy choices, it is important to assess the relative impact of idiosyncratic and covariate shocks on different groups of households disaggregated by their socio-economic characteristics.

For this purpose, we have adopted the methodology to estimate expected mean and variance in consumption and to decompose the variance into idiosyncratic and covariate components. Our results indicate that both idiosyncratic and covariate shocks have considerable impact on household’s vulnerability and idiosyncratic shocks have an even greater impact on household’s consumption vulnerability than the covariate shocks. Furthermore, idiosyncratic shocks have a relatively higher impact on relatively well endowed (i.e. in terms of human capital, land holdings, activity status etc.), well off households (than poor households) and covariate shocks have a relatively higher impact on poorer, less educated, household's vulnerability. The observed higher impact of idiosyncratic shocks on consumption implies that insurance mechanism within communities do not function any better than insurance mechanism across spatially separated communities. Alternatively, it may be the case that idiosyncratic shocks have higher impact on household's income and consumption than covariate shocks, just because idiosyncratic shocks are more difficult to anticipate than the covariate shocks; consequently, *ex-ante* coping strategies are difficult to implement. The relatively higher impact of covariate shocks on consumption for less endowed families might be explained by the fact that they are mainly engaged in agriculture. Mutual community based informal insurance works better for poorer than wealthier families, thus mitigating the adverse effects of idiosyncratic shocks.

Our results also reveal that rural vulnerability in Bangladesh is mainly poverty induced rather than risk induced. Around 78 per cent all who are vulnerable is accounted for by low expected mean consumption and only 22 per cent of them are due to high consumption volatility. Overall vulnerability in rural areas is estimated to be 50 per cent. The categorization of poverty into transient and chronic poverty is even more insightful. The regional dimension of poverty and vulnerability to poverty clearly shows the justification for this kind of analysis and certainly calls for differential treatment of poverty reduction efforts in different administrative regions. For example, vulnerability in coastal regions, (i.e., Barishal and Khulna) is higher than that of Dhaka region.

Another important finding is that education is found to be a key element in reducing poverty and vulnerability in Bangladesh. Poverty and vulnerability is highest among households headed by illiterates; whereas households headed by a person having more than higher secondary level education are significantly better poised to cope with risk and uncertainty. So investment in human capital along with other means of social protection and promotion could be instrumental for poverty reduction in Bangladesh. Agricultural households again are more vulnerable than the non-agricultural households emphasizing that more protection is needed for the agricultural community.

Because our analysis is based on the cross-sectional data, the above findings are subject to the limitations in using a single cross-section to estimate standard deviation of consumption and the assumption that cross sectional variability proxies inter-temporal variation in consumption (Hoddinott and Quisumbing, 2003). Nonetheless, the results of this study provide some insights, highlighting the importance of quantitative studies on vulnerability to poverty. A sizeable portion of households that are now non-poor are certainly vulnerable to falling into future poverty. This has policy implications and therefore such results should be taken into account, particularly when designing social policy. *Ex-ante* measures to prevent as many households as possible from becoming poor as well as *ex-post* measures to alleviate those already in poverty should be enhanced. The expansion of the concept of poverty does not alter the basic tenets of the usual poverty reduction strategies. The significance of governance, human capital and infrastructure as key drivers of growth, employment generation, and poverty reduction remain. The only issues that it puts ahead is the importance of social protection and promotion of programmes for ensuring inclusiveness in the development process so that growth becomes more pro-poor. However, in designing policies one should take note of the varying nature of poverty and vulnerability. For chronic poor who lack economic assets, priority may be given to reduce consumption fluctuations and build up assets through a combination of protective and promotional programmes. Access to financial services, for example, micro-credit might help build up assets as it smooth income and consumption, enables the purchase of inputs and productive assets, and provides protection against crises. On the other hand, transient poor and high vulnerable non-poor households are most likely to benefit from some combination of prevention, protection, and promotion. This gives them a more secure base from which to diversify their activity into higher-return, higher risk activities.

References

Ahmed, A., U. "Trends in Consumption, Nutrition, and Poverty." In *Out of the Shadow of Famine: Evolving Food Markets and Food Policy in Bangladesh*, by R. Ahmed, S Haggblade and T., E. Chowdhury. Baltimore: John Hopkins University Press for the International Food Policy Research Institute, 2000.

Ajay, T., and R. Hasan. *Conceptualizing and Measuring Poverty as Vulnerability: Does It Make a Different?* ERD Policy Brief Series No. 41, Manila: Asian Development Bank, 2005.

Alwang, J., P.B. Seigel, and S.L. Jorgensen. *Vulnerability: A View From Different Discipline.* Social Protection Discussion Paper No 0115, Washington DC: World Bank, 2002.

Atkinson, A., B. "On the Measurement of Poverty ." *Econometrica, Vol.55 No.4*, 1987: 749-764.

Baulch, B., and P. Davis. *Poverty Dynamics and Life Trajectories in Rural Bangladesh.* Q-Squared Working Paper no.42, Toronto: Center for International Studies, University of Toronto, 2000.

BBS. *Preliminary Report on Household Income & Expenditure Survey 2005.* Dhaka: Bangladesh Bureau of Statistics, Ministry of Planning, 2006.

BBS. *Report on The Household Income and Expenditure Survey 2005.* Dhaka: Bangladseh Bureau of Statistics, Ministry of Planning, Goverment of Bangladesh, 2008.

Binswanger, H, and M Rozensweig. "Wealth, weather risk and the composition and profitability of agricultural investments." *The Economic Journal, 103,* 1993: 56-78.

Binswanger, H. P. "The Policy Response of Agriculture." *Proceedings of the World Bank Annual Conference in Development Economics.* Washington DC: World Bank, 1990. 231-258.

Bryk, A. S, and S. W. Raudenbush. *Hierarchical Linear Models: Applications and Data Analysis.* Newbury Park: Sage Publications, 1992.

Calvo, C., and S. Dercon. *Measuring Individual Vulnerability.* Economics Series Working Papers No. 229, Oxford: Department of Economics, University of Oxford, 2005.

Carter, M. R., and C. B. Barrett. "The Economics of Poverty Traps and and Persistence Poverty." *Journal of Development studies, vol.42, No.2*, 2006: 178-99.

Chant, Sylvia. *New Contributions to the Analysis of Poverty: Methodological and Conceptual Challenges to Understanding Poverty from a Gender Perspective.* New York: United Nations Women and Development Unit, 2003.

Chaudhuri, S. *Empirical Methods for Assessing Household Vulnerability to Poverty.* Mimeo, New York: Department of Economics, Columbia University, 2002.

Chaudhury, S. "Assessing Vulnerability to Poverty: Concepts, Empirical Methods, and Illustrative Examples." *mimeo, Columbia University*, 2003.

Chaudhury, S, J Jalan, and A Suryhadi. "Assessing Household Vulnerability to Poverty: A Methodology and Estimates for Indonesia." *mimeo, Colombia University New York,* 2002.

Christiaensen, L., and K. Subbarao. "Towards an Understanding of Vulnerability in Rural Kenya." *Journal of African Economies, Vol.14, No.4,* 2005: 520-558.

Deaton, A. *Analysis of Household Surveys.* Baltimore, MD: John Hopkins University Press, 1997.

Dercon, S. "Growth and Shocks: Evidence from Rural Ethiopia." *Journal of Development Econnomics 74(2),* 2004: 309-329.

Dercon, S. "Income Risk, Coping Strategies, and Safety nets." *World Bank Research Observer, 17(2),* 2002: 141-166.

Dercon, S. "Risk, Crop-choice and Savings: evidence from Tanzania." *Economic Development and Cultural Change, 44(3),* 1996: 485-513.

Dercon, S. *Vulnerability: A Micro Perspective.* Discussion Paper Series, Oxford: Department of Economics, Univsersity of Oxford, 2005.

Dercon, S., and P. Krishnan. "In Sickness and in Health: Risk-sharing within Households in Rural Ethiopia." *Journal of Political Economy, Vol.108,* 2000a: 688-727.

Dercon, S., and P. Krishnan. "Vulnerability. Seasonality, and Poverty in Ethiopia." *Journal of Development Studies, 36(6),* 2000b: 25-55.

Duclos, J., A. Araar, and S. Giles. *Chronic and Transient Poverty: Measurement and Estimation, with Evidence from China.* Discussion Paper No.2078, Bonn: The Institute for the Study of Labour (IZA), 2006.

Fafchamps, M, C Udry, and K Czukas. “Drought and Saving in West Africa: Are Livestock a Buffer Stock?” *Journal of Development Economics*, 1998: 55(2): 273-305.

Filmer, D, and L. H. Pritchett. “Estimating Wealth Effects without Expenditure Data -or Tears: An Application to Educational Enrollments in States of India.” *Demography, 38(1)*, 2001: 115-132.

Foster, J, J. Greer, and E. Thorbecke. “A class of Decomposable Poverty Measures.” *Econometrica, 52*, 1984: 115-132.

Gaiha, R, and K. Imai. *Measuring Vulnerability and Poverty: Estimates for Rural India.* UNU-Wider Research Paper No.2008/40, 2008.

Gaiha, R., and K. Imai. “Vulnerability, Persistence of Poverty and Shocks- Estimates for Semi-Arid Rural India.” *Oxford Development Studies, 32(2)*, 2004: 261-281.

Gertler, P., and J. Gruber. “Insuring Consumption against Illness.” *The American Economic Review, 92(1)*, 2002: 55-70.

Glewwe, P, and G Hall. “Are Some Groups More Vulnerable to Macro-Economic Shocks than Others? Hypothesis Tests Based on Panel Data from Peru.” *Journal of Development Economics*, 1998: 56: 181-206.

Goldstein, H. *Multilevel Models in Educational and Social Research.* London: Griffin, 1997.

—. *Multilevel Staistical Models.* London: Arnold, 1999.

Gunning, J, and C Elbers. *Vulnerability in a Stochastic Dynamic Model.* Tinbergen Institute Discussion Paper TI 2003-070/2, Rotterdam: Tinbergen Institute, 2003.

Heitzmann, K., R. S. Canagarajah, and P. B. Siegel. *Guidelines for Assessing the sources of Risk and Vulnerability.* Social Protection Discussion Paper 0218, Washington D.C.: World Bank, 2002.

Hoddinott, J, and A Quisumbing. *Methods for Microeconometric Risk and Vulnerability Assessments.* Social Protection Discussion Paper, No. 0324, Washington DC: World Bank, 2003.

Hoddinott, J., and A. R. Quisumbing. *Methods for Econometric Risk and Vulnerability.* Mimeo, Washington DC: International Food Policy Research Institute, 2008.

Holzmann, R, and S Jorgensen. "Social Risk Management: A New Conceptual Framework for Social Protection, and Beyond." *International Tax and Public Finance*, 2001: 8: 529-56.

Holzmann, R., and S. Jorgensen. "Social Protection as Social Risk Management: Conceptual Underpinnings for the Social Protection Sector Strategy Paper." *Journal of International Development, 11*, 2000: 1005-27.

Hoogeveen, H. "A New Approach to Insurance in Rural Africa." *The Geneva Paper on Risk and Insurance 26(3)*, 2001: 505-513.

Hossain, M., and N. Nargis. "Dynamics of Poverty in Rural Bangladesh, 1988-2007: An Analysis of Household Level Panel Data." In *Development, Equity and Poverty: Essays in Honour of Azizur Rahman Khan*, by L. Banerjee, A. Dasgupta and R. Islam, 213-232. Delhi: Macmillan Publishers India Ltd., 2010.

Hossain, M., B. Sen, and Z.,H. Rahman. "Growth and Distribution of Rural Income in Bangladesh: Analysis Based on Panel Survey Data." *Economic and Political Weekly, Vol.XXXV, Nos. 52 & 53, Mumbai*, Dec.30, 2000.

Hox, J. *Multilevel Analysis - Techniques and Applications.* Mahwah: Lawrence Erlbaum Associates, 2002.

Hulme, D. "Conceptualizing Chronic Poverty." *World Development, Vol. 31, issue 3*, 2003: 403-423.

Imai, K., R. Gaiha, and W. Kang. *Vulnerability and Poverty Dynamics in Vietnam.* Working Paper, Manchester: The University of Manchester, 2007.

Imai, Katsushi, and Raghav Gaiha. *Vulnerability, Shocks and Persistence of Poverty-Estimates for Semi-Arid Rural South India.* Economics Series Working Paper 128, Oxford: Department of Economics, University of Oxford, 2002.

Jacoby, H., and E. Skoufias. "Risk, Financial Markets, and Human Capital in a Developing Country." *Review of Economic Studies, 64(3)*, 1997: 311-336.

Jalan, J, and M Ravallion. "Behavioral Responses to Risk in Rural China." *Policy Research Working Paper Series, World Bank, No. 1978*, 1998.

Jalan, J., and M. Ravallion. *Household Income Dynamics in Rural China.* Policy Research Working Paper Series, No. 2706, Washington, D.C.: The World Bank, 2000.

Justino, Patricia, and Julie Litchfield. *Poverty Dynamics in Rural Vietnam: Winners and Losers During Reform.* PRUS Working Paper 10, Poverty Research Unit at Sussex, Department of Economics, University of Sussex, 2003.

Kakwani, N., and E. Pernia. “What is Pro-poor Growth.” *Asian Development Review, Vol.16 No.1*, 2000: 1-22.

Kamanou, G., and J. Morduch. *Measuring Vulnerability to Poverty.* WIDER Discussion Paper No.2002/58, Helsinki: UNU-WIDER, 2002.

Khan, A. R. “Poverty in Bangladesh: A Consequence of and a Constraint on Economic Growth.” *The Bangladesh Development Studies, 18(3)*, 1990.

Kochar, A. “Explaining Household Vulnerability to Idiosyncratic Income Shocks.” *American Economic Review, Papers and Proceedings*, 1995: 85(2): 159-164.

Ligon, E, and L Schechter. “Measuring Vulnerability.” *Economic Journal*, 2003: 113: 95-102.

Ligon, E, and L. Schecher. *Evaluating Different Approaches to Estimating Vulnerability.* Social Protection Discussion Paper Series No. 0410, Washington DC: World Bank, 2004.

Lipton, Micheal, and Martin Ravallion. “Poverty and Policy.” In *Handbook of Development Economics, Vol.III*, edited by J. Behrman and T. N. Srinivasan. B.V.: Elsevier Science, 1995.

Mccullock, N., and M. Calandrino. “Vulnerability and Chronic Poverty in Rural Sichuan.” *World Development, Vol.31, No.3*, 2003: 611-628.

Morduch, J. “Between the Market and State: Can Informal Insurance Patch the Safety Net?” *World Bank Research Observer Vol.14(2)*, 1999: 187-208.

Morduch, J. “Income Smoothing and Consumption Smoothing.” *Journal of Economic Perspectives 9(2)*, 1995: 103-114.

Morduch, J. “Consumption Smoothing across Space: tests for village-level responses to risk.” In *Insurance Against Poverty*, edited by Stefan Dercon. Oxford University Press, 2003.

Morduch, J. “Poverty and Vulnerability.” *The American Economic Review, 84(2)*, 1994: 221-225.

Morduch, J. *Risk, Production and Saving: Theory and Evidence from Indian Households.* Massachusetts: Harvard University, Cambridge, 1990.

Neilson, C. D., R. Cooper Contreras, and J. Hermann. “The Dynamics of Poverty in Chile.” *Journal of Latin America Study 40*, 2008: 251-273.

Paxson, C. H. “Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand.” *The American Economic Review, 82(1)*, 1992: 15-33.

Pritchett, L., A. Suryahadi, and S. Sumarto. *Quantifying Vulnerability to Poverty: A Proposed Measure, Applied to Indonesia.* Policy Research Working Paper No.2437, Washington DC: The World Bank, 2000.

Quisumbing, A. *Poverty Transitions, Shocks, and Consumption in Rural Bangladesh: Preliminary Results from a Longitudinal Household Survey.* CPRC Working Paper-105, Manchester: Chronic Poverty Research Centre, The University of Manchester, 2007.

Rahman, H. Z. "Crisis, Income Erosion, and Coping." In *1987-94: Dynamics of Rural Poverty in Bangladesh*, by H. Z. Rahman, M. Hossain and B. Sen. Dhaka: Bangladesh Institute of Development Studies, 1996.

Rahman, H. Z. "Poverty: The Challenge of Graduation." *Bangladesh Development Studies XXVIII(4)*, 2002: 53-78.

Ravallion, M. "Expected Poverty under Risk-Induced Welfare Variability." *The Economic Journal, 98*, 1988: 1171-1182.

Ravallion, M., and B. Sen. "When Methods Matters: Monitoring Poverty in Bangladesh." *Economic Development and Cultural Change*, 1996: 8-24.

Ravallion, Martin. *The Challenging Arithmetic of Poverty in Bangladesh.* Policy Research Working Paper Series, 586, Washington DC: The World Bank, 1991.

Rosenzweig, M., and K. Wolpin. "Credit Market Constraint, Consumption Smoothing and the Accumulation of Durable Production Assets in Low-Income Countries: Investments in Low-Income Countries: Investments in Bullocks in India." *Journal of Political Economy*, 1993: 101(2): 223-44.

Rosenzweig, M., and O. Stark. "Consumption Smoothing, Migration, and Marriage: evidence from rural India." *Journal of PoliticalEconomy, 97*, 1989: 905-926.

Sen, A. "A plan for Asia's Growth." Asia Week. 25 October 8 1999. http://www.asiaweek.com/asiaweek/magazine/99/1008/viewpoint.html.

Sen, B. "Drivers of Escape and Descent: Changing Household Fortunes in Rural Bangladesh." *World Development, 31(3)*, 2003: 513-534.

Sen, B. "Movement in and out of Poverty: A Tentative Explanation." In *1987-94: Dynamics of Rural Poverty in Bangladesh*, by H. Z. Rahman, M. Hossain and S. Sen. Dhaka: Bangladesh Institute of Development Studies, 1996.

Siddiqui, K. *Political Economy of Rural Poverty in Bangladesh.* Dhaka: NILG, 1982.

Smith, N., and S. Middleton. *A Review of Poverty Dynamics Research in the Uk.* York: Joseph Rowntree Foundation, 2007.

Suryahadi, A., and S. Sumarto. "Poverty and Vulnerability in Indonesia before and after the Economic Crisis." *Asian Economic Journal, 17(1)*, 2003: 45-64.

Tesliuc, E., and K. Lindert. *Risk and Vulnerability in Guatemala: A Quantitative and Qualitative Assessment.* Social Protection Discussion Paper 408, Washington DC: The World Bank, 2004.

The World, Bank. *Attacking Poverty.* World Development Report 2000/1, New York: Oxford University Press, 2000.

Townsend, R. "Consumption Insurance: an evaluation of risk-bearing systems in low-income economies." *Journal of Economic Perspectives, 9(3)*, 1995: 83-102.

Townsend, R. "Risk and Insurance in Village India." *Econometrica, 62(3),* 1994: 539-91.

Udry, C. "Risk and Saving in Northern Nigeria." *American Economic Review, Vol.85 No.5,* 1995: 1287-1300.

Zhang, Y., and G. Wan. "An Empirical Analysis of Household Vulnerability in Rural China." *Journal of the Asia Pacific Economy, Vol.11 No.2*, 2006: 196-212.

Appendix 2.1

Table 11 Scoring Coefficients for Infrastructure Index

Variable Names	
Whether the village has Banking facility	0.4065
Grammen Bank/ NGO	0.2405
Market	0.3942
Food Godown/Purchasing centre	0.3594
Cyclone shelter	0.2563
Community centre	0.3821
Post office	0.3605

Pesticide/fertilizer shop	0.3409
Bus stop	-0.0363
Train stop	-0.0467
Launch stop	-0.0438
Whether the village has Electricity connection	0.1168
Whether the village has gas connection	0.0580
Whether the village has land phone facility	0.0741
Whether the village has cell phone facility	0.0811
Mean	0.00
Standard Deviation	1.00

Note: Computed with Principal Component Analysis

Appendix 2.3

With a vulnerability threshold $V_n = 0.5$ indicting the probability of falling into poverty at least once in the next *n* years, the probability of falling into poverty in the subsequent years, i.e., one , two or three years can be calculated using the following equation:

$$V^* = 1 - \sqrt[n]{1 - V_n} \qquad (2.18)$$

Table 14 below shows the different vulnerability threshold for three different years.

Table 12 Relationship of Time Horizon and Vulnerability Threshold

Time horizon	**Vulnerability Threshold** $\boldsymbol{V_n = 0.5}$
One year	0.500
Two year	0.292
Three year	0.206