Assessing Household Vulnerability and Coping Strategies to Floods: A Comparative Study of Flooded and Non-flooded Areas in Bangladesh, 2005

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Acronyms

ADB = Asian Development Bank
BBS = Bangladesh Bureau of Statistics
BLUE = Best Linear Unbiased Estimates
BRE = Brahmaputra River Embankment
CE = Certainty Equivalence
CRRA = Constant Relative Risk Aversion
FAP = Flood Action Plan
FEI = Food Energy Intake
FGD = Focus Group Discussion
FGLS = Feasible Generalized Least Square
GIS = Geographical Information System
GLM = Generalized Linear Model
GLS = Generalized Least Square
GNP = Gross National Product
IFRC = International Federation of Red Cross and Red Crescent Societies
ILO = International Labor Office
IV = Instrumental Variable
NGO = Non Governmental Organization
OLS = Ordinary Least Square
PL = Poverty Line
PMS = Poverty Monitoring Survey
PR = Permanent Component
Q-Q plot = Quantile-Quantile plot
RESET = Regression Equation Specification Error Test
TOL = Tolerance Limit
TR = Transitory Component
VEP = Vulnerability to Expected Poverty
VER = Vulnerability Exposure to Risk
VEU = Vulnerability to Expected Utility
VIF = Variance Inflating Factor
VPL = Vulnerability to Poverty Line

Abstract

The frequent occurrence of disastrous floods results in losses for both human life and property values in Bangladesh. This study thus is set forth to examine the relationships between socioeconomic conditions and vulnerability to flood hazards. A cross sectional household survey was carried out two weeks after floods in four districts of Bangladesh in the year 2005. In total 1050 households in rural areas were interviewed through a three stage stratified random sampling. Among the four sampled districts, three were affected by monsoon floods and only one, the Nilphamari district, was affected by a flash flood. Bivariate analyses depict that floods have significant downside effects on households' wellbeing, as overall headcount poverty level deteriorates by 17 percent. The worst welfare loss is measured in Jamalpur district where the majority of households are involved with agriculture.

A multivariate regression model is carried out that shows that some demographic, socioeconomic and community variables along with flood shock variables have a noteworthy impact on flooded and non-flooded households' income. Estimates of a multinomial logit model illustrate that flood height, duration and loss of working days are significant for the poor households' income deterioration, whereas non-poor households are significantly affected by flood duration and loss of assets during floods. To assess households' vulnerability to floods, this study incorporates four methodologies from the poverty dynamic literature. Vulnerability estimates from the 'vulnerability to expected poverty' approach depict that flooded households have a higher risk of falling below the poverty line compared with the non-flooded households. This is the only methodology out of four used in this study that could estimate households' vulnerability from cross-sectional data and thereby allowing to estimate non-flooded households' vulnerability. The results show that idiosyncratic vulnerability is higher for households affected by monsoon flood, whereas flash flood worsens households' covariate vulnerability. Households involved with agriculture are found to be more vulnerable than other income groups. The 'vulnerability to expected utility' approach illustrates that elimination of poverty would increase household welfare and thus lessen vulnerability the most. Poverty and idiosyncratic flood risks are positively correlated and highly significant. Households with higher educated members, being male-headed and owner of a dwelling place have been found to be less vulnerable to idiosyncratic flood risks. Possession of arable land and a small family size can reduce poverty and the aggregate flood risk. The vulnerability of households from flooded regions, estimated by the 'vulnerability to poverty line' and the Monte Carlo Bootstrap methodologies, shows higher values compared to actual poverty rates. In this study, stationary environment is assumed with measurement errors in cross sectional surveyed data, so that the 'vulnerability to expected utility' approach demonstrates better results and closer estimates with respect to actual poverty levels after floods than the other three methodologies.

This study also deals with the query whether crop diversification would be an option for mitigating flood risk for farmers and concludes with the finding that mix-crop culture with cash and staple crops would lessen households' vulnerability. In the time of the flooding, rural people in Bangladesh suffer from the lingering effects of labor market disruption, price fluctuations, and consumption deficiency. Households initiate coping with borrowing money after the realization of floods and gradually lead to cope with savings and selling assets as the duration of flood increases, which is illustrated from a tobit model approach. In addition, empirical analyses explain that the decision to migrate is often guided by the aspiration to replenish asset values damaged by the floods, as rural-urban migration emerges as a source of credit. Participation in social networks plays an important role for the households during flood crisis to get information about potential host areas for migration.

Keywords: Flood, Vulnerability, Coping Strategy

Zusammenfassung

Die in Bangladesch häufig auftretenden Überschwemmungen haben negative Auswirkungen auf Menschenleben und Besitz der Menschen. Die vorliegende Arbeit untersucht daher Zusammenhänge zwischen sozioökonomischen Gegebenheiten und der Anfälligkeit für Schäden durch Überschwemmungen. Dazu wurde in 2005, zwei Wochen nachdem es zu Überschwemmungen gekommen war, in vier Bezirken eine Querschnittsuntersuchung von Haushalten durchgeführt. Insgesamt wurden 1050 ländliche Haushalte, welche mittels einer dreifach geschichteten Zufallsstichprobe ausgewählt wurden, befragt. Drei der vier untersuchten Bezirke waren von Monsunfluten betroffen, lediglich Nilphamari war von einer unvorhergesehenen flutartigen Überschwemmung betroffen. Eine bivariate Analyse zeigt, dass Überschwemmungen erheblichen Einfluss auf die wirtschaftliche Situation der Haushalte haben, da in Folge von Überschwemmungen die Gesamtzahl der am Existenzminimum lebenden Personen um 17 Prozent zunimmt. In Jamalpur, einem Bezirk in dem die meisten Familien von der Landwirtschaft leben, wurden die größten Einkommenseinbußen nachgewiesen.

Im multivariaten Regressionsmodell ergeben sich als wichtige Faktoren für das Haushaltseinkommen, sowohl von Überschwemmungen betroffener als auch nicht betroffener Haushalte, demografische, sozioökonomische und Infrastruktur bezogene Variablen zusammen mit Variablen bezüglich Schocks durch Überschwemmungen. Die Multinominale Logit-Schätzung zeigt, dass Fluthöhe, Dauer der Überschwemmung sowie die Anzahl verlorener Arbeitstage erheblichen Einfluss auf die Einkommensentwicklung armer Haushalte haben, während Haushalte, die oberhalb des Existenzminimums leben, eher von Dauer der Überschwemmung und Verlust von Eigentum während der Überschwemmung betroffen sind. Zur Berechnung der Verwundbarkeit von Haushalten bei Überschwemmungen wurden in dieser Arbeit vier Methoden aus der Literatur zur dynamischen Armut angewandt.

Der Ansatz ‚vulnerability to expected poverty' schätzt, dass von Überschwemmungen betroffene Haushalte ein größeres Risiko haben, unter das Existenzminimum zu fallen als

nicht betroffene Haushalte. Die von Monsunfluten betroffenen Haushalte werden eher durch *idiosynkratische Schocks* tangiert, die von unvorhergesehenen flutartigen Überschwemmungen betroffenen hingegen von *kovariaten Schocks*. Von der Landwirtschaft lebende Haushalte sind verwundbarer, als Haushalte, die anderen Einkommensgruppen angehören. Dies ist die einzige Methode von den vier in dieser Studie verwendeten, welche die Verwundbarkeit der Haushalte aus Querschnittsdaten schätzen konnte. Hieraus ergibt sich, dass die Verwundbarkeit von Haushalten, die nicht von Überflutungen betroffen waren, nur mit Hilfe dieses Ansatzes geschätzt werden kann.

Der Ansatz ‚vulnerability to expected utility' zeigt, dass eine Eliminierung von Armut zu einer Verbesserung der Haushaltseinkommen führt und die Verwundbarkeit somit am stärksten verringern würde. Armut und das Risiko für idiosynkratische Überschwemmungen korrelieren positiv und höchst signifikant miteinander.

Es konnte weiterhin festgestellt werden, dass qualifizierte und männlich geführte Haushalte mit eigenem Wohnsitz weniger verwundbar gegenüber spezifischen Überschwemmungsrisiken sind. Besitz von landwirtschaftlicher Fläche sowie eine geringe Anzahl von Haushaltsmitgliedern können demnach zu Reduzierung von Armut und Verwundbarkeit bei Überschwemmungen führen.

Im Vergleich dazu ist die Verwundbarkeit von Haushalten in Überschwemmungsgebieten verhältnismäßig größer, wenn sie mit dem Ansatz ‚vulnerability to poverty line' sowie dem Monte Carlo Bootstrap-Ansatz gemessen wurde. In der vorliegenden Studie ist führt der Ansatz der ‚vulnerability to expected utility' zu besseren Ergebnissen als die drei anderen verwendeten Methoden, da die geschätzten Werte des Armutsausmaßes nach Überschwemmungen der Realität am nächsten kommen.

Die in der Arbeit ebenfalls untersuchte Fragestellung, ob Diversifizierung im landwirtschaftlichen Anbau das Risiko von Schäden durch Überschwemmungen senken könnte, kam zu dem Ergebnis, dass eine Mischung der Anbaukulturen bestehend aus

Export- und Grundnahrungsmitteln die Verwundbarkeit reduzieren würde. Während der Überschwemmung leidet die ländliche Bevölkerung Bangladeschs unter den andauernden Folgen der Marktzerrüttung, Preisschwankungen und Konsumrückgang. Haushalte begegnen diesen negativen Folgen der Überschwemmungen, indem sie sich Geld leihen und nach und nach ihre Ersparnisse aufbrauchen oder ihre Vermögenswerte verkaufen, wenn die Überschwemmungen andauern. Dies wurde durch den Tobit-Modell-Ansatz illustriert. Darüber hinaus zeigt die empirische Analyse, dass die Entscheidung zu migrieren oft durch die Hoffnung getragen wird, die Vermögenswerte, die durch die Überschwemmungen beschädigt wurden, wieder aufstocken zu können, da die Stadt-Land-Migration als eine Art Finanzierungsquelle angesehen wird. Die Integration in soziale Netzwerke spielt eine große Rolle, da die Haushalte, die sich mit der Frage der Auswanderung beschäftigen, auf diesem Weg Informationen über potenzielle Zielregionen in Erfahrung bringen.

Schlagwörter: Überschwemmungen, Verwundbarkeit, Bewältigungsstrategie

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Chapter One

1. Introduction

The characteristics and enormity of risks that households face, the access to risk management mechanisms, and the surroundings in which households operate their activities, play a significant role in poverty dynamics - these findings are supported by some theoretical analyses and empirical evidences (Holzmann and Jørgensen 2000, Heitzmann et al. 2002). Measurement of vulnerability would be an apposite approach to think about forward looking anti-poverty interventions, by explaining who is probable to be poor, how prone are they to be poor, why are they expected to be poor, and how poor they will be in the future. Vulnerability estimates could highlight the ex ante poverty reduction and alleviation efforts with some intrinsic instrumental values, such as: the risks that households face may cause a large variation in their income. In the absence of adequate assets and insurance to smooth income or consumption, such risks may lead to irreversible losses, such as damage of productive assets, the fall in a vicious cycle of debt, reduced nutrient intake, or disruption of education that eternally reduces human capital (Jacoby and Skoufias 1997). Therefore, vulnerability estimation to a recurrent flood disaster in Bangladesh could be an inherent aspect of well-being.

Bangladesh consists mostly of a low-lying river delta with over 230 rivers and tributaries situated between the foothills of the Himalayas and the Bay of Bengal. The country lies within the catchment areas of the Ganges, Brahmaputra and Meghna rivers which mainly drain through Bangladesh into the Bay of Bengal. In Bangladesh, floods are usually defined as the submerge of land by water which can damage crops and property, disrupt people's normal living conditions, communities infrastructures, household's communications and economic activities and endanger the lives of people and their livestock. The extent and depth of flooding vary from year to year depending on rainfall and river levels. Damages of floods also differ both in time and places. There may be a local flood affecting only a relatively small area in a particular part of the country, as in the year 2000 when a flash flood affected northern and eastern parts of the country. Or the floods may be extensive, as in the years 1988, 1998 and 2004, affecting large parts of the country's major floodplains. Flood damages are reported in one or more parts of Bangladesh almost every year. Even in years with average rainfall, large areas of low-lying floodplains go under water for several weeks or months, as in the year 2005.

1.1 Problem Statement

With a population of 123.85 million and an area of 147,570 sq. km, Bangladesh is one of the world's most densely populated countries (839 per square km; BBS 2003). The combination of its geography, population density, and extreme poverty makes Bangladesh very vulnerable to disasters.

According to the *World Disasters Report 2003* (IFRC 2004), Bangladesh is among the top three most disaster-prone countries in the world, being vulnerable to cyclones, tidal surges, tornadoes, floods, droughts, earthquakes, and cold spells. Every year, on average, one million people are affected by disasters, 500,000 people are made homeless, and the nation's rivers consume around 9,000 hectares of fertile land. Since its independence in 1971, serious floods occurred in 1971, 1974, 1980, 1984, 1987, 1988, 1998, 2004 and 2007 as disastrous events[1]. In addition, some cyclones and storm surges happened in May 1985, November 1988, April 1991 and November 2007. The 1974 flood was followed by a famine and as a result 30,000 people died (Alamgir 1980). In 1987, about 40 percent of the country was flooded in Bangladesh, affecting 30 million people and causing about 1,800 deaths. Loss of the main crop (paddy) was estimated to be 0.8 million tons. The floods in 1988 were even more serious, covering about 62 percent of the land area, affecting about 45 million people, and causing more than 2,300 deaths[2]. In 1998, Bangladesh experienced the worst flood in its history. Over 68 percent of the country was inundated (Ninno et al. 2001), there were about 2,380 deaths, 1.56 million hectares of crops were lost, and over 900,000 houses destroyed. In the years 2000 and 2002, floods affected some 20 million people. In the year 2004, during July and August, devastating monsoon floods submerged two-thirds of the country, resulting in 35.9 million affected people, 726 deaths, 160,000 cases of disease and millions of homeless

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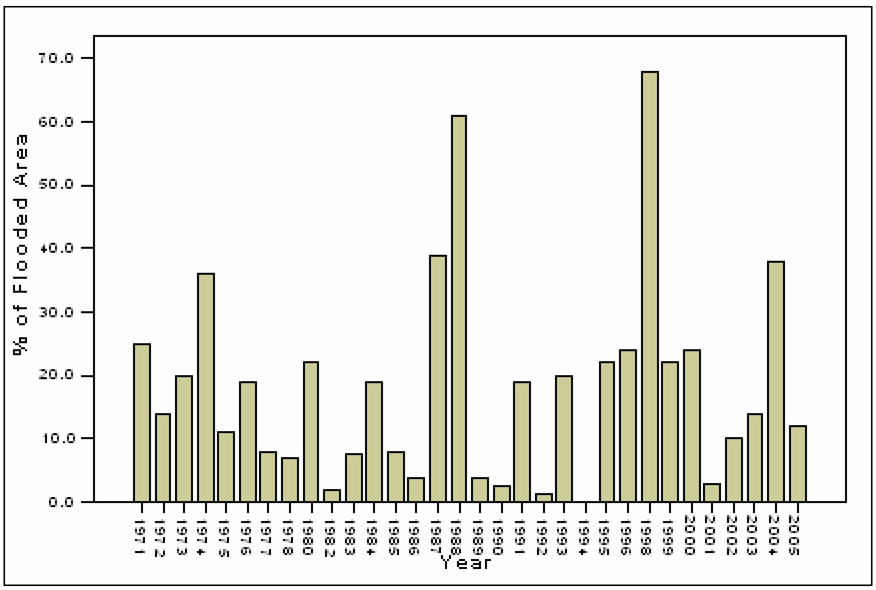
[1] Disaster Management Bureau of Bangladesh 2005 and http://www.reliefweb.int/rw/rwb.nsf/doc109?OpenForm&rc=3&cc=bgd (last access March 3, 2008)

[2] Irrigation Support Project for Asia and the Near East (1993: 1) by FAP, Bangladesh

people; overall flood damages were approximately Taka 127 billion (about US $2.2 billion) or 3.9 percent of GDP (US $56.9 billion; ADB 2004). Residential housing, roads, bridges, crops, fisheries, and livestock suffered the most damage. The largest asset and output losses occurred in the agriculture (including livestock and fisheries) sector, which was estimated at Taka 34 billion (US $580 million) or 27 percent of overall loss. About 12 percent of the country's area was flooded in the year 2005. Figure 1.1 below shows the frequency of floods by each year and the percentage of inundation area of Bangladesh since independence in 1971.

Figure 1.1: Frequency and area covered by floods in Bangladesh



Source: Flood Forecasting and Warning Centre, Bangladesh (2006)

1.2 Research Objectives and Questions

The frequent occurrence of disastrous floods results in losses for both human life and property values in Bangladesh. This study thus is set forth to examine the relationships between socioeconomic conditions and vulnerability to flood hazards. Such examinations would be instructive for both short term and long term poverty alleviation programs and risk management strategies in rural Bangladesh.

The endeavor of this study is to search the answers of the following key questions:

1. Who are the most vulnerable to monsoon and flash floods and how vulnerable are they?
2. What are the significant factors of vulnerability to floods in rural Bangladesh?
3. What coping strategies are followed by the flooded households and why?
4. Which methodology is suitable to estimate household vulnerability to floods in Bangladesh?
5. Which types of interventions are most likely to reduce vulnerability in rural Bangladesh?

Only a few studies exist which deal with floods and vulnerability in Bangladesh. Ninno et al. (2001) describe their findings from a survey of 757 rural households in seven flood-affected regions in Bangladesh after the flood in 1998. According to the authors, overall rice crop losses accounted for over half of the total agricultural losses that represent 24 percent of the total value of anticipated agricultural production for the year 1998. Brouwer et al. (2007) conduct a study on about 700 floodplain residents along the river Meghna in the southeast region of Bangladesh and show that households with lower income and lesser access to natural productive assets face higher exposure to risk of flooding. Kuhn (2002b) describes in his study from a floodplain in Bangladesh that households facing agricultural deficit are using remittances from urban migrants as a coping strategy instead of taking loans. Afsar (1999) shows from a study in rural Bangladesh that poorer households of the population tend to leave their homes immediately after the great floods and view migration as a temporary measure. In addition, households who lost their durable and productive assets are forced to become permanent migrants to nearby urban areas. Recurrent floods that cause crop and livestock losses impoverish many farmers, especially small-scale farmers, resulting in increased indebtedness, land sales, unemployment and migration to urban areas in Bangladesh (Currey 1978). Montgomery (1985) illustrates, from Bangladesh's crop production statistics from 1969 to 1984, that diversified rice production is usually higher in years with high floods. Farmers who cultivate deepwater rice instead of low-water rice during flood seasons get benefit in high flood years. The extra moisture provides a bumper production of wheat just after the flood season (Brammer 1990). Therefore, to unveil the main research questions this study initiates with the following hypotheses:

1. Flooded households are more vulnerable than non-flooded households in rural Bangladesh.
2. Households whose main source of income is from agriculture are more vulnerable than others.
3. Income and crop diversification reduce households vulnerability to floods.
4. Rural-urban migration plays a significant role to mitigate vulnerability to floods.

1.3 Outline of this Study

This study inaugurates with the introductory chapter that depicts the reasons for choosing this topic and the main objectives. Chapter two describes the conceptual ideas on vulnerability from a literature review. The theoretical framework and four different methodologies are shown in detail in chapter three. Chapter four delineates the historical background of floods in Bangladesh and gives a short description of the topography of Bangladesh. This chapter also illustrates the sampling design and a brief description of surveyed areas, exploration of data, detection of outliers and results of descriptive analyses. Econometric analyses on households' poverty and vulnerability and their estimates are revealed in chapter five. Chapter six enumerates the coping strategies of flooded households and some diversification issues to mitigate further flood risk to rural livelihoods of Bangladesh. Finally, chapter seven summarizes the findings from this study and derives some policy recommendations.

Chapter Two

2. Literature Review: Theoretical and Empirical

Researchers from different disciplines use different concepts and meanings of vulnerability. This chapter focuses on the literature that guided to build up the conceptual framework of this study and commence the analytical part. The following sections demarcate literature reviews from economics and non-economics literature. It includes theoretical and empirical literature alike.

2.1 Vulnerability Concept from Economics Literature

In economics literature, vulnerability generally defines as an outcome of a process of household responses to risks, given a set of underlying conditions (Alwang et al. 2001). Households are vulnerable if a shock (e.g. flood) is likely to push them below a predetermined welfare threshold (e.g. poverty line), so that vulnerability is a result of the cumulative process of risk and response. Many papers from the economics literature use a money matrix with the underlying presumption that all losses can be measured in monetary terms. The economics literature is disseminated through four subsections; firstly, focusing on poverty dynamics literature with its links to vulnerability; secondly, relating to asset-based economics literature where vulnerability is defined in terms of types and values of assets. Thirdly, literature on livelihoods is described; and lastly, food security literature is mentioned.

2.1.1 Poverty Dynamics Literature

The term *poverty* is used in all cultures and throughout history. Rowntree (1901) published the first concept to develop a poverty standard for individual families, based on estimates of nutritional and other requirements. In the 1960s, the level of income was the main focal point to measure poverty that was reflected in macro-economic indicators like Gross National Product (GNP) per head. In the 1970s, poverty measurements acquired new focus, notably as a result of MacNamara's celebrated speech to the World Bank Board of Governors in Nairobi in 1973. Following ILO's pioneering work in the mid-1970s, poverty came to be defined not just as lack of income, but also as lack of access to health, education and other services. New layers of perceptions were added in the 1980s, particularly as a result of the work on powerlessness and isolation from Chambers (1989) which created an interest in *vulnerability* to poverty and widely broadens the concept of poverty (Maxwell S. 1999).

In the poverty dynamics literature, indicators of well being are used in terms of identifying the poor, quantifying future poverty and estimating vulnerability with the poverty line being used as a benchmark. Many papers recognize that the poverty status can vary in different time periods (Jalan and Ravallion 1998). The concept of vulnerability is addressed in this literature as dynamic poverty. Coudouel and Hentschel (2000) differentiate between structural vulnerability (associated with chronic poverty) and transitory vulnerability (associated with transitory poverty). If a household is poor for the entire reference period, it is defined as chronically poor. Alternatively, if during the period the household moves in and out of poverty, then it is denoted as transitory poor. Transitory poverty may occur by structural shortcomings (e.g. low education) or risk (e.g. shock). Morduch (1994) classifies this risk oriented poverty as stochastic poverty. He further describes that transitory poverty is often caused by the failure to find protection against stochastic elements (e.g. risk) within the economic environment in low income countries, so the term stochastic poverty is convenient to describe risk induced occurrences.

Amin et al. (1999) use panel data from Bangladesh and detect households whose consumption tends to fluctuate with income, by controlling for household fixed effects and aggregate variation in mean consumption. One of their major findings is that female-headed households are more vulnerable than the male counterpart. Female-headed households in rural Bangladesh that are getting micro credits are assumed to be less vulnerable to flood shock. Thus, if two households have nearly the same consumption pattern in each state, but the second household has more variability in income, then from this literature, the second household is regarded as less vulnerable. Now, consider that the two households have the same vulnerability estimates, but one may face several income shocks, while the other may face fewer. Conceptually, the latter would be less vulnerable, but the measure from Amin et al. (1999) would show that both households' vulnerability estimates are the same. Thus, this measure is not suitable for inter-household comparisons.

Glewwe and Hall (1995, 1998) estimate vulnerability in Peru with the response of household's consumption to aggregate shocks. Their findings depict that households with better educated and female heads are less vulnerable, which discord with the result of Amin et al. (1999).

Pritchett et al. (2000) define vulnerability as the risk a household will fall into poverty at least once in the next few years. Here a household is denoted as vulnerable if it has 50-50 odds or worse of falling into poverty. This approach is applied to two sets of panel data (1998-99) from Indonesia and shows that a higher proportion of households is vulnerable to poverty than the actual headcount poor.

Ninno et al. (2001) examine the impact of disastrous floods in the year 1998 using 757 rural households in seven flood affected regions in Bangladesh. One of the findings is that poor households suffer substantial hardship during and after flood; especially day laborers are the most severely affected. Borrowing is the major coping mechanism of the sampled flooded households, in terms of both the value of borrowing and number of households that borrowed.

Chaudhuri et al. (2002) suggest that the 'natural' cut-off point for vulnerability would be a probability equal or larger than the expected poverty. It is indeed a flexible methodology for assessing household vulnerability to poverty using cross-sectional survey data. Authors use the mini-SUSENAS survey data from Indonesia in 1998 with the high vulnerability threshold point as probability of 0.50. A household whose probability of falling below a poverty line goes above 0.50 is to be considered as highly vulnerable. Among 13 different geographic domains, the estimated incidence of vulnerability is at least as high and in most cases higher than the observed incidence of poverty. A sharp drop in vulnerability rates is depicted with the increase of educational attainment. No such clear trend of vulnerability is observed with the employment status. Households with high dependency ratios are found as likely to be poor and vulnerable, but no difference is observed between gender groups. Households who have the community characteristics, such as availability of transport facilities, presence of bank, cooperatives in the community, industrial activity and access to clean water, are estimated as less vulnerable. Chaudhuri (2003) uses the same methodology for cross-sectional data from three countries, namely the Philippines, Indonesia and China.

Kamanou and Morduch (2002) propose another definition of vulnerability related to poverty dynamics and develop a general empirical framework combined with Monte Carlo and Bootstrap techniques. Authors estimate the expected distribution of future expenditures for each household and then calculate vulnerability as a function of estimated distributions. Using the panel data of Ivory Coast during 1985-86, estimated vulnerability rates are found to be higher than the actual headcount poverty rates.

Ligon and Schechter (2002) construct a utilitarian approach to define vulnerability and quantify the welfare loss associated with poverty, idiosyncratic risk, aggregate risk and uncertainty. Analyzing a panel dataset from Bulgaria, authors find that aggregate risks are more important than idiosyncratic risks. Households with employed, educated male heads are less vulnerable to aggregate risks compared to their counterparts.

Aggregate or covariate and idiosyncratic risks are defined differently in various papers from the economics literature (Dercon 2001, Ligon and Schechter 2003, Heitzmann et al. 2002). Heitzmann et al. (2002) state that the characteristic of a risky event (or downside shock) can be uncorrelated among individuals and regions. Risks that only affect individuals or households (e.g. death of household's main earner) are referred to as idiosyncratic risks. Risks that affect a group of households, the entire community (e.g. flood, cyclone), the whole nation (e.g. economic crisis) or even several nations (e.g. nuclear disaster) are called covariate risks. However, whether a shock is idiosyncratic or covariate depends on its underlying sources, impacts and perceptions. For example, job loss of a household head can be an idiosyncratic downside risk for a household, but if the job loss is the result of a macroeconomic crisis then it is identified as covariate risk (World Bank 2000).

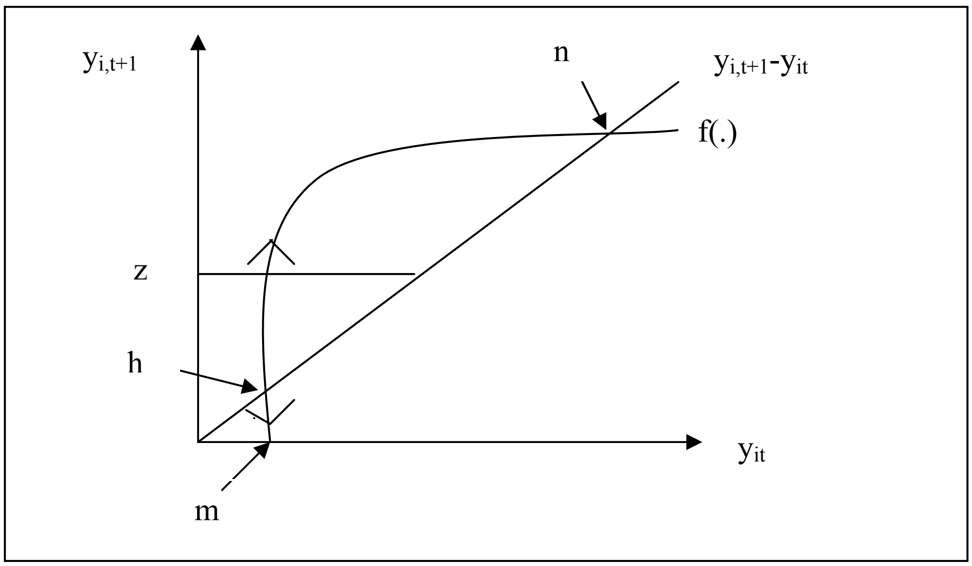
Skoufias and Quisumbing (2003) provide a new approach to identify vulnerability as risk exposure using longitudinal household data from Bangladesh, Mali, Russia, Mexico and Ethiopia. Data used for the Bangladesh study come from a four-round panel survey of 957 households. The surveys were conducted at four-month intervals between June 1996 and September 1997 in 47 villages. Consumption expenditure is used as an indicator of wellbeing and the variability of consumption is estimated in response to idiosyncratic shocks for subgroups of the population. Case studies from all countries show that food consumption is better insured than nonfood consumption from idiosyncratic shocks. The degree of consumption insurance is defined by the scale to which the growth rate of household consumption covariates with the growth rate of household income. For Bangladesh, the loss of livestock shows no significant role on the growth rate of food consumption per capita. This approach neither depends directly on a household's level of consumption or income, nor does it depend straightly on the risk a household bears. So, a household with large variation in consumption or income which does not stem from variation in observables would have a low vulnerability estimate. This approach also needs at least three rounds of panel data.

Kühl (2003) develops a stochastic process model for household consumption and distinguishes between the chronic and the transient parts of households consumptions. Monte Carlo bootstrap method is used to simulate two parts of household consumption using three rounds of survey data from rural Ethiopia during 1994-95. For various subgroups of the surveyed households, vulnerability levels are found to be higher than the poverty levels and poor households are found to be more vulnerable than non-poor.

Cafiero and Vakis (2006) address an augmented poverty line to measure vulnerability. Authors suggest a new poverty line where the traditional absolute poverty benchmark level is added up by the estimated cost of insuring against socially unacceptable risks.

Barrientos (2007) assumes that income of one state is related to the previous state of income. He starts with the notation that the income of one state of household i is $y_{i,t+1}$ and the income of the same household in the previous state is y_{it}, so that, $y_{i,t+1} = f(y_{it}, X_{it})$, where X_{it} is the vector of household i's endogenous characteristics. Assuming $f(.)$ is decreasing and concave in $y_{i,t+1}$ for all positive household income, the relationship of vulnerability and income poverty trap can be delineated by the following figure:

Figure 2.1: Vulnerability and non-linear income poverty



Source: Barrientos (2007, p.7)

Here, the poverty line z is arbitrarily chosen such that some of the poor will be on an upward path and others will be on a downward path. The assumption about concavity in $f(.)$ is taken with respect of the utility curve of risk averse households. The equilibrium points from the curvature are m and n, so that household income will gravitate towards one of the points. For $y_{i,t+1}$ below h, the income $y_{i,t}$ and inter-temporal variation do not support sufficiently to retain the same level of income, so that the household income will shift below and poverty will exacerbate until it reaches point m. This is a poverty trap. For points above h and below n, households' incomes $y_{i,t}$ and inter-temporal variations can support incomes $y_{i,t+1}$, so that they can be set into a prosperity cycle until reaching point n. From this simple model, the direct and buffer effect of vulnerability can be evaluated. If the flood shifts a household from point n to just below the point h, then the income will decrease, and the household will be detected as vulnerable. Some policies and social protection schemes can play a promotional role, by shifting the flood affected households just above point h, so that they will be on the prosperity income path.

2.1.2 Asset-based Literature

The asset-based literature has the genesis in Sen’s (1981) entitlement approach. Here, poverty is treated as a dynamic state, whereas vulnerability is demarcated with the probability of falling below a benchmark level of current consumption and the loss or degradation of assets by the impact of any downside risky event. The outcome of risky events is assumed to create current as well as future welfare losses in terms of productive assets, durable assets, income flows, consumption, and investment (Reardon and Vosti 1995, Moser 1998, Rakodi 1999). The lag effect of past disasters can also be associated with the current tangible and intangible assets value. Whereas tangible assets include land, labor, capital, savings (e.g. natural, human, physical and financial assets), intangible assets include social, institutional and political relationships, physical and social structure, and location (Siegel and Alwang 1999).

One of the focal views in the asset-based literature is the ability of households to manage risk. Risk management can be performed by allocating assets before and after a negative risky event. Before a risky event occurs households may take an ex ante risk management strategy (e.g. diversifying asset bases or migrating), or invest in risk mitigation (e.g. precautionary savings, purchasing insurance). After any risky event occurs households may take an ex post risk management strategy through coping activity (e.g. sales of assets, using underemployed labor). Therefore, the main strength of the asset-based literature is its focus on the types, amounts and activities of households’ assets. Moser and Holland (1997) state vulnerability and asset ownership are closely related, as the more assets people have the less vulnerable they are and the more depletion of assets cause the more insecurity. But it is still not established which type of asset effectively reduce vulnerability as the actual value of assets drops sharply during crisis periods

(Dercon 2001). *Susceptibility, resilience* and s*ensitivity*-these terms are used in the asset-based literature. According to Alwang et al. (2001), *susceptibility* is the probability that a household will experience a welfare loss from a specific event. It is a function of risks faced, assets of a household and response history. *Resilience* is the household's ability to resist downside pressures and to recover from a shock. *Sensitivity* is the amount of depletion of household's asset portfolios after responding to risks.

2.1.3 Livelihoods Literature

Livelihoods are defined in this literature as the way in which people satisfy their needs and earn a living (Ahmed and Lipton 1999), whereas vulnerability is described as the probability that livelihood stress will occur (Alwang et al. 2001). Chambers (1989) refers to vulnerability as having two sides: an external side of risks, shocks, and stress, and an internal side of defenselessness, meaning a lack of means to mitigate or cope without incurring losses.

Davies (1996) describes livelihood vulnerability as a balance between the sensitivity and resilience of a livelihood system. Livelihood resilience allows a system to absorb and utilize change. Livelihood sensitivity is the degree to which a given system undergoes change due to natural forces, following human interference. The author also distinguishes between structural and proximate vulnerabilities. The concept of structural vulnerability is delineated from household's underlying characteristics which are not changeable during time periods (e.g. old age, disability to work). Proximate vulnerability is associated with the household's varying characteristics (seasonal drought or flood). *Coping* strategies to mitigate vulnerability is defined here as a set of short-term responses to unusual food stress and *adaptation* as a long term coping strategy incorporated into the normal cycle of activities. Adaptation may also lead to an increased cycle of vulnerability by exhausting assets (e.g. withdrawal of children from schooling, cut firewood from forest). However, it is not explicit how one would specify vulnerability as there is concise perception of the threshold level of livelihood.

2.1.4 Food Security Literature

Maxwell *et al*. (2000) refer to vulnerability as a state of food insecurity. Food security is achieved when all people at all times have both physical and economic access to sufficient food to meet their dietary needs for a productive and healthy life (World Bank 1986). In this food security literature, food production and consumption are the main focal points. Barrett (1999a, p.1) defines food insecurity as *"the risk of irreversible physical or mental impairment due to insufficient intake of macronutrients or micronutrients."*

According to the food security literature, mapping exercises are performed to locate vulnerable areas through the indicators of rainfall patterns, forest cover, and soil productivity. These indicators are measured through remote sensing and geographical information systems (GIS) to determine vulnerability to food stress. Barrett (1999b) notes that food security is an ex ante concept, and ex post outcomes would be inadequate food intake, hunger, and under-nutrition as consequences of food insecurity. The author broadens the food security concept by incorporating intra-household dynamics, the role of assets, behavioral effects on response and exposure. However, this food security literature generally faces difficulty in finding a benchmark to which indicators can be compared.

2.2 Vulnerability Concept from Non-economics Literature

Vulnerability is defined in several dimensions using non-monitory terms. Sociologists and anthropologists emphasize the role of social capital in the context of vulnerability. Disaster management literature suggests incorporating the way and capacity to manage environmental shocks and disasters in the vulnerability concept. In the environmental and nutritional literature, the vulnerability concept evolves in terms of ecological and food intake perceptions respectively. The following sections demarcate the views from non-economic literature.

2.2.1 Sociology and Anthropology Literature

Sociologists and anthropologists are using the term *social vulnerability* as the lack of capabilities, deprivation and social exclusion (Moser and Holland 1997). Loughhead and Mittai (2000) argue that social vulnerability includes different perspectives from economic vulnerability. The authors classify children, elderly and disabled as vulnerable groups rather economically poor people.

Putnam (1993) identifies assets in terms of social capital and strength of household relations that are also vulnerable to downside risks. Serra (1999) states that the poor are more vulnerable to claim social capital following a disaster, as social capital itself requires time and some kind of investments. Narayan et al. (2000) propose that vulnerability estimates are to be formulated through participatory efforts. One major problem of this sociological and anthropological literature is that the outcomes from households or society are not measurable using a single metric or a pre-defined benchmark.

2.2.2 Disaster Management Literature

Common theme of this literature is to relate human vulnerability and natural disaster to the idea that people, households, communities and countries are vulnerable to damages from natural disasters (Kreimer and Arnold 2000). It is depicted that the poor are most vulnerable to natural disasters because low-income people and communities are usually the primary victims of natural disasters, because they are more likely to be located in areas vulnerable to bad weather or seismic activity (IDB 2000). Blackie et al. (1994, p.9) define vulnerability as *"…characteristics of a person or group in terms of their capacity to anticipate, cope with, resist, and recover from the impact of a natural disaster"*. This concept of defining vulnerability would help to assess the probability of different natural disasters and identify the communities in high natural risks.

Disaster management literature (Webb and Harinarayan 1999, Sharma et al. 2000) uses the methodology: *vulnerability = hazard – coping.* Here hazard is defined as a function of: probability; primacy (shock value based on time elapsed since previous occurrence);

predictability (degree of warning available); prevalence (the extent and duration of hazard impacts); and pressure (the intensity of impact). Coping is a function of: perceptions (of risk and potential avenues of action); possibilities (options ranging from avoidance and insurance, prevention, mitigation); private action (degree to which social capital can be invoked); and public action (Alwang et al. 2001). Sharma et al. (2000) also argue that the poor are more vulnerable and exposed to risky events because of their housing locations. Vulnerability is identified in this disaster management literature usually by two factors. Firstly, risk mitigation or disaster preparedness and secondly, disaster relief. The ex ante risk reduction and risk mitigation are added into the first factor, while ex post activities, such as coping resources coming from external sources to disaster areas, are lumped into the second factor.

2.2.3 Environmental Literature

The ecology-based environmental literature focuses on the vulnerability of species or ecosystems. Species are vulnerable to extinction and the whole ecosystem is degrading by human-plant-animal-environmental interactions. Ahmed and Lipton (1999) combine the livelihoods and environmental literature, and express vulnerability as exposure of individuals or groups to livelihood stress as a consequence of environmental change. Dinar et al. (1998) use models to make projections with respect to expected negative impacts of global warming and related climatic and ecological changes, such as less rainfall or flooding from rising tidewaters for melting polar ice. This environmental literature is inclined to focus on the risk and risk responses, with little attention to coping strategies.

2.2.4 Health and Nutrition Literature

Health and nutritional epidemiologists are defining vulnerability only with indicators of nutritional status. Vulnerability is referred in this nutritional literature as the nutritional vulnerability, defined as the probability of inadequate food intake with the standard to live a normal and active life (National Research Council 1986). Davis (1996) states nutritional vulnerability as the probability of suffering nutrition-related morbidity or mortality. General indicators of nutritional vulnerability are anthropometric indices, chemical analyses, and food intake analyses. Each individual is classified as stunted, wasted or malnourished depending on the health status. Kelly (1993) examines the association of malnutrition with probability of mortality and adult productivity. Empirical studies of vulnerability based on health and nutritional concepts require longitudinal data, detailed anthropometric measures of each person and costly, time consuming surveys.

2.3 Assessment of Literature from Different Disciplines

In the literature from different disciplines, vulnerability is conceptualized in multifaceted terms. Some of the definitions are conceptually strong but empirically weak and vice versa. In the asset-based, livelihood and sociological literature, different aspects of vulnerability are highlighted (like: possession and utility of assets, human and social capital, capability of adaptation, defenselessness, powerlessness, security, social exclusion, violence, corruption) but only with limited empirical applications. On the other hand, papers from the poverty dynamics, food security, and nutritional literature, have sound empirical estimates but with limited aspects of vulnerability. In the poverty dynamics literature, vulnerability is defined only as the probability of wellbeing to fall below the poverty line; in the asset-based literature the value of assets and their related activities are evolved no matter whether households' are affected by shocks or not; in the livelihood literature, attention is paid on how the risk and risk management strategies alter the way of living; in the food security literature vulnerability is related to weather-related crop failures; papers on health and nutrition focus on the impacts of downside risks on nutritional intakes; papers from the disaster management literature tend to evaluate the probabilities and damages associated with specific physical disasters; sociologists explore the poverty and vulnerability in non-monetary metric terms, introducing entitlement, defenselessness, social exclusion, gender and race discrimination, social violence and corruption.

2.4 Summary and Conclusion

Vulnerability is blessed with some rich literature with different methodologies and empirical studies from many countries. However, papers dealing with vulnerability and risk in Bangladesh, have not scrutinized households' vulnerability to a particular flood shock that might be the principal concern of policy making. Amin et al. (1999), in their study on Bangladesh, show that female headed households are still vulnerable to poverty after being a member of a micro credit program. Sen (1999) examines vulnerability as the variability of poverty levels from a panel survey of 62 villages in Bangladesh during the years 1989 and 1994. Siddiqui (2004) depicts that people of Bangladesh involved with different types of migration are vulnerable to situations that expose them to contract HIV; especially women are more vulnerable who may be infected by their emigrant worker husbands. Ninno et al. (2001) focus only on the coping strategies during and after floods in the year 1998 without any perception of vulnerability to floods. Skoufias and Quisumbing (2003) evaluate some vulnerability due to loss of livestock. Therefore, this study is set forth to examine households' vulnerability to floods in the year 2005.

As the literature review has shown, vulnerability may not only be captured by the income or consumption deficit due to a natural disaster (e.g. flood); it also needs to encompass risks related to health, violence or social exclusion. However, comparison of the insecurity (e.g. women in a flood shelter area) and the income or consumption shortfall of households due to floods is difficult. Therefore, this study focuses on the vulnerability to floods regarding measurable welfare (income) losses as suggested in the poverty dynamics literature and which is only one of the many facets of flood vulnerability.

Chapter Three

3. Conceptual Framework and Methodology

This chapter first describes a theoretical framework for defining and quantifying vulnerability, and then some current econometric methods that are suitable for survey data are explained more in detail.

3.1 Conceptual Framework: Poverty, Risk and Vulnerability

Vulnerability can be defined as the combination of risk, households' conditions and their actions to the risk. According to Alwang et al. (2001), some general principles related to vulnerability include: (a) it is a forward-looking approach, (b) it is defined as the probability of experiencing a future loss due to a downside risk, (c) the extent of vulnerability depends on the characteristics of the risk and the household's ability to respond to the risk, (d) a household may be vulnerable to risk over the very next period, e.g. next month, year, etc., and (e) the chronic and transient poor are vulnerable because of their exposure to risks and limited abilities to manage the risk. The following box 3.1 delineates the working concept of vulnerability used in this study.

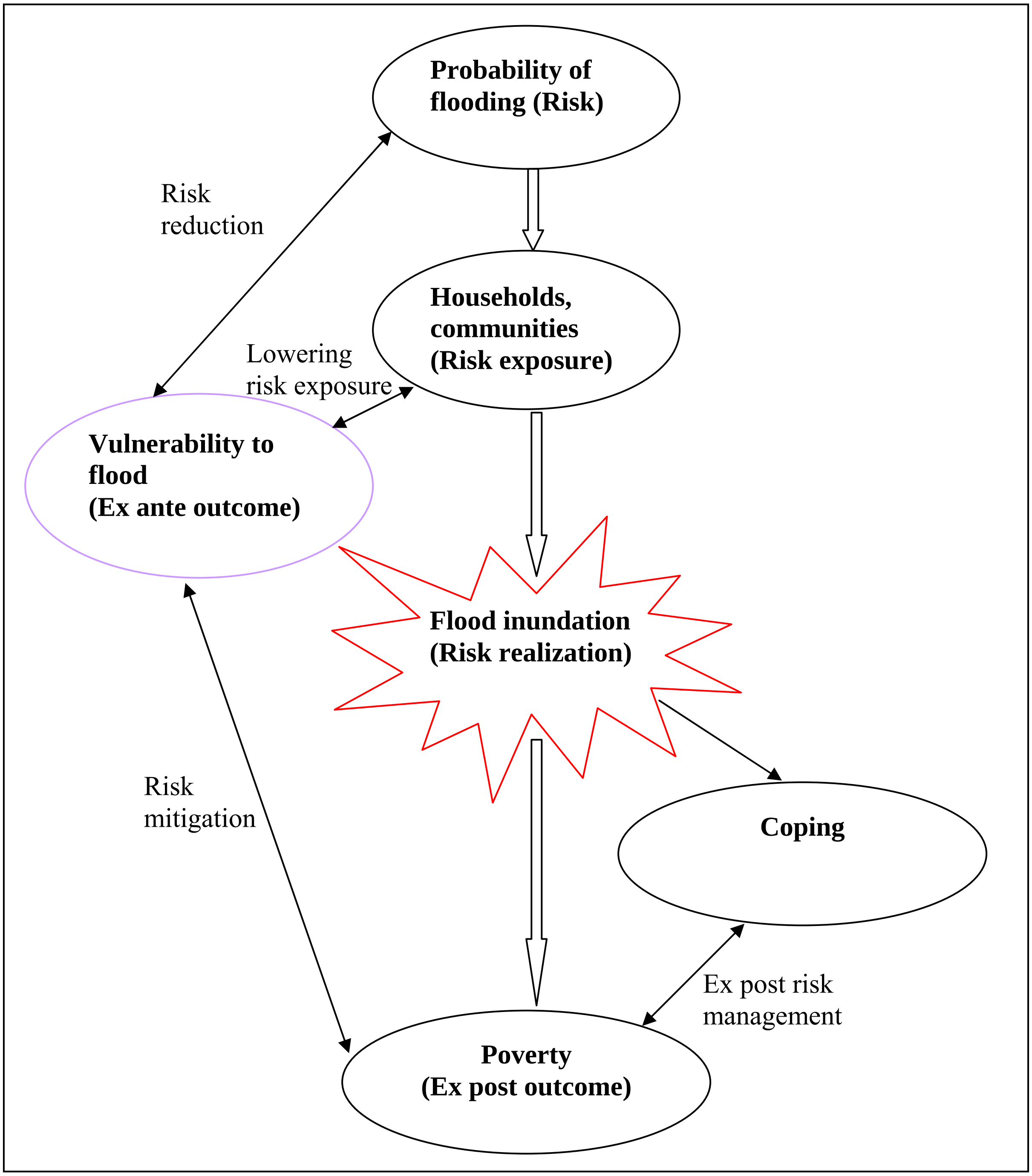
Box 3.1: Working concept of household vulnerability

A household is said to be vulnerable if any downside risk, e.g. flood in rural Bangladesh during the year 2005, causes loss of welfare below some socially accepted benchmark. The degree of vulnerability depends on the frequency and magnitude of the risk and the household's ability to respond to risk. The ability to respond to risk relies on household characteristics. A socially accepted benchmark refers to a poverty line.

Poverty and vulnerability relate to the term 'risk' (Chaudhuri 2003). The risk of a household relates to events possibly occurring. The household may have a priori sense of the likelihood of some events occurring, without overall knowledge of this likelihood. Risky events may relate to the environment or climate, to the death of a person, or to any action taken by households. The risk may be upside or downside for the individuals, households, communities and countries. Downside risk is defined here as the estimate of the potential that a security, income, expenditure or overall livelihoods might decline in real value if the area is flooded. If the decisions are taken under assumed certainty, based on the norm or best estimate of the consequences, then downside risk may occur if the distribution of actual outcomes is negatively skewed. It may also arise when a risky outcome depends on non-linear interactions of uncertain quantities (random variables). For example, income of a household may depend on some uncertainties and that household might be at risk if the deviations of these uncertain variables are quite high from their expected means. If the actual means after an event or shock are lower than the predicted means, it is classified as downside risk. This study is focusing more on the downside risk effect on the households of rural Bangladesh, albeit some fishermen or boatmen may face an upside risk meaning that their income in the flooded season increases.

The vulnerability framework for this study, drawn in box 3.2, begins with a notion of risk. Risk is characterized by a known or unknown probability distribution of floods. All individuals, households, communities or nations face multiple risks from floods in Bangladesh. Flood risks are characterized by the magnitude (including size and spread), their frequency and duration, and their history – all of which affect household's vulnerability from the risk. Households, communities, and even nations that are exposed to risk can respond to, or manage, flood risks in several ways. Households may use formal and informal risk management instruments depending on their access to these instruments. Vulnerability assessments for flood risks can imply risk management strategies that involve ex ante and ex post actions. Ex ante actions may be introduced before the next flood risks take place, and ex post risk management is generally taken after households have already been flooded (e.g. coping). Thus, risk reduction and lowering risk exposure strategies can be generated from vulnerability estimates. For example, when most vulnerable areas to floods are detected, then risk reduction strategy may take place through building dams or canals, or actions for lowering exposure to flood risks may include migration to upland areas. Vulnerability measures can also help people to take risk mitigation strategies that include formal and informal responses to expected losses such as self-insurance (e.g. precautionary savings) and building social networks. Ex post coping activities are responses of individuals, households or communities that take place after floods effects are realized. Such coping strategies after floods may comprise selling assets, borrowing money for food, removing children from school, changing agriculture and livestock practices, changing employment or working patterns, changing consumption habits, or migration of selected family members, or even begging. Some governments, NGOs and foreign aid agencies provide formal safety nets, such as public work programs, micro credit programs or food aid that help households to cope with flood risks in Bangladesh.

Box 3.2: Framework of this study: vulnerability to floods



Source: Author's own compilation based on Heitzmann et al. (2002)

3.1.1 Risk and Uncertainty

The two terms 'risk' and 'uncertainty' are defined in various ways in different articles. The risk may be defined as the imperfect knowledge where the probabilities of possible outcomes are known. The uncertainty can be identified as where the probabilities are unknown. The distinction can be clarified by simplifying uncertainty as the imperfect knowledge and risk as uncertain consequences, specifically exposure to unfavorable consequences (Hardarker et al. 2004). Therefore, risk usually indicating an aversion for some of the possible end results is not value free. For example, someone might say that he or she is uncertain about what the weather will be next summer-a value free statement which entails imperfect knowledge of the future. On the contrary, that person might mention that he or she is going to plan for a game for the next day and there is little risk of rain. Some knowledge is gained from the weather forecast which indicates the probability distribution. The people staying in riverside areas may be concerned about the monsoon rain for the next season, and hence their decisions on crop choice and livelihoods are significantly involved with the prediction of risk.

Every household living in such a risky environment has to make decisions, with risky payoffs, but there is a sum of money 'for sure' that would make that household indifferent to facing the risk or to accepting the sure sum. This sum is the lowest price for which the household would be willing to sell a desirable risky prospect, or the highest payment the household would make to get rid of an undesirable risky prospect. This sure sum is called the certainty equivalence (CE) of that household for that risky prospect. Normally, the CEs will vary among the households, even for the same risky prospect, because households have rarely identical attitudes to risk (utility functions) and the chances of better or worse outcomes they face may also differ.

3.1.2 Utility Function and Risk Aversion

The shape of a utility function is characterized by the preferences of the households. If the utility function has a positive slope over all the preferences or payoffs, it implies that more return from the decision is always preferable than less. Preferences like this kind are normal for money, but may not be appropriate for other things. For example, utility does not always increase with the amount of food taken. The catachrestic of the utility of money may be defined mathematically as $U^{(1)}(y) > 0$, where $U^{(i)}(y)$ is the i-th derivative of the utility function, $U(y)$, for the income y. The first derivative of the utility function for income is positive which represents the state that more is always preferred to less. The risk aversion is indicated by a utility function that focuses on decreasing marginal utility as the level of the preference is increased. In terms of second derivative three possible attitudes to risk can be classified, such as,

1. $U^{(2)}(y) < 0$, implies risk aversion
2. $U^{(2)}(y) = 0$, implies risk indifference or neutral and
3. $U^{(2)}(y) > 0$, implies risk preference

From the above three types, the risk aversion is commonly used to delineate a rational household's decision at risk. The distinction between the certainty equivalence and the expected value of a risky prospect, known as the risk premium (RP), is a measure of the value of the combined effects of risk and risk aversion. There are many literary confutes to measure risk aversion. It is reflected by the curvature of the household utility function. Measuring the curvature is not simple because a utility function is defined only up to a positive linear transformation. So, a measure of curvature is needed which is constant for such a transformation. One of the simple forms to measure risk aversion which is constant for a positive linear transformation of the utility function is the absolute risk aversion function, $r_a(y) = -\dfrac{U^2(y)}{U^1(y)}$, where $U^2(y)$ and $U^1(y)$ represent the second and first derivatives of the utility function (Pratt 1964; Arrow 1965, p. 33). It is assumed that the absolute risk aversion coefficient $r_a(y)$ will decrease with the increase in y, because people could better afford to take risks as they get richer. The problem for the absolute risk aversion function is that $r_a(y)$ depends on the monetary units of y. So, this measure derived in different currency units is not comparable. The currency units problem is overcome by defining a relative risk aversion function, such as $r_r(y) = yr_a(y)$. The relative risk aversion coefficient $r_r(y)$ is independent of the units of y and can be used for different currency units. So, both the absolute risk aversion coefficient and the relative risk aversion coefficient are not constant, but may change with y. The relative risk aversion may be categorized as increasing, constant and decreasing with income. The constant relative risk aversion (CRRA) is defined as 'preferences among risky prospects will be unchanged if all costs or values from different choices are multiplied by a positive constant'.

Two main functions are commonly used to define CRRA:

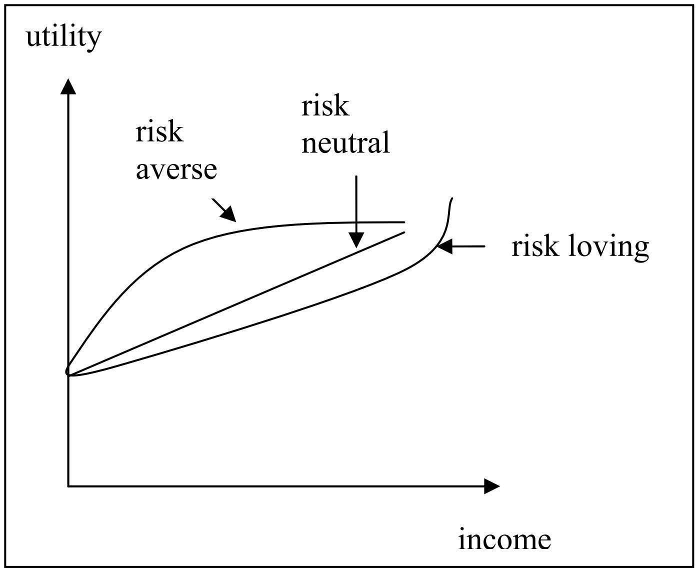
1. Logarithmic: $U = \ln(y), y > 0$, for which $r_a(y) = y^{-1}$ and $r_r(y) = 1$
2. Power: $U = \dfrac{y^{(1-\gamma)}}{1-\gamma}$, $y > 0$, for which $r_a(y) = \gamma / y$ and $r_r(y) = \gamma$

The power function is commonly preferred over the logarithmic functional form, because it directly incorporates γ as the constant coefficient of relative risk aversion for income, where γ is called the partial risk aversion coefficient. Risk aversion is a reflection of the diminishing marginal utility of income or wealth. For the values of γ of 4 or more, the function entails very high marginal utility for low values of income (y) with a sharp fall to give essentially zero marginal utility for higher values (Hardarker et al. 2004). This property suggesting that extreme risk aversion with a value of 4 or more is seldom possible.

The partial risk aversion coefficient can be measured by observed behavior of the sample data. The procedure to estimate risk aversion includes some stochastic elements to represent the risk faced by the households and coefficients to be estimated in order to reflect households' risk responses. For example, it might be assumed that households make crop production and resource or input allocation choices to maximize an indirect utility function in terms of the mean and variance of returns, with the regression coefficient on the variance term then assumed to reflect risk aversion. But the methodology suffers from two basic weaknesses: (i) the strong assumption that the analyst and the household share the same view of the uncertainty to be faced although they may be differing from each other. Generally, the access to information of household and research workers is different; (ii) such kind of modeling is subject to specification error. This specification error by turn affects the measuring of the risk aversion.

A household may be risk averse, risk loving and risk neutral; the utility function of income or wealth or expenditure also differs according to the former criteria. If a household prefers to have a certain expected value of income rather than taking risk, then the household is defined as risk averse. Again if the household prefers a random distribution of income to its expected value, then the household will be risk loving. The risk averse household has a concave utility function and the slope of the function will be flatter as income increases. The risk loving household has a convex utility function and its slope gets steeper as income increases. Thus, the curvature of the utility function measures the household's attitude towards risk. In general, the more concave the utility function, the more risk averse the household will be, and the more convex the utility function, the more risk loving the household will be (Varian 2003). The intermediate case is the linear utility function, in which the household is risk neutral. The expected utility of income is the utility of its expected value. At this stage the household does not care about the risk of income at all but only about the expected value.

Figure 3.1: Risk and utility curve



Source: Varian (2003, p.225)

It is a common practice to assume that all households are indifferent to risk, meaning that the utility function and risk aversion coefficient are the same as well. Arrow (1965) suggests to assume a relative risk aversion coefficient of 1 if no other information is available. Anderson and Dillon (1992) propose a classification of the degree of level of risk aversion, based on the magnitude of the relative risk aversion coefficient, as follows:

$r_r(y) = 0.5$, hardly risk averse at all

$r_r(y)$=1.0, somewhat risk averse (normal)

$r_r(y)$=2.0, rather risk averse

$r_r(y)$=3.0, very risk averse

$r_r(y)$=4.0, extremely risk averse

This study considers $r_r(y) = \gamma$ of 2.0 assuming households are rather risk averse for decision making on their livelihoods, crop pattern, education, savings, and overall income-expenditure routine from the previous experience of flood (downside risk) disasters.

3.2 Indicators of Vulnerability to Flood Risk

Vulnerability is not to be identified by simple indicators. A multifaceted system is needed to determine vulnerability of a society or households. The framework and measurement of vulnerability generally commence with the terminology risk, and the interaction of risk, risk exposure, risk management and outcomes is identified as vulnerability. The sources of risks are arranged by Holzmann and Jørgensen (2000, p.12) as follows (table 3.1):

Table 3.1: Sources of risks

Indicators	**Micro**		**Meso**	**Macro**
	Idiosyncratic			*Covariate*
Natural			Rainfall Landslides Volcanic eruption	Earthquakes **Floods** Drought Strong wind
Health	Illness Injury Disability		Epidemic	
Life-cycle	Birth Old age Death			
Social	Crime Domestic-violence		Terrorism	Civil strife War Social-upheaval
Economic		Unemployment Harvest failure Business-failure	Resettlement	Balance of payment Financial or currency crisis Trade shock
Political		Ethnic discrimination	Riots	Election of leadership
Environmental			Pollution Deforestation Nuclear disaster	

Note: Concepts are adopted from Holzmann and Jørgensen (1999), Sinha and Lipton (2000)

Holzmann and Jørgensen (2000) indicate floods as the natural source of risk which is a macro level covariate event. They also identify the idiosyncratic risk which is uncorrelated (micro), covariate risk which is correlated among individuals (meso as regional covariate and macro as nation-wide covariate), repeated risk which occurs over time, and bunched risk which occurs with other risks. Floods in rural Bangladesh occur almost each and every year but at different scales, and the ability to respond to such downside risks also differs among households. Therefore, this study considers the monsoon and flash floods during the year 2005 as downside risks that may cause idiosyncratic (households specific) and covariate (community level) vulnerabilities. Both these vulnerabilities to floods differ according to perceptions of flood risk, ability and intensity of flood risk management. Such a flood risk management strategy can be categorized into three broad strategies, as shown in table 3.2, such as: (i) *prevention strategy*-this strategy is to be introduced before a flood risk occurs to reduce the probability of downside effects of floods; it entails e.g. building dams, digging cannels or river beds; (ii) *mitigation strategy*- this strategy is also to be employed before the flood risk occurs as to decrease the potential impact of future downside flood risk. Diversification of income sometimes reduces the downside variability for floods by relying on a variety of assets. The acquisition and management of different assets, such as durable, productive, human and social capital, play significant roles in different forms. For example, if any woman cannot own or inherit land by any religious or ethnical rules, she may acquire gold and jewels that could help her for flood risk management. Introducing risk based formal and informal insurance systems may have advantages for the flood prone society. (iii) *coping strategy*- this strategy is to be taken after the flood occurs as to relieve the impact of flood. After the flood risk has occurred, different types of coping strategies are taken by the households, such as borrowing, migration, selling labor and assets, reduction of food intake, or the reliance on public or private transfers. Based on the above discussion, the following table summarizes the plausible flood risk management strategies in the context of Bangladesh.

Table 3.2: Strategies for flood risk management

Categories	Strategies
Risk Reduction	Building dams
	Digging cannels
	Digging river beds
	Relocation of households from floodplains/permanent migration
Risk Mitigation	Generate and regulate a good flood action plan
	Investment in multiple human, durable and productive assets
	Investment in social capital
	Diversification of incomes
	Early warning system of flood
	Building flood shelter
	Support for financial markets to the flood prone areas
	Introduce micro credit programs to initiate savings for flood risk
	Formal insurance system in flood prone areas
	Community based insurance system in flood prone areas
	Initiate some pension systems for women, disabled, old age, sick people
Risk Coping	Selling assets, labor
	Borrowing money, food items
	Spend money from savings
	Seasonal/temporary migration
	Sending children to work
	Charity, aid, relief

Source: Author's own compilation

Households facing risky events like floods may incur welfare loss due to inefficient risk management strategies. This inefficiency can be associated with the missing or incomplete financial and insurance markets in disaster prone areas, improper risk realization of households and absence of social networks (Holzmann and Jørgensen 1999, 2000). Although this study focuses only on the economic vulnerability to floods through income fluctuations of rural households, the following table 3.3 lists different indicators for the estimation of vulnerability to floods in rural Bangladesh:

Table 3.3: Indicators of vulnerability to floods

Areas	Proxy variables/ Indicators
Ecological	• Proportion of geographical area under river and distribution of water levels in different seasons and years • Proportion of coastal areas and population density • Projection of sea level rise and inundation of land • Drainage systems • Degradation of land, forest, vegetation and waterbed for floods • Quality of drinking water
Economic	• Per capita income (poverty, inequality) • Per capita consumption expenditure for food and non-food items (poverty, inequality) • Per capita durable and productive asset holding (poverty, inequality) • Inefficiency of insurance and credit markets • Economic corruption (competition for scarce resources and savings for risks)
Social	• Inefficiency of community organizations • Gender discrimination • Access to public services (electricity, roads, transport) • Flood shelter and warning system • Insecurity in flood shelter (specially for girls) • Insecurity and violence during floods (theft, robbery, highjack) • Social corruption (breakdown of customs, principles) • Discrimination among castes, tribes and different religious population
Empowerment	• Patron-client exploitation • Inactive chain of order
Policy oriented	• Institutional malfunction • Loopholes of Flood Action Plan (FAP) • Share of water levels with India and Nepal during, before and after monsoon seasons
Others	• Nutritional status • Educational level • Health condition (disease, illness) • Child labor

Source: Author's own compilation

3.3 Methodologies for Estimating Vulnerability

As Hoddinott and Quisumbing (2003, p.1) state concepts of vulnerability are still at the 'let a hundred flowers bloom' stage; therefore, it depends on the researchers how to define or estimate vulnerability on the basis of policy and intervention. This study includes cross-sectional data on rural households' income, expenditure and other characteristics to assess vulnerability to floods in Bangladesh during the year 2005. Four methodologies from the poverty dynamics literature are used in this study. These are suitable to estimate households' vulnerability for cross-sectional and short panel data and are described in the following sections.

3.3.1 Vulnerability to Poverty Line

Pritchett, Suryahadi and Sumarto (2000) define vulnerability as the probability that a household will experience at least one episode of poverty in the near future. The vulnerability threshold is defined by 50-50 odds, meaning that if a household has the probability of falling into future poverty is greater than or equal to 0.5, it will be vulnerable. They suggest a vulnerability to poverty line (VPL), as the level of expenditures (for this study per capita monthly income) below this line will be classified as vulnerable. The VPL also allows the calculation of the head count vulnerability rate which is the direct analogue of the head count poverty rate.

Vulnerability of household h for n periods {denoted here $R(.)$ for risk} is the probability of observing at least one episode of poverty within n periods, which is 1- probability (no episodes of poverty). The equation is:

(1) $$R(n, PL) = 1 - [(1 - P(y_{t+1}^{h} < PL)) * .... * (1 - P(y_{t+n}^{h} < PL))]$$

Here, PL is the poverty line, y is the per capita monthly income (the literature originally used real current consumption expenditures), $P(.)$ is the probability and t denotes time.

Some points can be highlighted from equation (1). Firstly, as the incomes at time t are known, it is also possible to calculate whether the household is currently poor or not. In the future, many households who are currently poor may rise out of poverty in the next n periods, so the future vulnerability of the currently poor is less than one. Secondly, the poverty line (PL) is assumed as time invariant and the real income value may be inflated or deflated, as a constant poverty line may represent a constant level of welfare over time.

A household is defined as vulnerable if the risk in n periods is greater than a threshold probability level p:

(2) $V_t^h(p,n,PL) = I[R_t^h(n,PL) > p]$

where $I(.)$ is an indicator function. So, the authors measure the vulnerability as a risk which comes in degrees (between zero and one). It was mentioned earlier that the threshold probability level, to define a vulnerable household, will be 0.5. This property has two good qualities. Firstly, 50-50 odds is a nice focal point and it makes a household to be vulnerable with equal probability if it faces even odds or worse. Secondly, if a household faces a mean zero shock while income is just at the poverty line, then the household has a one period ahead vulnerability of 0.5. In the limit theorem, if the time horizon n goes to zero, then 'in current poverty' and being 'in current vulnerability' coincide.

The change in income for two subsequent periods will naturally be $\Delta y_{t+1} = y_{t+1} - y_t$. This method also assumed that there is a time invariant trend (the expected increase of household h's income in each period is μ) and the variability of inter-temporal change in income (the literature used consumption) for each household is σ. This variability does not account for the income differentials across households. So, the probability of a household with income in the current period of y_t falling into poverty in the next period is just the probability that the negative shock to income is greater than the current amount of the poverty gap, by which the household's income exceed the poverty line $(y_t - PL)$, plus the expected change in income (μ).

(3a) $P(y_{t+1}^h < PL) = P(\Delta y_{t+1}^h < -(y_t^h - PL))$

or, (3b) $P(y_{t+1}^h < PL) = P((\Delta y_{t+1}^h - \mu^h)/\sigma^h < \{-(y_h^t - PL) - \mu^h\}/\sigma^h)$

The latter probability is:

(4) $$P = \int_{-\infty}^{(PL-y_t^h-\mu^h)/\sigma^h} f((\Delta y_{t+1}^h - \mu^h)/\sigma^h) d\Delta y$$

where $f(.)$ is the density function of Δy. The authors assume the household's expected income in each period to be the same, that is $\mu = 0$ and $E(y_{t+n}) = y_t$.

This assumption has two advantages. Firstly, it will give the answer to the hypothetical question: if the household's incomes were to remain constant but it faces the current variability of income by shocks, what is the probability that it will fall into poverty? Secondly, the assumption can be modified easily later on if one is willing to make explicit prediction about the expected future growth (or fall) in earnings (for average as well as specific household).

The authors also assume that Δy_{t+1} is independently and identically distributed (iid) in each period and that the distribution of the changes in income is normal. Assumptions of inter-temporal independence and normality are made for convenience in calculation. Now, the vulnerability of a household for any given level of current income (y) is:

(5) $$R(n, PL, y, \sigma) = 1 - [1 - \int_{-\infty}^{(PL-y)/\sigma} N(0,1)]^n$$

The number of vulnerable households can be measured by creating vulnerability to poverty line (VPL) as a function of time period, probability of poverty and the change in income. The VPL is that level of income such that, from the time period t, the probability of at least one episode of poverty in n periods is just p:

(6) $$VPL(p, n, PL, \sigma) solves, 1 - \int_{-\infty}^{(PL-VPL)/\sigma} N(0,1) = [1-p]^{1/n}$$

Cross-sectional data only gives the estimate of income variability across households. But with a two periods panel data set (like before and after flood income) one can estimate the variability of household specific income, but with extremely large imprecision. Moreover, such a two period's panel could give the variability of income by groups of households, for example, comparing farmers versus businessmen, or landless households to land owner households. An extension may be to estimate the variability as a function of a number of households' characteristics with a multivariate procedure and using the households' predicted variability in the vulnerability analysis.

Households from the panel data set could permit to estimate the variability of changes of income for the category j:

(7) $$\sigma_{\Delta y}^{j} = \sqrt{\frac{(\Delta y_h^j - \Delta y_h^{-j})}{N_j - 1}}$$

Now, the household specific variance may be caused by any macroeconomic shock that left all households' incomes changed at the same amount. This is a major limitation of this procedure for estimating household variability from panel with only two observations. This could even become worse by the inclusion of the measurement error. Any observed household income at time t can be decomposed into the three parts, namely, one: permanent component (PR) of income, two: transitory (TR) component, and three: measurement error (v).

(8) $$y_h^t = y_h^{PR,t} + y_h^{TR,t} + v_h^t$$

When the three variances (σ^2) are uncorrelated, the ratio of measurement error (or, noise) to total variance will be:

(9) $$\sigma_v^2 / (\sigma_{PR}^2 + \sigma_{TR}^2 + \sigma_v^2)$$

Some empirical studies find that the measurement error in cross-sectional surveys lies in between one-third to half of the total variance. This error is often ignored in poverty analysis for some reasons. Firstly, it may flatten the poverty profile by lowering the gap between groups. Secondly, no clear vision about the estimation and remedial procedure of measurement error is given.

One heuristic way followed by Pritchett et al. (2000) to estimate measurement error is to estimate any equation with income as the right hand side variable using both OLS (ordinary least square) and instrumental variable techniques. The expression for the lessening bias in OLS estimates in a bivariate regression is:

$$(10) \quad \beta_{OLS} = \beta(1 - \frac{\sigma_v^2}{\sigma_*^2})$$

Here * represents the total variance. When there exists an instrumental variables (IV) estimate which is consistent, then one minus the ratio of the OLS to the IV estimate is an estimate of the noise to total variance ratio.

3.3.2 Vulnerability to Expected Poverty

Chaudhuri, Jalan and Suryahadi (2002) define a household as vulnerable if it is expected to be poor in the near future. This concept is widely known as the vulnerability to expected poverty (VEP) approach. Poverty itself is a stochastic phenomenon. Currently, a poor household may or may not be future poor, consequently non-poor household may face a severe adverse shock and become poor after the disaster. A household's observed poverty is often defined as the household observed level of consumption or as income relative to a pre-selected poverty line. So, poverty is the ex post measurement of household's wellbeing. To reduce poverty permanently it is necessary to know the ex ante risk that a household will, if currently non-poor, fall below the poverty line, or if poor, will remain in poverty. This ex ante measure is defined by vulnerability, which helps to design a forward-looking poverty reduction strategy. This methodology was also described and used in other studies (Christiaensen and Boisvert 2000, Chaudhuri 2003). Despite the obvious limitations (heteroscedasticity and dynamic changes of household characteristics along time periods) of cross-sectional data, a detailed analysis may potentially be informative about the future. According to the VEP method, the vulnerability level of a household i at time t is defined as the probability that the household will be in income poverty at time $t+1$:

$$(1) \quad v_{it} = \Pr(y_{i,t+1} \le z)$$

where $y_{i,t+1}$ is the household's per capita income level (welfare indicator) at time $t+1$ and z is the income poverty line. Therefore, the level of vulnerability at time t is detected by the future income of a household at time $t+1$. This entails that the poverty status of a household is concurrently observable but vulnerability is not; only one could estimate or make inferences about whether a household is currently vulnerable to future poverty. Vulnerability estimate needs to make inferences about the household's future consumption or income prospects. So the inter-temporal variations across households and cross-sectional determinants of income levels are required for this approach.

Household future income may depend on its wealth, current income, expectations for future income, the risk (as flood shock) it faces regarding future income and its ability or options to mitigate the risk. Each of these determinants is depending on a variety of household characteristics, some of which are observable and some are not. From a general conceptual point of view, an expression for income level can be defined as:

(2) $y_{it} = f(X_i, \beta_t, \alpha_i, e_{it})$

where X_i is a bundle of observable household characteristics, f is the functional form, β_t is a vector of parameters representing the state of the economy at time t, α_i is an unobserved time-invariant household-level effect, and e_{it} represents the effect of a shock factor that contributes to differential welfare outcomes for households that are otherwise observationally equivalent.

From equations (1) and (2) the expression of vulnerability of a household can be rewritten as:

(3) $v_{it} = \Pr(y_{i,t+1} = f(X_i, \beta_{t+1}, \alpha_i, e_{i,t+1}) \leq z \mid X_i, \beta_t, \alpha_i, e_{it})$

The above equation shows that a household's vulnerability level derives from the stochastic properties of the inter-temporal income stream it faces, which in turn depends on a number of household characteristics. The expression in equation (3) has some suitable properties: firstly, it allows the possible interactions between the cross-sectional determinants of a household's vulnerability level; secondly, a household's vulnerability is defined in terms of the future income conditional on its current characteristics, both observed and unobserved, so the poverty traps and other non-linear poverty dynamics are also incorporated; thirdly, the time varying parameter β_t includes the possible contribution of aggregate shocks and unanticipated structural changes in the macro-economy to vulnerability of household level.

The probability that a household will be vulnerable depends not just on its expected (mean) income in a future period, but also on the volatility (variance from an inter-temporal perspective) of its income stream. To estimate vulnerability of a household the expected income and its income variance are needed. For longitudinal data, one may estimate the inter-temporal variance of income at the household level without any auxiliary assumption, but for a cross-sectional data set some assumptions are required. The assumptions also limit the degree of unobserved heterogeneity (measurement error) in the future income prospects of households who are observationally identical along a number of characteristics.

The assumptions for cross-sectional data begin with the stochastic process, generating the income of a household i:

(4) $\ln y_i = X_i \beta + e_i$

where y_i represents the per capita income before flood, X_i is a set of observable household characteristics, such as:

demographic factors: family size, dependency ratio (ratio of the number of household members of 0-14 years and 60 years over to the number of members of 15-59 years), number of male and female members above 18 years, age and age squared of household head, mean educational years of income earners, gender of household head and major source of income; and *economic factors*: per capita cultivable land, per capita asset value, distance and cost to reach nearest market place, access of media and ownership of dwelling place.

In equation (4), β is a vector of parameters and e_i is a disturbance term with mean zero, which captures the effect of a shock (loss of assets, income, expenditure and livelihood) that contributes to different per capita income levels of households that are otherwise observationally equivalent. It is also assumed that e_i is independently and identically distributed over time for each household, but e_i is not identically distributed across households. This assumption ruled out the effects of serially correlated flood shocks and unobserved household-specific variations. Another assumption is taken on the structure of the economy (captured by the vector β) that is relatively stable over time, so β is taken instead of β_t {as in the equation (3)}. This assumption ruled out the possible effect of any aggregate shock and unanticipated structural changes in the economy, so the uncertainty about the future income stems only from the changes of e_i. The zero mean assumption of e_i stands for the unbiasness property of the estimates of β's but the homogeneity assumption is not considered, as the variance of $\ln y_i$ is usually less than that of y_i; so the heteroscedasticity will also be less in the log-linear ($\ln y_i$) model than in the linear one (y_i).

Another assumption is made on the functional form of the variance of e_i (and hence of $\ln y_i$), that is, the variance of e_i depends on the observable household characteristics in the following parametric way:

(5) $\sigma^2_{e,i} = X_i\theta$

The estimation of the parameters β and θ from models (4) and (5) can be carried out by the three-step Feasible Generalized Least Squares (FGLS) procedure suggested by Amemiya (1977). The reasons for using FGLS estimates are: for the remedy of the heteroscedasticity in the error term in equation (4) GLS procedure could be suitable for estimating β, but obtaining the GLS estimator $\hat{\beta}$ requires knowing $\sigma^2_{e,i}$ up to a scale where $\sigma^2_{e,i}$ is a known positive definite matrix but this study assumed the matrix in terms of the households characteristics X_i and a vector of parameters θ. Therefore, the analysis takes into account FGLS estimation procedure (Wooldridge 2002, p. 157). In FGLS estimation the unknown matrix $\sigma^2_{e,i}$ is replaced with a consistent estimator. FGLS also gives the robust estimation through checking the autocorrelation in the e_i's .The estimation steps are described as follows:

Firstly, the estimation procedure applies the OLS method to equation (4) and estimates the residual. Then, the estimated residual is squared to estimate the following equation:

(6) $\hat{e}^2_{OLS,i} = X_i\theta + \eta_i$

An OLS procedure is again utilized by regressing $\hat{e}^2_{OLS,i}$ on some households' characteristics to measure inter-temporal variance of log-income across households. The OLS estimate $\hat{\theta}_{OLS}$ of the parameter θ is found from the equation (6). For overall sample and non-flooded households, the $\hat{e}^2_{OLS,i}$ would be regressed on demographic and economic factors. For flooded households, $\hat{e}^2_{OLS,i}$ would be also regressed on demographic and economic factors but with the addition of *coping factors* (such as: per capita loan for flood, withdrawal of savings for flood, membership of the cooperation), *shock factors* (such as: flood height and duration, loss of working days, loss of asset value, loss of crop value), and *community characteristics* (such as: availability of electricity, flood shelter, public hospital, primary school). The term η_i is the disturbance term which allows the measurement error in the survey data that inflates the volatility. Here the simultaneity problem arises because the regressors are endogenous according to equations (4) and (6), that is, the error term in equation (4) is correlated with the X_i's. Therefore, the next steps are taken to find the consistent and efficient estimators.

Secondly, the estimate $\hat{\theta}_{OLS}$ is used to transform the equation [6] as follows:

(7) $$\frac{\hat{e}^2_{OLS,i}}{X_i\hat{\theta}_{OLS}} = \left[\frac{X_i}{X_i\hat{\theta}_{OLS}}\right]\theta + \frac{\eta_i}{X_i\hat{\theta}_{OLS}}$$

The transformed equation is estimated once more using OLS and to get the estimate $\hat{\theta}$ of the parameter θ, which in turn is the asymptotically efficient FGLS estimate, $\hat{\theta}_{FGLS}$. Thus it solves the inefficiency problem as a consequence of heteroscedasticity. It is also feasible to get a consistent estimate, $X_i \hat{\theta}_{FGLS}$, of $\sigma^2_{e,i}$, the variance of the shock factor of household income. The standard deviation can be evaluated as follows:

$$(8)\ \hat{\sigma}_{e,i} = \sqrt{X_i \hat{\theta}_{FGLS}}$$

Thirdly, to estimate β, equation [4] is transformed as follows:

$$(9)\ \frac{\ln y_i}{\hat{\sigma}_{e,i}} = \left[\frac{X_i}{\hat{\sigma}_{e,i}}\right]\beta + \frac{e_i}{\hat{\sigma}_{e,i}}$$

An OLS estimation of equation (9) yields a consistent and asymptotically efficient estimate $\hat{\beta}_{FGLS}$ of the parameter β. Therefore, using the FGLS estimates of β and θ, the methodology finally estimates the expected value and variance of log per capita income as follows:

$$(10)\ \hat{E}\{\ln y_i | X_i\} = X_i \hat{\beta}_{FGLS}$$

and the variance of log per capita income for each household i as given below:

$$(11)\ Var\{\ln y_i | X_i\} = \hat{\sigma}^2_{e,i} = X_i \hat{\theta}_{FGLS}$$

By assuming that income y_i is log-normally distributed (that is, $\ln y_i$ is normally distributed) and using the above estimates, it is possible to form an estimate of the probability that a household with characteristics X_i will be poor after flood or vulnerable due to flood shock. Letting $\Phi(.)$ denote the cumulative density of the standard normal distribution, the estimated probability can be expressed as follows:

$$(12)\ \hat{v}_i = \hat{\Pr}(\ln y_i < \ln z | X_i) = \Phi\left[\frac{\ln z - \{\ln y_i | X_i\}}{\sqrt{Var\{\ln y_i | X_i\}}}\right]$$

$$= \Phi\left\{\frac{\ln z - X_i \hat{\beta}}{\sqrt{X_i \hat{\theta}}}\right\}$$

The value of $\hat{v}_i$ varies from 0 to 1. The estimate $\hat{v}_i$ thus denotes the vulnerability of the ith household with the characteristics X_i. The vulnerability threshold is assumed 0.50.

The choice of a vulnerability threshold is somewhat arbitrary, so this study uses a threshold of 0.50 as a possible focal point that a household whose vulnerability level exceeds 0.50 is more likely to be poor in the near future (Chaudhuri et al. 2002). Then another point remains to be addressed about the time horizon over which a household's vulnerability to poverty or flood shock is to be identified. This study considers a time horizon of one year which is also an arbitrary decision. The variance of the disturbance term $\sigma_{e,i}^2$ is incorporated in this framework as the economic term representing the inter-temporal variance of log income. The estimates of the mean and variance of income are not monotonically related across households allowing the possibility that a household with lower mean income may nevertheless face larger income volatility than a household with a higher average level of income. Accounting for heteroscedasticity in the disturbance term in equation (4) shows that the OLS estimate $\hat{\beta}$ is still linear, unbiased and consistent despite heteroscedasticity, that is, if the sample size increases indefinitely, the estimated β converges to its true value. But with a loss of efficiency, $\hat{\beta}$ is no longer best and has not the minimum variance (Gujarati 2003, p.394). That is why the estimation procedure incorporates weighted least squares estimates (WLS) in the equation (7) for the remedy of heteroscedasticity.

Some unavoidable issues are addressed in this methodology to estimate vulnerability. One important issue is measurement error in the observed data on income or consumption expenditure from a household survey. The presence of such error could lead to a significant overestimate of the variance of log income. To control for this error the predicted mean income is equalized with the actual mean income for each of the four districts for which separate sets of regressions are executed. This adjustment also fixes the overestimates of variance because of deterministic factors of income which remain unobserved. This study does not incorporate any district-wise dummy variables to estimate vulnerability for overall, flooded and non-flooded sample households. It could be interesting to measure the effect of unobserved district-wise shocks that are common to households in particular areas. If a set of area dummies is introduced in log income {in equation (4)} to capture the effects of district-wise common shocks, and if it includes the estimates of dummies for estimating the mean of log income, then the later estimate would be biased (upside or downside). If a set of area dummies is included in the variance-estimating equation, then another risk would appear by overestimating the variance of log income for households in districts that experience higher relative shocks. The reason for including district-wise dummies is to control for the unobserved but deterministic factors of income, but for the above mentioned issues this study does not include any district-wise dummy in any of the regressions. Therefore, vulnerability estimates are performed for each district separately.

3.3.3 Vulnerability to Expected Utility

This study also applies the utilitarian approach defined by Ligon and Schechter (2003), which is known as vulnerability to expected utility (VEU). Household's welfare depends not only on the average income or expenditure or the value of resources, but also on the risk it faces. A household with low income and facing fewer risks, might be in poverty but future well-being may be higher than for a household with a high level of income but facing a higher risk. That is why vulnerability comes into the focal point.

It is assumed that a finite population of households indexed by i = 1,2,…..,n and $\omega \in \Omega$ denote the state of the world. For the analysis of welfare, the authors choose household's consumption expenditure but here it is explained by household's per capita monthly income. Households want to stable their welfare over time, even if consequent risks occur. Presumably, consumption expenditure is preferred over income because the latter is more volatile (Dercon and Krishnan 2000). But due to limitation of the consumption data in the given sample, this study uses rather income as welfare measure. The distribution of household i's income is denoted by: $y^i(\omega)$. If the household is risk averse, then the utility function will be concave and its slope will be flatter as the wealth increases. So, the curvature of the utility function measures the household's attitude towards risk. Basically, the more concave the utility function, the more risk averse the household will be (Varian 2003). To measure vulnerability, for each household, a strictly increasing and weakly concave function U^i is chosen, such as: $\Re \rightarrow \Re$ mapping income into the real line. Given the utility function, vulnerability of household i is defined as

(1) $V^i(y) = U^i(z) - EU^i(y^i)$

Here z is some certainty-equivalent income, such that if household i had certain income greater than or equal to this number, the household would not be regarded as vulnerable. So, the choice of z may be analogous to the 'poverty line'. This study considers z as the poverty line. The survey data was collected after flood, 2005, so poverty line is taken from the nationally representative report (BBS 2004), which is 594.60 Taka[3] per capita per month. The properties of the utility function imply that vulnerability estimates will include mean and variance of household's income. But for some cases, while a certain individual household (whose expected income is greater than the expected per capita income) may have a negative measure of vulnerability, the concavity of U ensures (by Jensen's inequality[4]) that the average vulnerability of the total sample is a non-negative number.

For a better understanding, the vulnerability measure in this study is decomposed into distinct factors, such as: poverty, aggregate risk, idiosyncratic risk, and unexplained risk and measurement error respectively. The idiosyncratic risks such as unemployment, illness or death of a household member affect the individuals of any household and are measured by the variation of the inter-household variables. Aggregate or covariate risks like natural disasters, financial crises or epidemics affect a large number of people in a community or region and are estimated from the alteration of inter-community variables (Dercon 2001). In equation (1), the static nature of the vulnerability function is defined to estimate risk. Equation (2) is introduced to capture variation over time, the household i's income at time t is denoted by y_t^i, idiosyncratic variables as x_t^i and the vector of aggregate variables as $\bar{x}_t$.

[3] In the year 2005, 80 Taka = 1 Euro, so the poverty line (594.60 Taka) = 7.43 Euro

[4] Jensen's inequality: let X be a non-degenerate random variable and $f(X)$ be a strictly concave function of this random variable. Then $Ef(X) < f(EX)$.

(2) $V^i = [U^i(Ey) - EU^i(Ey_t^i)]$ (Poverty)

$+[EU^i(Ey_t^i) - EU^i(E(y_t^i \mid \bar{x}_t))]$ (Aggregate Risk)

$+[EU^i(E(y_t^i \mid \bar{x}_t)) - EU^i(E(y_t^i \mid \bar{x}_t, x_t^i))]$ (Idiosyncratic Risk)

$+[EU^i(E(y_t^i \mid \bar{x}_t, x_t^i)) - EU^i(y_t^i)]$ (Unexplained Risk and Measurement Error)

The first bracketed term in equation (2), which measures poverty, involves no random variable. It is just the difference between a concave function evaluated at the poverty line and at household i's expected income. The concavity of U^i implies that as Ey^i approaches the poverty line, an additional unit of expected income has diminishing marginal value in reducing poverty. For a suitable choice of $\{U^i\}$ the methodology claim's that the poverty measure will satisfy all the axiomatic requirements enumerated in Foster et al. (1984)[5]. The rest of the terms in equation (2) jointly focus on the risk faced by household i, which is consistent with the ordinal measures of risk proposed by Rothschild and Stiglitz (1970) and Ligon and Schechter (2003) further decomposed the risk terms claiming that any monotone transformation would retain the properties.

Three additional assumptions were taken for estimating vulnerability to floods through this approach: first, $\{U^i\}$ takes the simple form $U^i(y) = (y^{1-\gamma})/(1-\gamma)$ for some parameter $\gamma > 0$; as γ increases, the function U^i becomes increasingly sensitive to risk. The parameter can be interpreted as the household's relative risk aversion. In the microeconomic literature (Hardaker et al. 2004, Ligon and Schechter 2002), it is often assumed that γ=2. This study also estimates vulnerability by assuming γ=2.

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[5] Foster, Greer and Thorbecke (1984) proposed a class of poverty measures, $p_\alpha = \frac{1}{N}\sum_{i=1}^{G}\left(\frac{z - y_i}{z}\right)^{\alpha}$, where z is the poverty line, y_i is the i th household's income, N is the total population size, p is the poverty, α is the risk averse parameter and households are ordered from bottom to top: $y_1, y_2, \ldots., y_G, z, y_{G+1}, \ldots. y_N$.

The second assumption relates to the estimate of conditional income to measure vulnerability. It is assumed that $E(y_t^i \mid \bar{x}_t, x_t^i) = \alpha^i + \eta_t + x_t^i\beta + v_t^i$, where $\theta = (\alpha^i, \eta_t, \beta')$ is a vector of unknown parameters to be estimated. Here, $\{\alpha^i\}$ shows the influence of household's fixed characteristics on predicted per capita income and is restricted to sum to zero; $\{\eta_t\}$ captures the effect of changes in aggregates and $\{\beta'\}$ is the vector of parameters for household's idiosyncratic variables; v_t^i is a disturbance term equal to the sum of both measurement error in income and prediction error.

The fourth bracketed term in equation (2) shows unexplained risk and measurement error which can neither be explained by the household characteristics, nor by aggregate variables, but which is due to unobservable and to measurement error in income. Idiosyncratic risk {third bracketed term in equation (2)} could further be decomposed into k distinct sources following the procedure of Gram-Schmidt to find an orthogonal set of predictors.

The third assumption for the estimation procedure relates to the stationary environment. So, the unconditional expectation of household i's income is estimated by $Ey_t^i = \frac{1}{T}\sum_{t=1}^{T} y_t^i$. For this analysis, θ is chosen so as to optimally predict y_t^i in a least square application. Here the measurement error is separated from other explanatory variables, which will only influence the measure of unexplained risk. So, the measures of aggregate and explained idiosyncratic risk will not be biased by the measurement error.

3.3.4 Vulnerability Estimate using Monte Carlo Bootstrap Simulation

Kamanou and Morduch (2002) developed a framework that combined Monte Carlo and Bootstrap statistical techniques to estimate vulnerability. This approach estimates the expected distribution of future expenditures for each household based on panel data from the Ivory Coast. The vulnerability for households is measured as a function of the distribution of future expenditures. This study adopts the methodology for estimating vulnerability from a short panel data set of flooded people and applies income as the welfare measure instead of consumption expenditure.

In many survey studies, poor households are often identified as vulnerable for the condition that takes into account both exposure to serious risks (as a consequence of flood shock) and defenselessness against deprivation. Often defenselessness is defined as a function of social marginalization that ultimately results in economic marginalization (Kanbur and Squire 2001).

The microeconomic theory of expected utility shows that the expected utility of risk averse individuals falls as the variability of income or consumption rises, keeping all other factors the same. If the utility function and expected income patterns of all individuals are known, then poverty could be measured in terms of certainty-equivalent level of income. An alternative and interesting measure of poverty and variability is found in the income mobility literature (Shorrocks 1978, Fields and OK 1999). The mobility literature focuses on historical patterns, not forthcoming ones. This study is set forth to examine the transient poor and vulnerable due to flood from the two observations on a set of households. Historical pattern is of course important to examine the path of progress, but for policy purposes it is more crucial to generate measures that allow targeting groups that are vulnerable to shock, not just those households that can be identified as actually having suffered in retrospect.

Monte Carlo simulation with the bootstrap is a nonparametric method for estimating the standard error of sample parameters (Efron and Tibshirani 1994). The initiative is to generate a distribution of possible future outcomes for households, based on their observed characteristics and the observed income fluctuations. In this framework (Kamanou and Morduch 2002) vulnerability in a population is defined as the difference between the expected value of a poverty measure in the future and its current value.

(1) $EP_{\alpha t+1} - P_{\alpha t} = \frac{1}{N}\sum_{i=1}^{G_{t+1}}\sum_{S}\Pr(s, y_{it+1})\left(\frac{z-y_{it+1}}{z}\right)^{\alpha} - \frac{1}{N}\sum_{i=1}^{G_t}\left(\frac{z-y_{it}}{z}\right)^{\alpha}$

Where E is the expectation operator, and s is a given state of the world. The joint probability distribution with Y_{t+1} is $\Pr(s, y)$, G_t and G_{t+1} are the number of poor households in the before and after flood periods respectively, and y_{it} and y_{it+1} denote the before and after flood per capita income, respectively of household i. The assumption is that the true distribution of possible outcomes in the next period for households (y_{it+1}) could be known. The empirical problem is that the joint distribution of s and y_{it+1} is not known and the states of the world might be latent variables with an unknown distribution. So the idea is to generate a distribution of possible future outcomes for households to take up the unknown joint distribution $\Pr(s, y)$, based on the households observed characteristics and the observed income fluctuations of similar households. The bootstrap technique allows to construct several versions of possible future data by re-sampling the original data. The expected value is then estimated by the mean of the bootstrap estimate of $P_{\alpha t+1}$.

The approach is initiated with the base year (before flood) of the panel and generating a large number (B = 1000) of independent bootstrap samples. A bootstrap sample is a random sample of size n drawn with replacement from the empirical distribution of some observed data of size n (Efron and Tibshirani 1994). For each bootstrap sample, a regression equation is constructed to predict the variation in income based on its correlation with a set of households' characteristics. The linear predicted value is then augmented with predicted residuals regressed on some households' covariates and flood shock variables. This yields a predicted per capita income of the future period (after flood) for each household in each of the bootstrap samples. From these bootstrap samples, $P_{\alpha t+1}^{b}$ for each b from 1 to 1000 can be estimated and then $EP_{\alpha t+1}$ can be enumerated as the mean of $P_{\alpha t+1}^{b}$. The algorithm may be described by the following steps for each district:

Step1: First the analysis has to draw 1000 bootstrap samples from the original data, where $X = (x_1, x_2, x_3, \ldots\ldots, x_n)$ be the data on a given district (n is the number of households in the region) with $x_i = (y_{i1}, y_{i2}, h_1, h_2, \ldots\ldots, h_p)^T$; y_{i1} and y_{i2} are the first and second wave of household income and $h_1, h_{2,} h_3, \ldots\ldots h_p$ are the *pth* household covariates. Then $X^b = (x_1^b, x_2^b, x_3^b, \ldots\ldots, x_n^b)$, $b = 1,2,3,\ldots\ldots 1000$ are the bootstrap samples drawn by re-sampling $X = (x_1, x_2, x_3, \ldots\ldots, x_n)$ with replacement.

Step2: For each new bootstrap sample, a regression is run with the dependent variable $\delta_i = (y_{2i}^b - y_{1i}^b) / y_{i1}^b$ on the covariates $h_1, h_{2,} h_3, \ldots\ldots h_p$ and the Monte Carlo estimates of the future period of income are formed by: $\hat{y}_i^{mcb} = y_{1i}^b(1 + \hat{\delta}_i + \hat{\varepsilon}^{mc})$ where $\hat{\delta}_i$ is the fitted value from the regression for the household i, and $\hat{\varepsilon}^{mc}$ is formed from the following process: firstly, the residuals is found from the regression of estimating the future period income, secondly, the residuals are regressed on the households' covariates and flood shock variables (value loss of assets, change in cost to reach market place, loss of working days, height of flood water from homestead, duration of flood), and finally, the predicted dependent variable of second regression is taken as $\hat{\varepsilon}^{mc}$ with specification error check (by Ramsey's RESET test). The construction of the predicted equation for second period income is generated by a Generalized Linear Model (GLM) to fit the proportional change in the per capita income (δ_i) on household covariates including household size, age of the household head, per capita asset, average educational years of household earners and six dummies for seven categories of income sources (income from remittance is selected for benchmark or base category). GLM includes response variables that follow any probability distribution in the exponential family of distributions. The exponential family possesses distributions of Normal, Binomial, Poisson, Multinomial, Gamma, Negative Binomial, and others. GLM does not require normality assumption of the response variable to test the hypothesis, nor does it require homogeneity of variances. So, it is preferable to use GLM when response variables follow distributions other than the normal distribution, and when variances are not constant.

Step3: An estimate of the after flood poverty level based on the bootstrap sample is generated as: $\hat{P}^{mcb}_{\alpha t_2} = \frac{1}{n}\sum_{i=1}^{G_b}\left(\frac{z-\hat{y}^{mcb}_i}{z}\right)^{\alpha}$. So this is the Monte Carlo estimate of the after flood poverty obtained from the bootstrap sample.

Step4: The Monte Carlo bootstrap estimate of vulnerability for the population for the period (t_1, t_2) can be defined by: $V^{mcb}_{\alpha} = \hat{P}^{mcb}_{\alpha t_2} - P_{\alpha t_1}$.

3.3.5 Poverty Line

The value of the poverty line (z) measured by the Bangladesh Bureau of Statistics (BBS) 2004, is Taka 594.60 per person per month for rural Bangladesh. This poverty line measured by the FEI (Food Energy Intake) method is used in this study. The functional form of the relation between calorie intakes and expenditures considered by the BBS (2004) in estimating the poverty line is as follows:

(1) $\ln y_i = a + bx_i + e_i$

where y_i = per capita monthly expenditure (on food) for the ith individual

x_i = per capita daily calorie intake of the individual, and

e_i = disturbance term

Based on the above model and calorie intake (x_i) as well as monthly expenditure (y_i), obtained from Poverty Monitoring Survey (PMS) of 2004, the estimated poverty line equation for the rural areas was as follows:

(2) $\ln y_i = 3.862919735 + 0.001189897\ x_i$

To calculate the average poverty line for rural households ($\ln y$), the threshold per capita per day calorie intake (x) value is taken as 2122 kilo calorie. From the above equation, the poverty line was estimated at about Taka 594.60 per person per month. So the final equation results as follows:

(3) $\ln y = 3.862919735 + 0.001189897 * 2122$

$= 6.387881169$

(4) $y = 594.60$ (Taka)

3.4 Summary and Conclusion

There are a number of articles in the poverty dynamics literature which define and measure vulnerability in different ways. Four different types of methodologies are applied in this study, which are suitable for cross-sectional survey data, to estimate vulnerability to floods in rural Bangladesh.

Chaudhuri et al. (2002) and Chaudhuri (2003) use the vulnerability to expected poverty (VEP) method which is generalized from expected headcount measure of poverty. This measure endures some of the shortcomings of the headcount measure of poverty. According to this measure, a household might be denoted as highly vulnerable if its consumption is just above the poverty line and if the probability of facing risk is very low. Again, a household facing no risk but living in chronic poverty might be detected as less vulnerable. Pritchett et al. (2000) calculate vulnerability to poverty line (VPL) which is also the direct analogue of the headcount poverty line. The limitations of using standard deviation of consumption changes also exist in the VPL approach. Kamanou and Morduch (2002) introduce the Monte Carlo Bootstrap method to overcome the shortcomings of using standard deviation, and use cross-sectional variation to predict inter-temporal variation in consumption pattern of households similar to the VEP and VPL approaches. The vulnerability to expected utility (VEU) methodology suggested by Ligon and Schechter (2003) needs short panel data. This methodology disaggregates the vulnerability estimates among poverty, idiosyncratic risk, aggregate risk and unexplained risk. The following table 3.4 highlights concepts, shortcomings and advantages of the four methodologies used in this study.

Table 3.4: Comparison of four methodologies to estimate vulnerability

Indicators	Vulnerability to poverty line (VPL)	Vulnerability to expected poverty (VEP)	Vulnerability to expected utility (VEU)	Vulnerability using Monte Carlo Bootstrap
Concept	Vulnerability is the probability of a household falling into poverty at least in one episode during a specific period	Vulnerability is the probability that a household's consumption expenditure will fall below the poverty line in next time point	Vulnerability is the difference between the household's utility of certainty equivalent consumption and expected utility of consumption	Vulnerability is the difference between the estimated future period's poverty from bootstrap sample through Monte Carlo procedure and poverty of current period
Assumptions	• Future vulnerability of currently poor is less than one • Households consumption expenditure is expected to be the same in each period • Inter-temporal variation in expenditure is independent and identically distributed • Distribution of changes of expenditure is normally distributed	• cross-sectional variability of expenditure captures inter-temporal variability • Household's vulnerability to poverty is a non-linear function of its future consumption levels • Household's consumption is log-normally distributed • Inter-temporal variance of log consumption is interpreted as the variance of disturbance term and assume heteroscedasticity across households	• Strictly increasing, weakly concave utility function • Stationary environment • Households are risk averse	• Bootstrap simulation of future consumption expenditures with Monte Carlo technique • Stationary environment • Distribution of future outcomes of households depend on observed characteristics and observed consumption fluctuations of similar households
Outcomes	• The proportion of households that are vulnerable is higher than the current poverty rate • Female-headed households have higher variability in expenditure changes than male-headed households • The average vulnerability and headcount vulnerability rate are lower the higher educational level of households head	• Estimated vulnerable households are higher in rate than existent poverty level • Rural households are more vulnerable than urban households • Educational attainment of household head reduces vulnerability • Vulnerability is lower for salaried workers in the public and private sectors than other occupations • Households with high dependency ratio tend to be vulnerable	• Vulnerability could be reduced significantly by reducing poverty • Aggregate risks are more important than idiosyncratic risks • Households with employed and educated male heads are less vulnerable to aggregate risks than other households	Vulnerability rate is higher than the current poverty level

	• Rural household owners of land have lower vulnerability than rural landless • Average vulnerability and headcount vulnerable rate is higher in agriculture sector than other occupation	• Female-headed households are less likely to be poor and vulnerable than male-headed households • Access to clean water is associated with the sharpest drops in vulnerability		
Shortcomings	• Assumes cross sectional variation as inter-temporal variation • Limitations of using standard deviation of consumption expenditure to estimate vulnerability • Suffers from the same problems of absolute poverty line	• Strong assumption that cross-sectional variability of expenditure captures inter-temporal variability • Household with low average expenditure (chronic poor) may be identified as less vulnerable to any risk • More focused on consumption variability than mean level of consumption • Household exposed to increase level of uninsured risk may be identified as less vulnerable • Incorporates similar problems of absolute poverty line	• Needs panel data • Assume stationary environment rather than using any dynamic analysis	• Use cross-sectional households consumption variation to predict inter-temporal variation • Suitable only for stationary environment • Suffers with the problems related to absolute poverty measure
Advantages	• Needs only two rounds of panel data • Suitable for non-stationary environment • Robust to measurement error	• A single cross-sectional data set can be used to estimate vulnerability • Easily understandable approach • Currently non-poor households may be identified as vulnerable	• Robust to measurement error • Disaggregate vulnerability into poverty; idiosyncratic, covariate and unexplained risks • Suitable for stationary environment with measurement error	• Robust to measurement error • Overcome the problems of using standard deviation to estimate vulnerability • Needs short panel data

Source: Author’s own compilation based on Chaudhuri et al. (2002), Pritchett et al. (2000), Ligon and Schechter (2003), Kamanou and Morduch (2002)

Ligon and Schechter (2004) conduct Monte Carlo experiments to explore the performance of different estimators proposed by different authors, under different assumptions and economic environments. They find that if the environment is stationary, vulnerability is risk sensitive but consumption is measured with error, then the estimator based on the Ligon and Schechter (2003) approach performs best. When the distribution of consumption is non-stationary, then the estimator from the Pritchett et al. (2000) approach is suitable. This study considers a stationary environment before and after flood periods but with measurement error and heterogeneity in the household's income data. Therefore, theoretically the estimator from Ligon and Schechter (2003) would perform better than the other three methodologies used in this study; empirical analyses from survey data in later chapters could support this statement.

Chapter Four

4. Case Study: Bangladesh, Survey Area Profiles and Descriptive Analysis

This chapter gives some country-specific details on topography, climate, hydrology and flood patterns of Bangladesh which is relevant in the context of this study on floods. Details on the design of the survey sample, a brief description of the survey areas and some basic assumptions on the data set are also revealed in this chapter. Lastly, some descriptive results, as well as demographic and socioeconomic characteristics of flooded and non-flooded households among four different districts are shown in this chapter.

4.1 Country Background: Bangladesh

4.1.1 Topography of Bangladesh

The following section describes briefly the topography of Bangladesh that includes land condition, climate variability, the nature of hydrology and level of ground water (information adopted from Brammer 2004, BBS 2005). The geographical location, complex and diverse climatic phenomenon and exposed topography to floods make people of Bangladesh vulnerable to natural disasters.

Land

Bangladesh comprises a great diversity and complexity of geology combined with differences in climate, vegetation and land use. The topography of Bangladesh is mainly covered by the floodplain, terrace and hill areas. Floodplains occupy about 80 percent of the land area of the country, the terrace area about 8 percent and the northern and eastern hills about 12 percent. Floodplains are regionally diverse and physically complex. The floodplains are built up by alluvial deposits from the Ganges, Brahmaputra and Meghna rivers and their tributaries and distributaries over a period of thousand years and under diverse conditions of floods and sedimentation.

Climate

The climate in Bangladesh can be described on a seasonal basis. There are mainly four seasons, such as, pre-monsoon, monsoon, post-monsoon and dry season. Pre-monsoon (March to May) is the hottest or summer season, consisting of the highest temperatures and evaporation rates. This season is characterized by some thunderstorm rainfalls, strong winds and occasionally hail and tornadoes in the coastal areas. Monsoon (June to September) is the season with the highest rainfall and humidity. Floods are most likely to occur in this season following heavy rainfall across the country, especially in the catchments of rivers. Post-monsoon (October to November) is also a hot and humid season with decreasing rainfall and increasing sunshine. Tropical cyclones and flash floods are likely to affect some parts of the country. The dry season (December to February) is also known as the winter season. This is the coolest, driest and sunniest phase of the year.

The average annual temperature throughout Bangladesh is about 25^0 Celsius (C). Average monthly temperature ranges between about 20^0 C in the winter and 30^0 C in the summer season. Extreme temperatures range between about 5^0 C in the winter to 43^0 C in the summer season. Average annual rainfall in Bangladesh is the lowest in the west (1250 to 1500 millimeters) and highest in the east (>3500 millimeters). In general, about 80 to 90 percent of the annual rainfall occurs between April and September (the rainy season). However, rainfall does vary from year to year (BBS 2005:1).

Hydrology

As a result of snow-melt in the Himalayas and heavy pre-monsoon rainfall in the north-east of Bangladesh, the water levels of the Brahmaputra and Meghna rivers begin to rise in March-April. The water level of the river Ganges starts to rise only in May, because most of its catchments lie in relatively drier parts of India and Nepal where the rains start a bit later. The water level of all three rivers rises rapidly with the beginning of the monsoon season in June-July. The Brahmaputra and Meghna normally reach the peak levels in July-August and the Ganges about a month later, in August-September. Nonetheless, the Brahmaputra occasionally reaches its peak in late-August or September that may coincide with the Ganges peak. All the rivers' water levels usually fall from September to November and more rapidly in the dry season.

Ground Water

Monsoon rainfall and riverbeds are sufficient to recharge groundwater annually where aquifer conditions are suitable, except in the western part of the country in years when severe drought occurs. Besides rainfall water, the groundwater level benefits from the seasonal flooding. Therefore, in some floodplain and terrace areas, groundwater stays sufficiently close to the surface level even in the dry season that normal pumps can be used for domestic water supplies and irrigation. However, where the groundwater is deeper from the surface area, forced pumps are used for irrigation and for domestic water supplies. Sporadically, groundwater is saline near the coastal areas and in some parts of the old Meghna estuarine floodplains.

4.1.2 Patterns and Types of Floods

The keynote of flooding in Bangladesh is that each flood is different. There are many reasons for different types of floods, such as: (i) the monsoonal rains and snowmelt in the Himalayas are, to some extent, unpredictable in terms of both timing and absolute quantity. This, in turn, influences the timing and extent of flooding in the river basins; (ii) the river systems themselves are highly dynamic in nature, and changes in the levels of the river beds may radically alter patterns of flooding; (iii) episodic event in the catchments, such as seismic activity and landslides, may have a sudden and marked influence on flooding patterns; (iv) human intervention on the floodplains may alter radically the patterns of water flow and sedimentation; and (v) the outflow of floodwaters from the basin is controlled ultimately by the sea level (Hughes et al. 1994, Disaster Management Bureau of Bangladesh 2005, Flood Forecasting and Warning Centre of Bangladesh). Many of the drainage problems experienced in the lower delta are a reflection of the fundamental difficulties inherent in draining extremely low-lying land. Some of the principle categories of floods that occur in Bangladesh are outlined below.

River Floods

This type of flood occurs after snow-melt in the high Himalayas, often combined with heavy monsoon rainfall in the catchments of the country's major river systems. In general, river flooding is indispensable for the sustenance of agriculture and fishery systems of the floodplains. However, floods can also be damaging when river levels become particularly high, for example, when the Brahmaputra peaks synchronize with the peaks of Ganges and Meghna. If this occurs, as in 1988, extensive parts of the country become inundated.

Rainwater Floods

Heavy rainfall during monsoon season over the hills and floodplains of Bangladesh (and adjacent areas in India) is another cause of extensive flooding in many areas. In general, rainfall floods play an important and beneficial role in supporting the agricultural and fishery systems in Bangladesh. However, extremely heavy rainfall, sometimes combined with river flooding, can cause extensive damage if rainfall is particularly intense and prolonged. It was heavy rainfall that caused the 1987 and 1998 floods which inundated large areas of floodplains in Bangladesh.

Flash Floods

This type of flood occurs mainly in hilly areas where rivers from India enter the country in northern and eastern parts. These floods are caused by rapid surface water run-off due to heavy monsoonal and pre-monsoonal rainfall in the lower Himalayan foothills and the hills of Meghalaya and Tripura. Flash floods in the north-west and north-east parts of the country regularly cause extensive damage of Boro crops (one special type of rice in Bangladesh; Disaster Management Bureau of Bangladesh 2005). The intensity of flash flooding may be accentuated by the clearance of forest vegetation and its replacement by small crops. These activities can reduce the water retention capacity of soils, and increase the rate of surface run-off. The sediments, often consisting of infertile coarse sands, may then be deposited in large quantities on cropland and may contribute to the silting-up of river beds, particularly within embankments of rivers.

Storm-surge Floods

Storm-surge floods are associated with cyclones and hurricanes which periodically move up from the Bay of Bengal. The incoming storm-surge itself lasts for only a few hours, but the return outflow from these surges can be prolonged as water gets trapped behind roads and embankments. Although the area affected by such flooding is usually limited to within three to five miles of the coastlines, the impact is usually devastating, wiping-out human settlements, infrastructure, crops, livestock and inundating huge areas of cropland with damaging saline water. The loss of human life was estimated at over 130,000 following the cyclone of April 1991, and over 4,000 human lives were lost during the cyclone 'Sidor' on 15th November 2007.

Miscellaneous Floods

Paradoxically, the construction of flood control embankments has actually contributed to flooding in many parts of the country. In such areas, river embankments and polders have prevented rainfall and river overspill water, leading to drainage congestion, water logging and flooding. A notable example is provided by the areas behind the Brahmaputra River Embankment (BRE) in the north and west of the country. Drainage congestion behind embankments has often forced affected people to deliberately breach or cut embankments to allow water to drain away.

Flood in urban areas is an identical example of man-made flood. Encroachment and blockage of drainage channels and filling up of lakes and low-lying areas are main causes of flooding during a monsoon. Water logging problem is on the rise in many cities and municipalities because of unplanned human settlement activities. Development schemes of constructing new roads and buildings have meant that water cannot drain from the land as quickly as it should.

The Farakka dam in India was built in the river channel of the Hugli River, a tributary of the Ganges[6]. In the dry season, the dam reduces the discharge of the river, encouraging sedimentation on the riverbeds in Bangladesh. Therefore, the risk of flooding is increasing during monsoon season.

[6] http://www.sos-arsenic.net/english/source/dam_as.html

4.1.3 Some Statistics on Rural Bangladesh

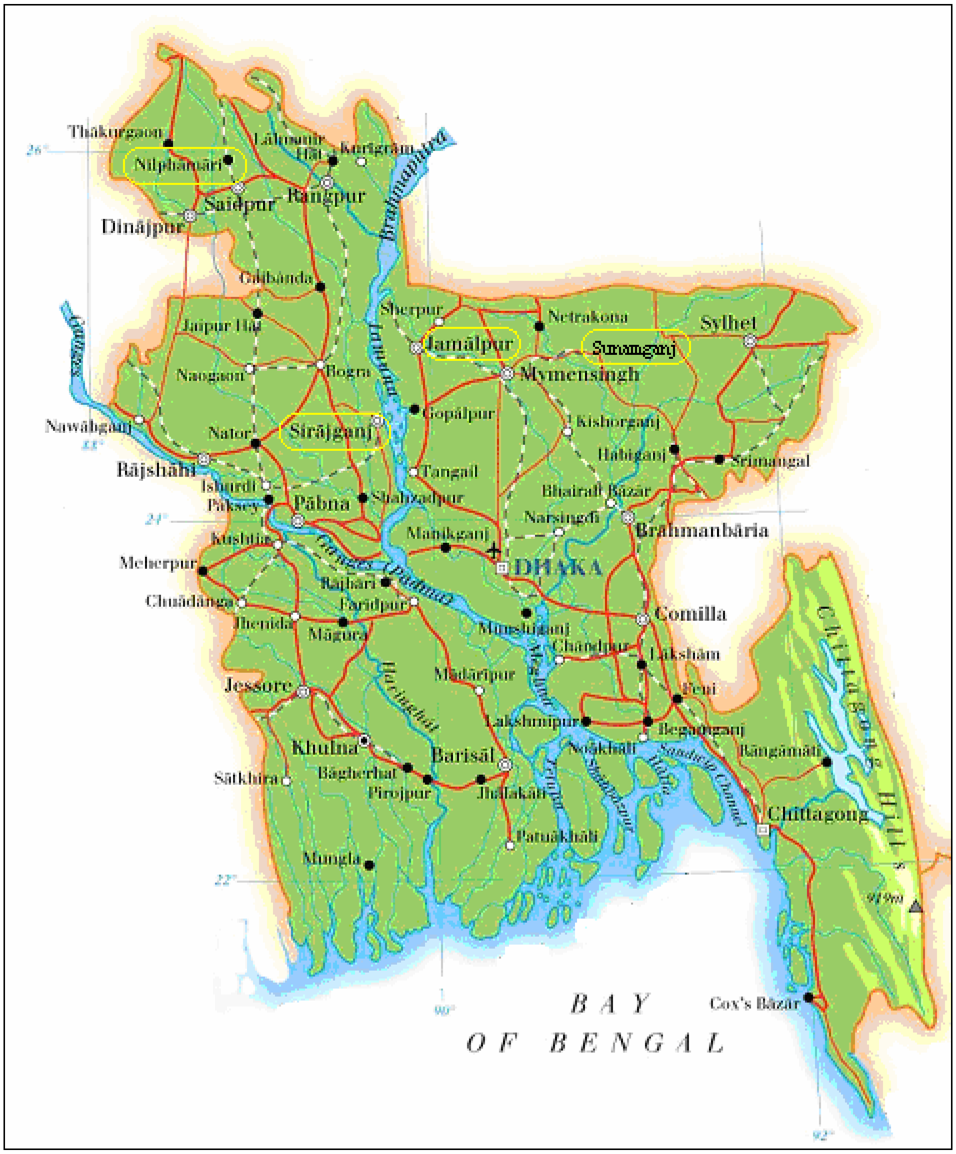
40 percent of the total population in Bangladesh is living under the poverty line (by cost of basic needs approach). In urban areas the poverty rate is 28 percent and for rural areas 43 percent (BBS 2005:2). The average household size in the rural area of Bangladesh is 4.9 (BBS 2003). The threshold of per capita per day calorie intake is 2122 kilo calorie. A person, whose daily calorie intake is less than 2122 kilo calorie is considered to live in absolute poverty. Similarly, a person having daily calorie intake less than 1805 kilo calorie is considered to live in hard core poverty. The estimated poverty line for the rural areas is Taka 594.60 per person per month according to the Food Energy Intake (FEI) method, whereas for urban areas the poverty line is estimated at Taka 905.90 per capita per month (BBS 2004).

4.2 Profile of Survey Areas

In the year 2005, Bangladesh was affected by two types of floods, once in mid August to September by a monsoon flood and then in November, a flash flood occurred in some parts of northern areas. A survey was carried out in the rural areas of randomly chosen four districts in Bangladesh. Figure 4.1 shows major rivers in Bangladesh and the four districts of sample survey (flooded and non-flooded areas are shown in appendix A). They were located in three different divisions to cover the diversity among the divisions. In Bangladesh, administrative units are defined as: Divisions-Districts-Unions-Mouzas (sorted by ascending order).

Sirajganj is a district in central Bangladesh, lying just west of the Brahmaputra and Jamuna rivers and about 70 miles (110 km) northwest of Dhaka. It consists of 9 Upazilas, 79 Unions and 1467 Mouzas. The district has a population of 2.6 million with 56 thousand households. The survey in Sirajganj district covered 2 Upazilas, 3 unions and 4 Mouzas. Two flooded Mouzas were surveyed, named Chack Bahuka and Shuvagasa. Two non-flooded Mouzas were surveyed, named Shialkol and Silonga.

Figure 4.1: Map of Bangladesh, major rivers and survey areas in 2005



Note: Districts with yellow boundaries are the survey areas

Jamalpur is a district in Dhaka Division, Bangladesh. Jamalpur district consists of 7 Upazilas, 67 Union and 844 Mouzas with 336 thousand rural households and 922 persons per square kilometer. The Jamuna river flows besides the Jamalpur district and is usually overflowed during monsoon seasons. The survey of this study was held in Madarganj Upazila with 3 flooded Mouzas, named Shukhnagari, Char Shuvogasa and Khudra Zonail and one non-flooded Mouza, named Baniganj.

Sunamganj district is situated in the north-eastern part of Bangladesh in the Sylhet division and close to the Indian boarder. The rivers Surma and Kushiyara run through this district. There are 10 Upazilas, 81 Unions and 1682 Mouzas with 261 thousand rural households in Sunamganj district. After the flood of 2005, households from 2 Upazilas, 2 Unions and 2 flooded Mouzas, named Islampur and Joyforpur and 2 non-flooded Mouzas, named Ramessharpur and Fatehpur were interviewed.

Nilphamari district is situated in Rajshahi division with an area of 1640.91 square km. The main rivers are Teesta, Jamuneshwari, Chikli and Dhaigan. Nilphamari district has 6 Upazilas, 61 Unions and 371 Mouzas with 287 thousand rural households. The survey covered only Dimla Upazila with one flooded Mouza, named Baishpukur.

4.3 Sampling Design: Quantitative and Qualitative Data Collection

A cross sectional household survey was carried out after the floods, to examine the household vulnerability and significant coping strategies to floods. Keeping the objectives in mind, the study used both quantitative and qualitative techniques. The quantitative technique involved face to face interviews between the household head (or representative of the house) and the field interviewer based on a fully structured questionnaire. In addition, focus group discussions with different people in the community at spontaneous gatherings were conducted to gain some qualitative information.

To select the households in the four districts a three stage stratified random sampling technique was applied in this study. The population within a district was stratified into two strata, namely i) flooded and ii) non-flooded. Flooded households were detected if at least the home or homestead was submerged by flood water. The survey was conducted just two weeks after the flood inundation.

Initially, a total of 300 households per district was targeted in order to have representative figures for that particular area and also justified by the formula (Cochran 1977, p.75) for determining the sample size by estimated proportion.

$$n = \frac{t^2 pq}{d^2} \qquad \Pr(|p - P| \geq d) = \alpha$$

where t = abscissa of normal curve = 1.96, P = population proportion, p = estimated proportion = .433 (poverty rate in rural areas, BBS 2005:2), α= probability of type I error, or, level of significance, d = some margin of error in p (sampling error) = .07, n = 192.48 * design effect (1.5) = 288.72[7]. So, the sample households from each region (district) reached 300, except for Nilphamari district where 150 households were selected. Each district was equally divided by flooded and non-flooded households. Stratified random sampling was used to select the listing, and systematic sampling was used for the households' interviews. Three districts, Jamalpur, Sirajganj and Sunamganj, were randomly chosen after the monsoon flood, so a total of 900 households were surveyed. Shortly after that a flash flood affected the northern part of the country. Then, a second survey of 150 households was conducted, but only in the flooded area of Nilphamari. Primarily, one or more mouzas were selected randomly from the flooded and non-flooded unions. For 150 flooded households, 300 households were listed from both sides of the main road of a mouza. Mouzas with less than 300 households were supplemented by adjacent ones and mouzas with more than 300 households were segmented. At this stage, household listing was necessary for systematic sampling and questionnaire interviews. The total number of rural households from different regions amounted to 1050, where 600 households belong to the flooded sample and 450 households to the non-flooded

[7] here * is the multiplication sign

sample. The following box 4.1 summarizes some definitions of sampling units and sample characteristics, used in this study during field survey.

Box 4.1: Some definitions used in survey of this study

Household: A group of people who normally live and eat together in the same dwelling, sharing the same kitchen and considering themselves a unit in making plans and decisions about daily life.
Head of household: The oldest person or key decision maker in a household.
Female headed household: A single or extended household headed by a woman.
Flooded household: Households whose homesteads were submerged by the flood water in the year 2005 at least for two days.
Income of household: Total value (in Taka) of earning by the households' working members.
Expenditure of household: total costs of food and non-food consumption by all members of households.

Source: Adopted from BBS 2003

The quantitative survey was conducted through structured questionnaires with some open ended questions (see appendix B). There were nine major parts of the formatted questionnaire. Part-A contains data entry records; Part-B is for socio-demographic information; Part-C collects the information of flood damages; Part-D gathers coping strategies of households during and aftermath of floods; Part-E assembles socioeconomic information; Part-F incorporates food consumption data; Part-G is for health care information; Part-H includes profession and salaries of women; and Part-I concludes with the migration information of household members. The following table 4.1 indicates major characteristics of individual, household and community levels which have been asked by this quantitative survey.

Table 4.1: Main types of information obtained through the sample survey

Data on individual level	Data on household level	Data on community level
• Name • Relation with household head • Sex • Age • Religion • Education (>5 years old) • Marital status (>12 years) • Employment (>6 years) • Income from employment	• Income • Borrowing/loan/debit • Savings • Coping strategies • Consumption expenditure (food and non-food) • Distance and cost to reach market place • Structure of dwelling place and length of staying • Flood damage • Durable and productive assets • Food intakes • Disease and Health care • Migration and remittance	• Electricity, schooling, health care service • Transport • Flood shelter, aid, warning system • Community organization • Dams to control floods • Cannels for passing flood water

Source: Author's own compilation

Qualitative approach was taken through Focus Group Discussion (FGD) approach in each of the flooded and non-flooded areas of three districts affected by monsoon flood and only flooded area after flash flood (Nilphamari district). FGDs included open questions on the flood damage, risk management strategy, crop diversification, migration, flood aid programs. People from different professions (farmers, businessmen, service holders etc.) and social groups (chairperson of the locality, widow, disabled etc.) were invited to participate and on average fifteen persons were gathered for each FGD.

4.4 Exploring Data and Checking Assumptions

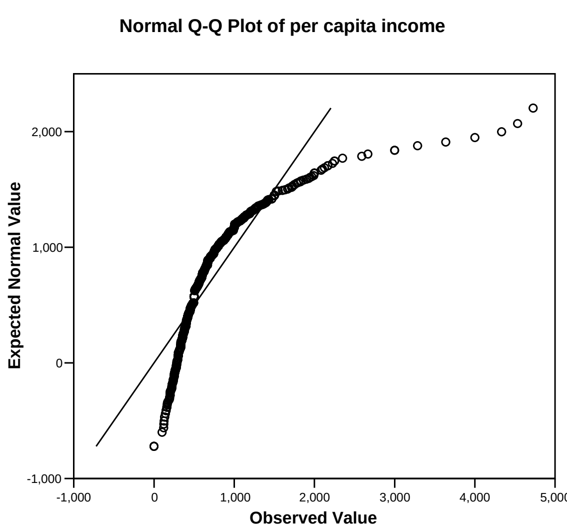
4.4.1 Randomness of Sample

The assumption of randomness of the sample is essential for all tests and it is checked for this study through the 'Run test'. There are several methods for testing the randomness of observed data, but among those the Run test is usually used since it is easy to apply. This run test is a nonparametric test. The test begins with the null hypothesis (H_0) that the sample is random and checked for some variables (per capita income, asset value, arable land holding, family size, age of household head and educational years of earners) used in regression model with the cut off point as median. The test results show that the null hypothesis cannot be rejected at 5 percent level of significance, that is, the sample data set is random.

4.4.2 Normality Test

If the sample is proved to be random on the basis of the Run test, then the next step is to test for the normality assumption. It is also known as 'goodness of fit test' that applies to determine whether a set of random samples comes from a population with specific distribution. This study starts with the null hypothesis that the sample is drawn from a normally distributed population. The nonparametric Kolmogorov-Smirnov goodness of fit test (Chakravarti et al. 1967) is used for this purpose. If the test statistic result shows that the null hypothesis (i.e. the sample came from a normally distributed population) is rejected then the only option available is to run a nonparametric test. There is another graphical method to detect the normality assumption, called normal Q-Q plot for any specified variable. If the data come from normally distributed population, then the observed values (the dots on the normal Q-Q chart) will fall exactly along the straight line. The following two graphs show Q-Q charts of per capita income before flood and log of per capita income before flood in the overall sample respectively.

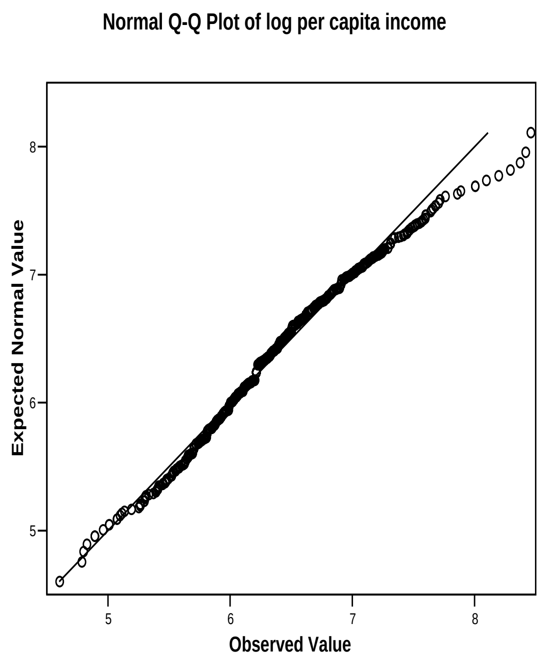
Figure 4.2: Normal Q-Q plot of per capita income



This graph 4.2 shows that the expected straight line is deviated from the actual or observed sample values of per capita monthly income of households before flood. The Kolmogorov-Smirnov test statistic shows the significant p-value (0.0398), that is, the null hypothesis on the normally distributed population can be rejected at 5 percent level of significance.

Source: Author's own compilation from survey data

Figure 4.3: Normal Q-Q plot of log per capita income



Source: Author's own compilation from survey data

The normal Q-Q plot of log per capita monthly income of households before flood shows that observed points almost fall into the normally distributed straight line. The Kolmogorov-Smirnov test statistic also shows the insignificant p-value (0.262), that is, the null hypothesis about normally distributed population cannot be rejected at 5 percent level of significance. Therefore, this study could perform parametric tests with the dependent variable of log per capita income.

4.4.3 Detection of Outliers

Outliers can cause the estimated model to be biased by affecting the values of the estimated regression coefficients. There are several ways to detect outliers of the sample data. This study follows four approaches which are described below.

One statistic measure which considers the effect of a single case on the model as a whole is Cook's distance. Cook and Weisberg (1982) suggested that values of the distance greater than 1 might be cause for concern. Stevens (1992) stated that if a point is a significant outlier on the dependent variable, but its Cook's distance is less than 1, there is no real need to delete that point since it does not have a large effect on the regression analysis.

The box plot is a useful graphical display for describing the behavior of the data and detecting the moderate and extreme outliers. This approach uses the median and the lower and upper quartiles (defined as the 25th and 75th percentiles). If the lower quartile is denoted as Q1 and the upper quartile as Q2, then the difference (Q2 - Q1) is called the inter-quartile range (IQ). A box plot does not need any parametric assumption and is constructed by drawing a box between the upper and lower quartiles with a solid line drawn across the box to locate the median. The following quantities (called *fences*) are identified to detect extreme values: lower inner fence: Q1 - 1.5*IQ; upper inner fence: Q2 + 1.5*IQ; lower outer fence: Q1 - 3*IQ; upper outer fence: Q2 + 3*IQ. A point beyond an inner fence on either side is considered a moderate outlier. A point beyond an outer fence is considered an extreme outlier. This study only identifies extreme outliers.

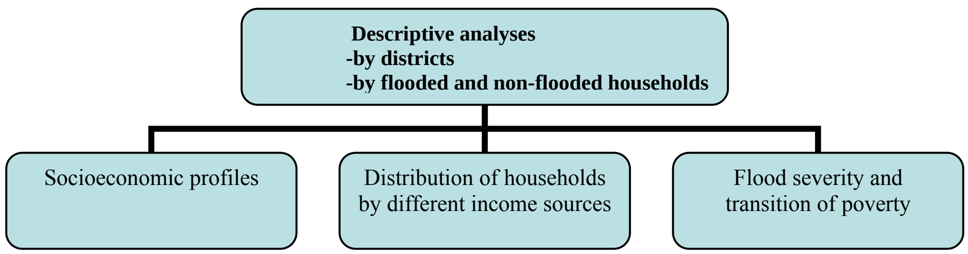
The extreme outlier cases could also be determined after modeling the log per capita income on some households' characteristics. Any cases that have a standardized residual less than -3 or greater than +3 are assumed to be outliers. In a sample from a normally distributed population, 95 percent of the cases have standardized residuals within ± 2, and 99 percent of the cases should lie within ± 3.

Another way to detect an outlier is to take the mean or median (of any variable) ± 3 standard deviations. Outliers can greatly affect this evaluated mean and standard deviations (mean is usually upward value biased), where the median is somewhat robust compared to the mean.

This study also checked for the median before flood income ± 3 standard deviations (for each household in different districts), to detect outliers in the flooded and non-flooded samples. The outliers also verified with the box plot approach, standardized approach and Cook's distance. The cases, detected as outliers using all four approaches, are deleted from the sample to get the robust estimates of the regression coefficients. In total, 11 outliers are detected from the whole sample of 1050 households, so that after deletion the overall sample contains 1039 households.

4.5 Descriptive Analysis of Sample Households

Out of 1039 households, 595 households are from flooded and 444 households from non-flooded areas. This section summarizes some descriptive statistics of households by the four sampled districts, and also by the flooded and non-flooded areas. Socioeconomic profiles of households include information on family size, education level, income, asset holding, savings and loans. Subsequently, the section incorporates distributional patterns of sample households with respect to different income sources. Lastly, some statistics on flood severity in the year 2005 and its effects on poverty level are given. The following flow chart demonstrates the sections described in this chapter:



4.5.1 Socioeconomic Profiles of Sample Households

Descriptive statistics begin with the socioeconomic profiles of surveyed households according to district and flood status. Table 4.2 depicts that the average per capita income per month of sample households is about 673 Taka[8], only 78 Taka more than the poverty line. The difference between mean income of flooded and non-flooded households is 52 Taka. The highest average income is revealed from Sirajganj district households (804 Taka) and the lowest average income among the flooded households is shown in Nilphamari district (534 Taka). The survey areas are heterogeneous in terms of socioeconomic characteristics, which also justify the randomness of the dataset. Households from the Sunamganj district have the largest family size with more than 6 members compared to around 5 members per households in the other three districts. The average educational level of working members is the highest in Sirajganj district (about 4th grade completed). It is hypothesized that households with more educated members have smaller family sizes, but results from the empirical study show that this is not

[8] In the year 2005, 80 Taka = 1 Euro, so 673 Taka = 8.41 Euro

necessarily true. Education seems to have a positive impact on the per capita and per equivalence income and asset holding for Sirajganj inhabitants. The per adult equivalence scale[9] is used because children are not usually getting the same weight for household's income and consumption expenditure compared to an adult member. Per capita income for households in Jamalpur district (596 Taka) is almost equal to the poverty line, while for households in Nilphamari district the average per capita income (534 Taka) is lower than the poverty line. In terms of the per capita asset value, households of Sunamganj district have the lowest amount (2924 Taka) compared to the other three districts. On average, the per capita savings are the highest in Sirajganj district (1351 Taka) and the lowest in Nilphamari district (430 Taka), while per capita loans are the highest for Jamalpur district (about 2143 Taka) and the lowest for Nilphamari district (1184 Taka)[10].

When comparing the socioeconomic profiles of flooded with non-flooded households, the table 4.2 depicts that the average family size is higher in flooded than non-flooded households. The mean educational level of overall flooded working people is higher (2.68) compared to non-flooded working people (2.63). On average, per capita income, per adult equivalence income and per capita asset values are higher for non-flooded households than flooded households. For non-flooded households, per capita income is higher than the poverty line by 108 Taka, whereas for flooded households the difference is only 56 Taka. Interestingly, flooded households are in better condition before flood in terms of per capita savings and loans. Within Sirajganj and Sunamganj districts, non-flooded households have higher per capita income, per adult equivalence scale income, asset value, and lower per capita savings and loans than the flooded households. In Jamalpur district, flooded households show the opposite picture from the Sirajganj and Sunamganj districts, where per capita and per adult equivalence scale income and asset holding of households are higher in amount for flooded households than for their counterparts.

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[9] Per capita adult equivalence scales proposed by Ligon and Schechter (2002) are used in this study. The adult equivalence assigns a weighted value of 1 to adult males of households, and to adult females a weight of 0.9 (adult means age of sixteen or older). Children aged 0 to 4 are weighted as .32, aged 5 to 9 as .52 and of ages 10 to 15 as .67.

[10] For a better understanding appendix 4.1 shows the frequency distribution of flooded and non-flooded households in the four different districts.

Table 4.2: Socioeconomic profile of surveyed flooded and non-flooded households

Area	**Flood status**	**Family size**	**Educa-tion of working members**	**Per capita income before flood**	**Per adult equivalence scale income before flood**	**Per capita asset value**	**Per capita savings**	**Per capita loans**
Overall	Flooded	5.22	2.68	650.37	846.73	3333.34	1105.35	1565.07
	Non-flooded	5.06	2.63	702.23	906.95	3773.29	712.94	1855.63
	Total	5	2.66	672.53	872.46	3521.35	937.66	1689.24
Sirajganj	Flooded	4.76	4.47	796.95	1009.96	4268.23	1981.37	1675.77
	Non-flooded	4.96	3.49	810.86	1035.85	4394.17	699.36	1557.36
	Total	4.86	3.99	803.79	1022.69	4330.15	1351.01	1617.55
Jamalpur	Flooded	4.66	1.75	603.92	791.80	3404.68	1103.75	1758.35
	Non-flooded	4.42	2.09	587.36	757.83	3156.59	1015.36	2529.61
	Total	4.54	1.92	595.67	774.88	3281.06	1059.41	2142.68
Sunamganj	Flooded	6.67	2.03	661.80	872.43	2064.79	963.15	1639.49
	Non-flooded	5.79	2.32	707.66	926.02	3765.00	340.87	1486.95
	Total	6.23	2.17	684.97	899.59	2923.54	648.85	1562.45
Nilphamari	Flooded	4.83	2.39	533.99	707.55	3546.93	429.98	1183.94
	Total	4.83	2.39	533.99	707.55	3546.93	429.98	1183.94

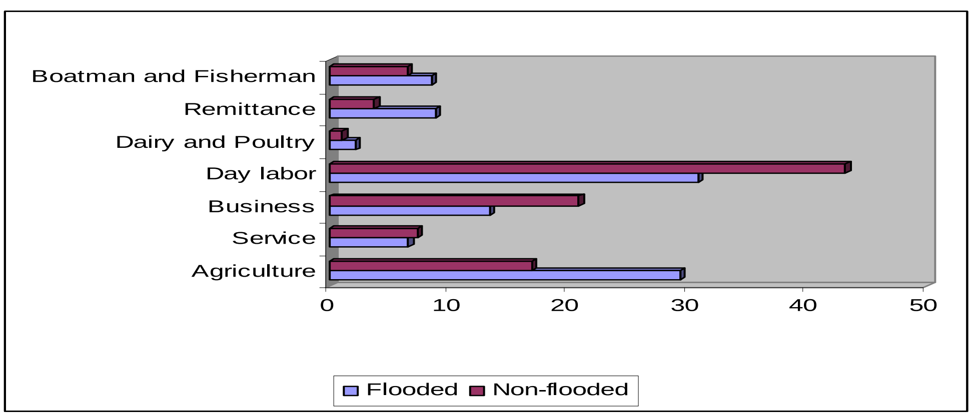
Note: Figures shown in the table are average values of variables
Source: Author's own compilation from survey data

The next step is to check whether the difference in per capita income before flood between flooded and non-flooded households is statistically significant or not. Parametric and non-parametric tests are done for the robustness of the statistical results. For parametric tests, the *two-sample t test* is used to test for the difference between two independent populations (flooded and non-flooded) means. So the log per capita income and log per adult equivalence income for flooded and non-flooded households are clustered separately and a two-sample t test is done with the null hypothesis that there is no difference between the flooded and non-flooded households' average income. At 5 percent level of significance the null hypothesis cannot be rejected for both log per capita income and log per adult equivalence income. In other words, there is no statistically significant difference between flooded and non-flooded households' per capita and per adult equivalence scale income before flood. For the robustness check, this study also performs a non-parametric test, known as *Mann-Whitney* test which shows similar results as the parametric *two sample t test*.

4.5.2 Distribution of Households in Different Income Sources

The sample of flooded and non-flooded households is asymmetrically distributed into different sources of income. Table 4.3 shows that the highest percentages (36%) of households' major earnings come from day labor activities, followed by the agriculture sector (24%). About 17 percent of households' main income source is business, which consists of small and large scales of business. Service holders in Non Governmental Organization (NGO), private and Government sectors are low in proportion, only about 7 percent. About 7 percent of the households' major source of income is remittance from migrants and 8 percent households are occupied mainly in boating and fishing. Figure 4.4 illustrates that percentages received from day labor activities are higher than the other income sources for both flooded and non-flooded areas. 29 percent of the households in flooded areas have agriculture as the main source of income, and about 17 percent of non-flooded households' major source of income is from agriculture. The proportion of businessmen as main earners for the households is higher in non-flooded areas than in the flooded areas, whereas flooded households are getting more remittances as main income source compared to non-flooded households.

Figure 4.4: Percentage distribution of households by different income sources



Source: Author's own compilation from survey data

Households in Jamalpur and Nilphamari districts have to depend on agriculture in higher proportion than the other two districts, as delineated from table 4.3. Day laborers are playing a major role in Sirajganj and Sunamganj districts as main income earners. 14 percent of the households responded that migrants are the main earners in Nilphamari district. Boatmen and Fishermen are contributing significantly to one-fourth of the households in Sunamganj district (appendix 4.2).

Table 4.3: Cross tabulation of districts and households' income sources by flood status

Flood status	**District**	**Income sources**						
		Agriculture	*Service*	*Business*	*Day labor*	*Dairy and Poultry*	*Remittance*	*Boatmen and Fishermen*
Overall		24.1	6.9	16.7	36.2	1.7	6.7	7.7
Flooded	Sirajganj	6.5	17.6	20.3	42.5	2.0	10.5	0.7
	Jamalpur	63.5	1.4	10.8	16.9	2.0	4.7	0.7
	Sunamganj	4.1	5.5	18.5	32.2	0	6.2	33.6
	Nilphamari	43.9	1.4	4.1	31.8	4.7	14.2	0
	Total	29.4	6.6	13.4	30.9	2.2	8.9	8.6
Non-flooded	Sirajganj	7.4	10.8	26.4	50.0	1.4	2.7	1.4
	Jamalpur	19.0	4.8	27.9	41.5	0.7	6.1	0
	Sunamganj	24.2	6.7	8.7	38.3	1.3	2.7	18.1
	Total	16.9	7.4	20.9	43.2	1.1	3.8	6.5

Note: Figures are showing percentage distributions for overall 1039 households, flooded 595 and non-flooded 444 households. Source: Author's own compilation from survey data

In the flooded sample, the agriculture sector is depicting a major role for Jamalpur and Nilphamari districts. Percentages of day laborers as main earners are high in Sirajganj and Sunamganj districts for both flooded and non-flooded areas. Remittances are contributing considerably more in proportion to flooded households than to non-flooded households. Appendix 4.3 shows that Sirajganj district possesses about 63 percent of the households who live below the poverty line who are day laborers. Above three-fourth of the non-poor households belong to service, business and day labor categories. In Jamalpur district, the majority of the households are belonging to agriculture and the day labor sector. Overall in all districts, poor households have the higher percentages of day laborers, but lower percentages of service holders and businessmen than the non-poor households. For the flooded sample, poor households also have the higher percentages of day laborers, but lower percentages of service holders and businessmen than the non-poor households (appendix 4.4). The percentage distribution of non-flooded households by different income sources are demonstrated in appendix 4.5. For the non-flooded sample, in Sirajganj district 63 percent households who live below the poverty line are day laborers, in Sirajganj and Sunamganj districts, poor households have the higher percentages of day laborers, but lower percentages of service holders and businessmen than the non-poor households. Appendix 4.6 shows that among the poorest quartile in flooded households, about 39 percent are day laborers, but only 3 percent of the households are service holders and 5 percent of the households are businessmen. For the 2nd, 3rd and richest quartiles, the numbers of service holders and businessmen are considerably higher than those of the poorest quartile. Frequency of flooded households, whose major sources of income are remittances, is higher in the poorest and richest quartile than in the other two quartiles.

4.5.3 Flood Severity and Transition of Poverty

Flooded and non-flooded household samples are almost equally distributed within the three districts (Sirajganj, Jamalpur and Sunamganj); Nilphamari district only contains flooded sample. The following table 4.4 shows the severity of floods in the year 2005 in rural Bangladesh. Overall duration of flood water on homestead was 7 days. Households in Sirajganj district were the most affected in terms of inundation days and height of flood water at the homestead. Households in Nilphamari district were affected by flash flood, while households in the other three districts were affected by monsoon floods.

Table 4.4: Flood severity in four districts

Area	Sample group	Average flood height at homestead in feet	Average flood duration at homestead in days
Overall	Total	0.841	6.97
	Poor	0.814	6.29
	Non-poor	0.878	7.89
Sirajganj (monsoon flood)	Total	1.446	13.4
	Poor	1.374	12.4
	Non-poor	1.509	14.3
Jamalpur (monsoon flood)	Total	1.052	7.12
	Poor	1.057	7.29
	Non-poor	1.043	6.87
Sunamganj (monsoon flood)	Total	0.055	6.46
	Poor	0.039	6.45
	Non-poor	0.735	6.47
Nilphamari (flash flood)	Total	0.782	2.57
	Poor	0.806	2.39
	Non-poor	0.719	3.02

Source: Author's own compilation from survey data

The overall sample data set depicts that the poverty rate is 6 percent higher in flooded areas before flood as shown in appendix 4.7. Among flooded households, Nilphamary district shows the largest poverty rate (72.3%). The following table 4.5 shows the impact of flood in the year 2005 in four districts. 17 percent flooded households fall into poverty after flood. The drastic change into poverty occurs in Jamalpur district by the monsoon flood, where head count poverty rate fluctuates by about 30 percent. Households from the Sunamganj district face comparatively less disastrous effects of floods. In the initial period (before flood), the poverty rate was the highest in Nilphamari district and it is augmented by 15 percent due to flood.

Table 4.5: Income and poverty for flooded households

Indicators		**Before flood**	**After flood**	**Change in poverty level (after-before flood)**
Head count poverty	Overall	57.8	74.8	17
District-wise head count poverty	Sirajganj	47.1	66	18.9
	Jamalpur	58.8	88.5	29.7
	Sunamganj	53.4	57.5	4.1
	Nilphamari	72.3	87.2	14.9

Note: Figures are showing percentages
Source: Author's own compilation from survey data

The next step is to check the transition of poverty levels in poor and non-poor clusters due to floods. Appendix 4.8 shows that a large proportion (about 42%) of non-poor households falls into poverty after flood. Though the severity of flood was highest in Sirajganj district, in terms of income or wellbeing, the flooded households of this district suffered less than the people of the Jamalpur district. About 74 percent of non-poor households' in Jamalpur district fall under the poverty line due to flood damage. Flash flood in the Nilphamari district caused over 50 percent fluctuation of poverty status in the non-poor cluster. Households who are currently non-poor, may also be counted as vulnerable; some events (such as, flood, a bad harvest, illness of main earner) could push them into poverty. Using a six years panel data from rural households of China, Jalan and Ravallion (1998) investigate chronic and transient poverty with the classification: persistently poor (households whose expenditures in each period below the poverty line), chronically poor (mean expenditures over all periods less than the poverty line but not poor in each period), transiently poor (mean expenditures over all periods above the poverty line but experiencing at least one episode of poverty), and never poor. They found that the proportion of transient poor is much higher than that of chronic poor and never-poor. Also Baulch and Hoddinott (2000) show from inter-country panel data that the share of the 'sometimes poor' is higher than that of the 'always poor' and 'never poor'. To compare these results with own data, flooded households' data set is used, but substituting the expenditure on consumption by per capita monthly income.

Table 4.6: Classification of transient and chronic poverty in flooded households

	Chronically poor (mean per capita income below poverty line)		**Transiently poor only (mean per capita income above the poverty line)**	**Never poor**
	Always poor	*Not persistently poor*		
Overall	56.38	13.27	5.05	25.3
Sirajganj	47.06	11.76	7.2	33.98
Jamalpur	57.33	25.34	6.0	11.33
Sunamganj	50.0	6.0	2.67	41.33
Nilphamari	71.33	10.0	4.67	14.0

Note: Figures are showing percentages
Source: Author's own compilation from survey data

The results from the above table 4.6 are showing that in the overall sample about 56 percent of households were always poor and 25 percent were never poor compared with only 18 percent of transient poor, which contradict with the results of other authors (Jalan and Ravallion 1998, Baulch and Hoddinott 2000).

4.6 Summary

The results from this chapter summarize that flooded and non-flooded household samples are almost equally distributed within the three districts (Sirajganj, Jamalpur and Sunamganj), only Nilphamari district contains flooded sample. Before flood, the difference between mean income of flooded and non-flooded households is very low and not statistically significant. On average, per capita income, per adult equivalence income and per capita asset values are higher for non-flooded households than flooded households. Interestingly, flooded households are in a better condition before flood in terms of per capita savings and loan. The highest percentages of households' major earnings come from day laborers, followed by the agriculture sector. Sample households in Jamalpur and Nilphamari districts have to depend on agriculture in higher proportion, while day laborers are playing a major role in Sirajganj and Sunamganj districts as main income earners. Households in Sirajganj district were the most affected in terms of inundation days and height of monsoon flood water at the homestead. Among flooded households, Nilphamary district shows the largest poverty rate and over half of the non-poor households have fallen into poverty due to a flash flood. About three-fourth of non-poor households' in Jamalpur district have fallen under the poverty line due to monsoon flood damage. Illustrating a noteworthy impact of floods on poverty levels among the four districts, the next endeavor of this study is to find out who are the most affected and how much downside effects of floods they have faced. Therefore, the next chapter comprises poverty and vulnerability measurements caused by monsoon and flash floods.

Chapter Five

5. Econometric Modeling of Poverty and Vulnerability

Bivariate analyses from chapter four show that floods have some disastrous effects on households' wellbeing; that drastically change the poverty levels. Therefore, this chapter commences with the econometric analyses to determine significant and influential factors of households' income, and then the study moves forward to check whether some socioeconomic factors besides floods have any causal effect on households' downside poverty levels. Four different methodologies, as described in chapter three, are then used to estimate vulnerability levels of rural households in Bangladesh. This chapter concludes with the comparison of these four methodologies used in this study.

5.1 Determinants of Households' Income: Multivariate Regression Analysis

To determine whether the flood had any significant effect on household income, this study follows several steps. Multivariate regression of log per capita income before flood on household's demographic, economic and community characteristics (as listed in appendix 5.1) is performed for 1039 households to determine the factors which significantly affect households' income. After choosing the best fitted model for the data set, the second step is to predict the flooded and non-flooded households' after flood income. The predicted log income is then again regressed on the dummy variable of the flood status (1, if flooded and 0, if non-flooded) to check the assumption whether flood has a significant downside effect on households' income.

The result of the multivariate regression analysis is given in table 5.1. Family size is significantly and negatively related to the log per capita income, so addition of one person to the household membership would cause 12 Taka decrease in income on average. But if the member is a male adult, then the average income will increase and it is also verified by the negative but insignificant coefficient of the variable dependency ratio. Average educational years of earners, arable land holding, asset value and savings are highly significant and positively related with the household income level. Out of six dummies of major sources of income four are found to be significant. The more distance to the market, the lower the income of a household would get; owners of the dwelling places would earn higher income compared to non-owners.

Table 5.1: Multivariate regression of log per capita income before flood

Variables	**Coefficients (β)**	**Standard Errors**	**t**	**P>|t| (sig.)**	**95% confidence interval for β**	
					Lower bound	*Upper bound*
Family size	-0.1211***	0.02271	-5.33	0.000	-0.1657	0.0765
Family size squared	0.0033	0.00447	0.73	0.218	-0.0011	0.0678
Dependency ratio	-0.0152	0.02236	-0.68	0.496	-0.0591	0.0286
No. of adult males	0.1055***	0.02884	3.66	0.000	0.04890	0.1621
No. of adult females	0.0274	0.02652	1.04	0.301	-0.0245	0.0795
Age of household head	-0.0047	0.00518	-0.92	0.356	-0.0149	0.0053
Age square of household head	0.00003	0.00005	0.52	0.602	-0.00007	0.0001
Average education of earners	0.0325***	0.00597	5.45	0.000	0.0208	0.0442
Gender of household head	0.0487	0.05588	0.87	0.383	-0.0608	0.1584
Years of staying in house	0.0005	0.00076	0.68	0.496	-0.0009	0.0020
Agriculture	-0.0264	0.04013	-0.66	0.511	-0.1051	0.0523
Service	0.2168***	0.06190	3.50	0.000	0.0953	0.3383
Business	0.1662***	0.04144	4.01	0.000	0.0848	0.2475
Dairy & Poultry	0.3550***	0.10543	3.37	0.001	0.1481	0.5619
Remittance	0.0484	0.06178	0.78	0.433	-0.0728	0.1696
Boating & Fishing	0.1907***	0.05562	3.43	0.001	0.0815	0.2998
Arable land	0.2128***	0.05744	3.71	0.000	0.1001	0.3256
Asset value	0.0273***	0.00326	8.39	0.000	0.0166	0.0476
Distance to market	-0.0306**	0.01193	-2.57	0.011	-0.0541	-0.0072
Cost to reach market	0.0103*	0.00531	1.95	0.052	-0.00008	0.0207
Access to media	0.0601*	0.03306	1.82	0.069	-0.0047	0.1250
Ownership of dwelling place	0.0626**	0.03132	2.00	0.046	0.0012	0.1241
Housing materials	-0.0818***	0.03130	-2.61	0.009	-0.1432	-0.0204
Loan	-0.0006	0.00042	-1.42	0.156	-0.00002	0.0014
Savings	0.0298***	0.0073	4.08	0.000	0.00565	0.1521
Membership of cooperatives	0.0376	0.14461	0.26	0.208	-0.0063	0.0943
Electricity	0.0342	0.03668	0.93	0.351	-0.0377	0.1062
Primary school	0.0041	0.12675	0.03	0.974	-0.2528	0.2445
Public hospital	0.0038	0.07838	0.05	0.961	-0.1576	0.1499

Note: Dependent variable: Log of per capita income before flood; * = at 10 percent, ** = at 5 percent, *** = at 1 percent level; Number of observations 1039 households; $F(29, 1009) = 22.14$, Prob > F = 0.000, R-squared= 0.6827, Adjusted R-squared= 0.6729

Source: Author's own compilation from survey data

Diagnostics of the model for regressing log of per capita household income before flood on a bunch of characteristics is fitted well to the data; the F-statistic for the overall model is highly significant (p-value is 0.000). The R-square is 0.6827, that is, 68 percent of the average variation of log income before flood is explained by the predictors. The Durbin-Watson (1951) test statistic value is 1.972, which is close to the value of 2. According to the rule of thumb if the Durbin-Watson statistic of a model possesses a value near 2 (Gujarati 2003, p.469), then no autocorrelation or serial correlation is assumed between the error terms. The multicollinearity assumption is also checked for the model; both the VIF (variance-inflating factor) and TOL (tolerance) values are measured for each of the regressors in the model. The VIF of four variables, such as: family size, family size squared, age of household head and age squared of household head, are near to 10 and the TOL values also closer to zero (Gujarati 2003, p.362), which means family size and family size squared are highly correlated but in a non-linear way. The same relationship exists with respect to the age of household head and age square of household head. The R-square is not greater than 0.90, so the variables are not highly collinear. Even in the presence of high multicollinearity the OLS estimates are BLUE (best linear unbiased estimates) but with large standard errors. To check whether the omitted variables are significant or not, the Ramsey RESET test (Gujarati, 2003, p.521) is performed using powers of the fitted values of log per capita income. The null hypothesis is: H_0: model has no omitted variables and the test result shows that the F-statistic is 3.49 with a probability value (p-value) of 0.110. Therefore, the conclusion would be that the null hypothesis cannot be rejected at 5 percent level of significance and the model has no omitted variables.

Homogeneity of the variables is checked by plotting regression standardized residuals over regression standardized predicted values (appendix 5.2), which shows the heteroscedastic pattern of the data. The homogeneity assumption is also violated for other variables and some are shown in the appendix 5.2. In addition to the graphical method, the Breusch-Pagan test is conducted to detect whether there is any heteroscedasticity in the error variance. The null hypothesis (H_0) assumes constant variance for the error terms and the test result shows that $\chi_{(1)}^{2}$ (chi-square with 1 degree of freedom) = 70.13 and p-value is 0.00; so at 5 percent level of significance the null hypothesis can be rejected, i.e. the data exhibit heteroscedasticity.

The sample of 1039 households contains both flooded and non-flooded households. The *sample selection bias or selectivity bias* concerns the problems where the dependent variable (log of per capita income) is observed only for a restricted and non-random sample. The households staying in the flooded or non-flooded areas are not self-selected and even non-flooded households in this sample were flooded in the previous years, but some underlying factors may cause the flooded households to suffer from the frequent flooding, such as: inability of the poor households to migrate into upland areas, height of the homestead from the ground level, distance from the nearest water source. Therefore, this study does not assume any selectivity bias but considers the *endogeneity or simultaneity bias*. Endogeneity refers to the problem that the independent variables included in the model are potentially choice variables and correlated with the unobservable variables captured by the error term. The regression coefficients are estimated through the remedial of endogeneity bias.

To predict after flood income of flooded and non-flooded households, the estimation procedure begins with the stochastic process. Assuming the income of a household i at time t in equation (1):

$$(1) \ln y_{it} = \alpha_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \alpha_1 D_{1it} + \alpha_2 D_{2it} + \alpha_3 D_{3it} + \alpha_4 D_{4it} + \alpha_5 D_{5it} + \alpha_6 D_{6it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \alpha_7 D_{7it} + \beta_6 X_{6it} + \alpha_8 D_{8it} + \alpha_9 D_{9it} + \alpha_{10} D_{10it} + e_{it}$$

where t is the index of before flood time, y is the household per capita income, α is the vector of parameters of dummy variables, β is the vector of continuous variables, X_1 is indicating family size, X_2 is the number of adult males in household, X_3 is the education of earners, D_1 to D_6 are the dummies for income sources, agriculture, service, business, dairy and poultry, remittance and boating & fishing respectively, X_4 is for arable land, X_5 is for asset value, D_7 is the house material, X_6 is for savings, D_8 to D_{10} are for district dummies, namely Sirajganj, Jamalpur and Sunamganj districts with Nilphamari district as reference category. The term e_{it} is a disturbance term with mean zero, which captures the effect of shocks (e.g. flood shock) that contribute to different per capita income levels of households that are otherwise equivalent. It is also assumed that the error term is independently and identically distributed over time for each household, but not identically distributed across households. The zero mean assumption of e_{it} stands for the unbiasness property of the estimates of β's and α's but the homogeneity assumption is not considered. The estimated results of the above regression are given below:

Table 5.2: Regression of log per capita income for flooded households

Variable	**Coefficient**	**Standard Error**	**t**	**P>t**	**95% Confidence Interval**	
					Lower limit	*Upper limit*
Family size	-0.0721***	0.0102	-7.03	0.000	-0.0922	-0.0519
No. of adult males	0.1252***	0.0296	4.23	0.000	0.06711	0.1834
Education of earners	0.0350***	0.0078	4.47	0.000	0.0196	0.0504
Agriculture	0.0291	0.0563	0.52	0.606	-0.0816	0.1398
Service	0.1905**	0.0837	2.27	0.023	0.0260	0.3550
Business	0.2796***	0.0615	4.55	0.000	0.1588	0.4004
Dairy & Poultry	0.4767***	0.1251	3.81	0.000	0.2310	0.7224
Remittance	0.1096	0.0691	1.59	0.114	-0.026	0.2454
Boating & Fishing	0.1277*	0.0770	1.66	0.098	-0.0236	0.2791
Arable land	0.2815***	0.0840	3.35	0.001	0.1165	0.4466
Asset value	0.0277***	0.0047	5.83	0.000	0.0152	0.0394
House materials	-0.1238***	0.0420	-2.95	0.003	-0.2064	-0.0413
Savings	0.0805***	0.0250	3.22	0.001	0.0322	0.1772
District dummy 1 (Sirajganj)	0.1282**	0.0589	2.18	0.030	0.0125	0.2439
District dummy 1 (Jamalpur)	0.1400***	0.0525	2.66	0.008	0.0368	0.2432
District dummy 3 (Sunamganj)	0.3287***	0.0630	5.21	0.000	0.2048	0.4526

Note: Dependent variable: Log of per capita income before flood; * = at 10 percent, ** = at 5 percent, *** = at 1 percent level; Number of observations 595 households; F(16, 578) = 23.09, Prob > F = 0.001, R-squared= 0.490, Adjusted R-squared= 0.473, Root MSE=0.428, Ramsey RESET test (F-statistic)=0.058
Source: Author's own compilation from survey data

The estimated income after flood for flooded households is measured by Amemiya's (1977) three step procedure. This methodology gives the robust estimates with the remedial of heteroscedasticity and endogeneity problems. The estimates are asymptotically efficient and consistent for the true value of parameters. At this stage the squared error term from the equation (1) is regressed through OLS on the household characteristics (all variables in the above table) and some shock variables, such as:

(2) $\hat{e}^2_{OLS,it} = X_{it}\theta + \eta_{it}$

where θ is the vector of parameters and X_i is a bunch of shock variables described in appendix 5.3. η_{it} is the normally distributed error term with mean zero. The squared error term is again weighted by the predicted value from the equation (2) and another OLS regression is done to get the feasible generalized least square estimate of θ.

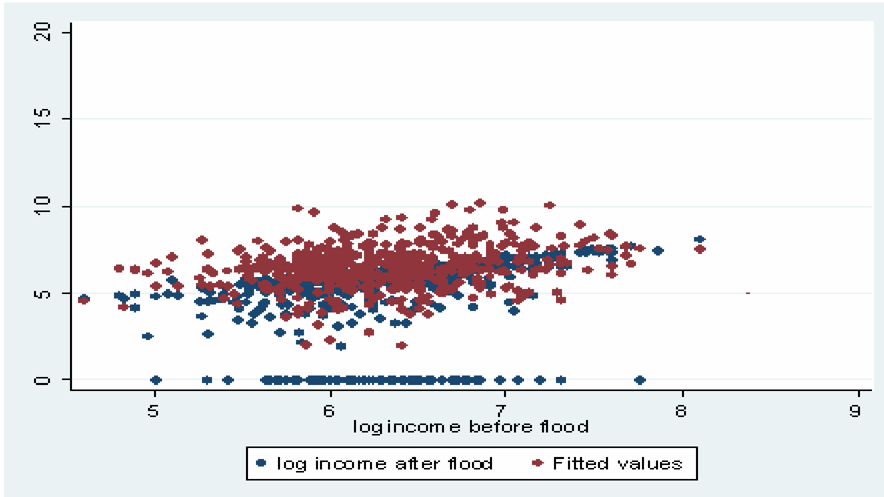
(3) $$\frac{\hat{e}^2_{OLS,it}}{X_{it}\hat{\theta}_{OLS}} = \left[\frac{X_{it}}{X_{it}\hat{\theta}_{OLS}}\right]\theta + \frac{\eta_{it}}{X_{it}\hat{\theta}_{OLS}}$$

To get the estimated values of $\ln y_{it+1}$, the third step OLS is run on the following equation:

(4) $$\frac{\ln y_{it}}{\sqrt{X_{it}\hat{\theta}_{FGLS}}} = \left[\frac{X_{it}}{\sqrt{X_{it}\hat{\theta}_{FGLS}}}\right]\beta + \frac{e_{it}}{\sqrt{X_{it}\hat{\theta}_{FGLS}}}$$

This study thus compares the predicted per capita income of households' after flood and the actual income per capita after flood from the survey data. The predicted values do not fluctuate so much and the following graph is delineating the comparison.

Figure 5.1: Predicted and actual per capita income after flood for flooded households



Source: Author's own compilation from survey data

The statistical test is performed by a paired t-test with the null hypothesis that the mean values of predicted and actual incomes after flood do not differ significantly. The significance level (p-value = 0.106) of the t-test statistic shows that the null hypothesis may not be rejected. Therefore, the conclusion would be that there is no significant difference between the mean values of the predicted and actual incomes after flood.

For the non-flooded households, estimates of the income after flood are measured by the same procedure followed for the flooded households except that the error term is regressed excluding shock variables (only demographic, economic and community characteristics are taken as the regressors). The estimation process begins with the income of a household i at time t for the non-flooded households as in equation (5):

$$(5) \ln y_{it} = \alpha_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \alpha_1 D_{1it} + \alpha_2 D_{2it} + \alpha_3 D_{3it} + \alpha_4 D_{4it} + \alpha_5 D_{5it} + \alpha_6 D_{6it} + \alpha_7 D_{7it} + \alpha_8 D_{8it} + e_{it}$$

where t is the index of before flood time of non-flooded households, y is the household per capita income, α is the vector of parameters of dummy variables, β is the vector of continuous variables, X_1 is indicating family size, X_2 is the number of adult males, X_3 is the education of earners, X_4 is for asset value, X_5 is for savings, D_1 to D_6 are the dummies for income sources, agriculture, service, business, dairy & poultry, remittance and boating & fishing respectively, D_7 to D_8 are district dummies. The term e_{it} is a disturbance term with mean zero and it is assumed that the error term is independently and identically distributed over time for each household, but not identically distributed across households. The estimated results of the above regression are given below:

Table 5.3: Regression of log per capita income for non-flooded households

Variables	**Coefficients**	**Standard Errors**	**t**	**P>t**	**95% Confidence Interval**	
					Lower limit	Upper limit
Family size	-0.094***	0.0120	-7.9	0.000	-0.1185	-0.0713
No. of adult males	0.1320***	0.0325	4.06	0.000	0.0681	0.1959
Education of earners	0.0348***	0.0087	4.0	0.000	0.0177	0.0519
Asset value	0.0249***	0.0033	7.44	0.000	0.0124	0.0415
Savings	0.0441***	0.0105	4.2	0.000	0.0231	0.0643
Agriculture	-0.0350	0.0604	-0.58	0.562	-0.1538	0.0837
Service	0.1975**	0.0883	2.24	0.026	0.0239	0.3711
Business	0.0927*	0.0536	1.73	0.085	-0.0126	0.1982
Dairy & Poultry	0.1315	0.1886	0.7	0.486	-0.2393	0.5023
Remittance	0.0129	0.1062	0.12	0.903	-0.1957	0.2217
Boating & Fishing	0.0619	0.0873	0.71	0.478	-0.1096	0.2336
Sirajganj	-0.0477	0.0532	-0.9	0.371	-0.1523	0.0569
Jamalpur	-0.2602***	0.0539	-4.83	0.000	-0.3662	-0.1542

Note: Dependent variable: Log of per capita income before flood; * = at 10 percent, ** = at 5 percent, *** = at 1 percent level; Number of observations 444 households; F(13, 430) = 23.49, Prob > F = 0.000, R-squared= 0.415, Adjusted R-squared= 0.398, Root MSE=0.412, Ramsey RESET test (F-statistic)=0.072.
Source: Author's own compilation from survey data

The estimated incomes after flood for both the flooded and non-flooded households are then merged into an aggregate file. Finally, the predicted incomes are regressed on the dummy variable of flood status (1, if flooded, 0 otherwise) to check whether there is any significant effect of flood on the households' income level. The following equation shows a simple regression model with the dependent variable log of income after flood and D stands for a dichotomous flood status variable:

(6) $\ln y_{it+1} = \alpha_0 + \alpha_1 D_{it+1} + e_{it+1}$

The result of the above model is shown below:

Variable	Coefficient	Standard Error	t	P>t	95% Confidence Interval	
					Lower limit	*Upper limit*
Flood status	-0.3614***	0.0954	-3.79	0.000	-0.54879	-0.17412

Note: Dependent variable: Log of per capita income after flood; *** = significance at 1 percent level; Number of observations 1039 households; F(1, 1037) = 14.33, Prob > F = 0.002, R-squared= 0.0136, Adjusted R-squared= 0.0127, Root MSE=1.521
Source: Author's own compilation from survey data

The statistical test (p-value<0.01) shows that flood has a highly significant effect on the households' income after flood. Therefore, the study justifies examining the poverty and vulnerability due to flood in the rural Bangladesh.

If it is assumed that the error term and the covariates or explanatory variables are uncorrelated, then the *random effects model* may be appropriate, whereas if the error term and explanatory variables are correlated, then the *fixed effects model* may be appropriate (Gujarati 2003, p.650). This study applies a short panel data set from a cross-sectional survey and thus considers some correlation between the error term and the independent variables. The household's income is predicted from the observed characteristics and in addition, some shock variables are included for modeling the flooded sample. Therefore, some unobserved household characteristics, such as innate ability or family background may be in the error term when modeling the income function. These unobserved characteristics may well influence the observed variables. Thus for a short panel data set, it is reasonable to allow the unobserved effects (error term) to be correlated with the explanatory variables (Wooldridge 2000, p.450). The validity of applying the fixed effects model in this study is also checked by the Hausman test (1978). The null hypothesis for this test is that the fixed effects model and random effects model estimators do not differ substantially. The test statistic suggested by Hausman has an asymptotic χ^2 (Chi-square) distribution. The p-value (0.188) of this test shows that the null hypothesis can be rejected at 5 percent level of significance, that is, the fixed effects model is more likely to measure consistent parameter estimates from this sample than the random effects model.

5.2 Determinants of Poverty to Floods: Multinomial Logit Model Approach

In the previous sections, it was demonstrated that floods in the four districts have a noteworthy effect on households' wellbeing and livelihood. After examining the determinants of income before floods and the significant downside effect on after flood income, this section aims to scrutinize the determinants of poverty after floods in rural sample households. The transition of poverty levels shows that even non-poor households become poor after floods and very few households upgrade their poverty status after floods. Therefore, this study runs a multinomial discrete choice model with the dependent variable: 0 = non-poor households after flood, 1 = households remain poor, 2 = households become poor from non-poor status before floods. A multinomial logit model is chosen because the dependent variable is discrete with three distinct choices that are not orderly assigned. The explanatory variables for this model are chosen from the significant determinants of flooded households' income in addition to shock variables. The model and estimation procedure are described below:

Let y be a random variable taking on the values {0,1,……,*j*) for j a positive integer (here, j is 2) and x denotes a set of conditioning variables, where (x_i, y_i) is a random draw from the population. The multinomial logit model (Wooldridge 2002, p.497) has the response probabilities,

$$(1)\ P(y=j \mid x) = \exp(x\beta_j) \Big/ \left[1 + \sum_{h=1}^{j} \exp(x\beta_h)\right], \qquad j = 1,......j$$

where β_j is $K \times 1, j = 1,......j.$ Because the response probabilities must sum to unity,

$$(2)\ P(y=0 \mid x) = 1 \Big/ \left[1 + \sum_{h=1}^{j} \exp(x\beta_h)\right]$$

when $j = 1, \beta_1$ is the $K \times 1$ vector of unknown parameters, and the partial effects of this model are given as,

$$(3)\ \frac{\partial P(y=j \mid x)}{\partial x_k} = P(y=j \mid x)\left\{\beta_{jk} - \left[\sum_{h=1}^{j} \beta_{hk} \exp(x\beta_h)\right] \Big/ g(x,\beta)\right\}$$

where β_{hk} is the k th element of β_h and $g(x,\beta) = 1 + \sum_{h=1}^{j} \exp(x\beta_h)$

A simpler interpretation of β_j is given by

(4) $p_j(x,\beta)/p_0(x,\beta) = \exp(x\beta_j), \quad j = 1,2,........j$

where $p_j(x,\beta)$ denotes the response probability in equation (1). Thus, the change in $p_j(x,\beta)/p_0(x,\beta)$ is approximately $\beta_{jk}\exp(x\beta_j)\Delta x_k$ for x_k. The log-odds ratio is linear in $x: \log[p_j(x,\beta)/p_0(x,\beta)] = x\beta_j$. Estimation of a multinomial logit model is best carried out by maximum likelihood. For each i the conditional log likelihood can be written as

(5) $l_i(\beta) = \sum_{j=0}^{j} 1[y_i = j]\log[p_j(x_i,\beta)]$

where the indicator function selects out the appropriate response probability for each observation i. The estimate of β is evaluated by maximizing $\sum_{i=1}^{N} l_i(\beta)$. Estimated maximum likelihood estimate (MLE) coefficients with robust standard errors from multinomial logit modeling on flooded data set are given in the following table 5.4. Among the shock variables, flood height, flood duration, loss of crops, loss of working days, coping amount from loan and selling assets are significantly and positively related with the after flood poverty of the poor households. The variables which have positive and significant effects on the non-poor households' welfare are: flood duration, loss of assets, cost of disease during flood and coping from savings and selling assets. If the flood duration is one day longer, then the log-odds between after flood poverty from poor households and after flood non-poor households would increase by 0.04 and the log-odds between after flood poverty from non-poor households and after flood non-poor households would increase by 0.05. Since many of the poor households are day laborers, the loss of working days due to floods has a highly significant effect on the downside poverty level. Coping from savings would deplete the non-poor households' income generating resources as shown in the empirical results. An extended family size has a significant increase of poverty level of before flood poor households; an additional male adult in the household would decrease the probability of a non-poor household to become poor after flood; another year of education reduces the log-odds between before flood poor to fall into poverty and after flood non-poor by 0.11; and farmers are facing significant downside effects by floods that change the poor and non-poor households after flood poverty levels. Among the economic factors, arable land holding, possession of assets and savings show statistically significant and negative effects of floods as the unit of economic variables increase. Especially for the non-poor households, one unit increase of asset value and savings would minimize the log-odds of after flood poor from non-poor status before flood to after flood non-poor by 0.01 and 0.007 units respectively.

Table 5.4: Determinants of poverty to floods: multinomial logit model

Factors	Variables	Poor remains poor (Coded as 1)	Non-poor to poor (Coded as 2)
		Coefficients	*Coefficients*
Shock factors			
	Flood height	0.06 (0.03)*	0.36 (0.31)
	Flood duration	0.04 (0.001)***	0.05 (0.01)***
	Loss of crops x 100	0.05 (0.01)**	0.03 (0.01)*
	Loss of assets x 100	-0.06 (0.05)	0.02 (0.01)**
	Loss of working days	0.12 (0.03)***	-0.14 (0.03)
	Cost of disease x 100	0.03 (0.02)	0.13 (0.04)**
	Coping from loan x 100	0.06 (03)**	-0.04 (0.11)
	Coping from savings x 100	-0.27 (0.17)	0.17 (0.09)*
	Coping from selling assets x 100	0.67 (0.29)**	0.61 (0.27)**
Demographic factors			
	Family size	0.40 (0.09)***	0.08 (0.11)
	No. of adult males	-0.71 (0.22)	-0.19 (0.08)**
	Education of earners	-0.11 (0.06)*	-0.02 (0.05)
	Agriculture	1.44 (0.56)**	0.55 (0.29)*
	Service	-0.44 (0.53)	-0.53 (0.71)
	Business	-0.87 (0.93)	-0.86 (0.49)*
	Dairy and Poultry	-1.91 (0.90)	-0.89 (0.78)
	Remittance	-0.74 (0.52)	-0.08 (0.62)
	Boating and Fishing	-0.46 (0.45)	-0.48 (0.72)
Economic factors			
	Arable land	-3.65 (3.45)	-0.38 (0.21)*
	Asset value x 100	-0.02 (0.01)*	-0.01 (0.004)**
	House materials (raw materials=1)	0.16 (0.33)	-0.26 (0.43)
	Savings x 100	-0.12 (0.02)	-0.007 (0.002)***
Community factors			
	District dummy 1 (Sirajganj=1)	-1.46 (0.55)**	0.51 (0.64)
	District dummy 2 (Jamalpur=1)	-0.34 (0.62)	1.65 (0.68)**
	District dummy 3 (Sunamganj=1)	-3.03 (0.53)***	-2.63 (0.73)***
	Flood shelter (yes=1)	0.07 (0.74)	-1.65 (0.98)*
Number of observations		595	
Log pseudo likelihood		-376.78	
Wald chi-square (52 degrees of freedom)		210.63	
Probability>chi-square		0.000	
Pseudo R^2		0.349	

Note: Dependent variable 0 = non-poor households after flood, 1 = households remain poor from before flood below poverty level, 2 = households become poor from non-poor status before floods, robust standard errors are in parenthesis, values are statistically significant at ***=1%, **=5% and *=10% level
Source: Author's own compilation from survey data

One *specification* issue which needs to be checked is independence from irrelevant alternatives (IIA). The odds ratios in the multinomial logit model are independent of the other alternatives. The property of the logit model whereby P_j / P_k (ratio of probabilities) is independent of the remaining probabilities is called the IIA (Greene 2003, p.724). This independence assumption follows from the initial assumption that the disturbances are independent and homoscedastic. Hausman and McFadden (1984) suggest that if a subset of the choice set is truly irrelevant, omitting it from the model altogether will not change parameter estimates systematically. Exclusion of these choices will be inefficient but will not lead to inconsistency. But if the remaining odds ratios are not truly independent from these alternatives, then the parameter estimates obtained when these choices are included will be inconsistent. This observation is the usual basis for the Hausman's specification test. The test statistic is

$$\chi^2 = \left(\hat{\beta}_s - \hat{\beta}_f\right)' \left[\hat{V}_s - \hat{V}_f\right]^{-1} \left(\hat{\beta}_s - \hat{\beta}_f\right)$$

where s indicates the estimators based on the restricted subset, f indicates the estimator based on the full set of choices, and $\hat{V}_s$ and $\hat{V}_f$ are the respective estimates of the asymptotic covariance matrices. The statistic has a limited chi-squared distribution with K degrees of freedom. To check the specification issue, this study examines the full model with three distinct choices of dependent variable against another logit model omitting one choice from the dependent variable (choice 2, that is, households becoming poor from non-poor status before floods are omitted). The null hypothesis (H_0) is that differences in coefficients are not systematic. The calculated value of the Hausman test statistic (χ^2 with 26 degrees of freedom) is 12.633, which is less than the tabulated value of chi-square test statistic with 26 degrees of freedom (15.397) at 5% level of significance. Therefore, the concluding remark is that the null hypothesis cannot be rejected and the odds ratios in the fitted multinomial logit model are independent of the other alternatives.

5.3 Interpreting Vulnerability Estimates

Results from previous sections depict that poverty levels of households after floods are fluctuating with the differentiation of some demographic, socioeconomic and community factors along with the flood damages. One of the major objectives of this study is to check vulnerability of surveyed households due to floods in different segments of the sample. After examining the downside poverty levels as an observed outcome of floods and its determinants, this section is concerned with the vulnerability or expected outcome of floods on surveyed households and their characteristics. Four methodologies, such as, the vulnerability to poverty line (VPL) proposed by Pritchett et al. (2000), vulnerability to expected poverty (VEP) suggested by Chaudhuri et al. (2002), vulnerability to expected utility (VEU) introduced by Ligon and Schechter (2003) and vulnerability estimate using Monte Carlo Bootstrap simulation proposed by Kamanou and Morduch (2002), are used in this study to estimate households' vulnerability to floods that are described in chapter three.

5.3.1 Vulnerability to Poverty Line Estimates

The vulnerability to poverty line (Pritchett et al. 2000) methodology uses an OLS estimation that is very sensitive to measurement errors. The data set of this study contains only two periods (before and after flood) of household characteristics, so it may include an inter-temporal measurement error and unexplained factors. The analysis incorporates the fixed poverty line (monthly per capita 594.6 Taka) for both periods (before and after flood). Applying the poverty line and measured standard deviation of income changes, the estimate of vulnerability for flooded sample is performed. The value of the time horizon n is taken as 1 to estimate the household's vulnerability to floods. In addition, a vulnerability threshold of 0.5 is assumed for calculating the proportion of vulnerable households and VPL. To inaugurate vulnerability estimates according to this methodology, elimination of measurement errors is needed (see appendix 5.4).

After detection of the measurement error, vulnerability estimates are performed through the steps described in section 3.3.1. The results which are delineated in table 5.5, show that the measurement error has some effect on the vulnerability estimates. The adjusted measure also depicts that the head count vulnerability rate is about 8 percent higher than the existing poverty rate. Here the coefficient of variability is defined as the ratio of the standard deviation of first differences of log per capita income to the average of the log per capita income of the initial period (before flood). The estimated standard deviation of changes in the log income is 0.717, while the average of log income before flood is

6.342, so the ratio is 0.113. A household is defined as vulnerable if the log per capita income in any state (before or after flood) is less than the VPL.

Table 5.5: Estimates of vulnerability of flooded households by the VPL approach

	Flooded households data set	
	Ignoring measurement error	*Net of measurement error (30%)*
Mean of log per capita monthly income at initial period	6.34	6.34
Inverse of mean of log per capita income	567.93	567.93
Standard deviation of changes in log income during the period	0.72	0.50
Coefficient of variability	0.11	0.08
Vulnerability to poverty line [VPL(0.5,5,PL)]	6.63	6.55
Log poverty line	6.39	6.39
Head count poverty rate (before flood)	57.82	57.82
Head count vulnerability rate	67.33	65.51
Ratio of vulnerable to poor	1.16	1.13

Source: Author's own compilation from survey data

Apart from estimating vulnerability for the total sample, it would be also interesting to show the vulnerability level by different groups. Even though two groups head count poverty measures are the same, the vulnerability level may differ due to different kinds of resilience power from each group. The following table shows the poverty and vulnerability level across various groups of households, using estimated standard deviation with adjustment. The easiest way to compare the results among the groups is to look at the ratio of vulnerable to poor which also focuses on the relative importance of transient poverty.

Table 5.6: Estimates of poverty and vulnerability across groups by the VPL approach

Indicators	**Categories**	**Mean of log per capita income before flood**	**Head count poverty rate (%)**	**Head count vulnerability rate (%)**	**Ratio of vulnerable to poor**	**Sample proportion of categories (%)**
Gender of household head	Male	6.4	58.1	68.2	1.2	89.2
	Female	6.3	55.4	60.0	1.1	10.8
Education of household's earners	primary	6.1	64.3	77.1	1.2	47.1
	secondary	6.4	33.3	60.2	1.8	45.3
	Above secondary	6.9	31.2	31.8	1.0	7.6
Districts	Sirajganj	6.5	47.1	60.8	1.3	25.4
	Jamalpur	6.3	58.8	62.0	1.1	24.9
	Sunamganj	6.4	53.4	74.0	1.4	24.9
	Nilphamari	6.1	72.3	72.7	1.0	24.9
Cultivable land ownership	Landless	6.3	61.1	78.1	1.3	67.2
	Landowner	6.5	50.8	55.7	1.1	32.8
Ownership of dwelling place	No	6.3	60.3	66.1	1.1	46.4
	Yes	6.4	55.4	68.4	1.2	53.6
Have loan	No	6.6	46.3	60.1	1.3	16.4
	Yes	6.3	60.0	68.4	1.1	83.6
Have Savings	No	6.3	61.4	75.0	1.2	52.4
	Yes	6.4	53.8	58.0	1.1	47.6

Source: Author's own compilation from survey data

In quantitative poverty studies, female headed households are often found less well off than the male counterpart (Pritchett et al. 2000). Female household heads are mostly widows, divorced or single mothers, who often face social insecurity and religious obligations apart from natural calamities. The results of the above table show that even though the poverty level is lower for female headed households than for the male counterpart (about 3 percent), the ratio of vulnerability to poverty is slightly higher for male (1.1 for female and 1.2 for male). The male headed households have slightly higher mean per capita monthly income, but their poverty rate is higher than for the female headed households. This result contradicts with the findings of Pritchett et al. (2000). Male headed households also have higher income variability than female headed ones. One point to mention is that female headed households' amounts are only to 11 percent in the sample of 595 flooded households.

This analysis uses completed average educational years of the working members of a household. The educational years of household earners are then classified as having primary school if the value is between 0 to 5 years, secondary schooling with 5.1 to 10 years and above secondary schooling with more than 10 years. It is depicted from the table 5.6 that the poverty, vulnerability and also the vulnerability ratio decrease as the average educational years increase for the households. Above secondary level schooling households show the lowest proportion of head count poverty and vulnerability among the three classifications. According to the VPL methodology, the measure of vulnerability and the vulnerability to poverty ratio show the highest figures in Sunamganj district, while the poverty level before flood was the highest in Nilphamari district (about 72 percent). The rural households who have cultivable land show a higher mean of per capita income and a lower vulnerability rate than the rural landless. It is also an interesting finding from the data set that owners of dwelling places have slightly higher mean income levels, and lower poverty rates but higher vulnerability rates than the non-owners. The reason may be that owners of dwelling places face higher damage during flood due to inundation of durable assets and their houses. Households, who possess loans, have higher poverty and vulnerability rates than those who have no loans. For savings, the results show that the poverty and vulnerability rates are lower among households with savings than those without any savings.

5.3.2 Vulnerability to Expected Poverty Estimates

Another methodology to estimate household's vulnerability, introduced by Chaudhuri et al. (2002), is used in this study. This approach is known as the vulnerability to expected poverty (VEP) method that has the advantage to be applied to cross-sectional data and thus for flooded and non-flooded households. The focal assumption for this approach is that much of the variation across the households can be attributed to the differences in the observable characteristics of households, so that also a single cross-sectional data set can be quite useful for estimating future poverty. Predicted probabilities of poverty are generated based on households' demographic, socioeconomic, community and shock characteristics. Flood shock variables, such as flood height, duration, loss of working days, assets and crop losses, as well as the options available to the households to mitigate flood risks (as savings, membership of cooperation) are incorporated for the vulnerability estimation in this study. Applying the steps as described in section 3.3.2, the following vulnerability estimates are obtained (table 5.7).

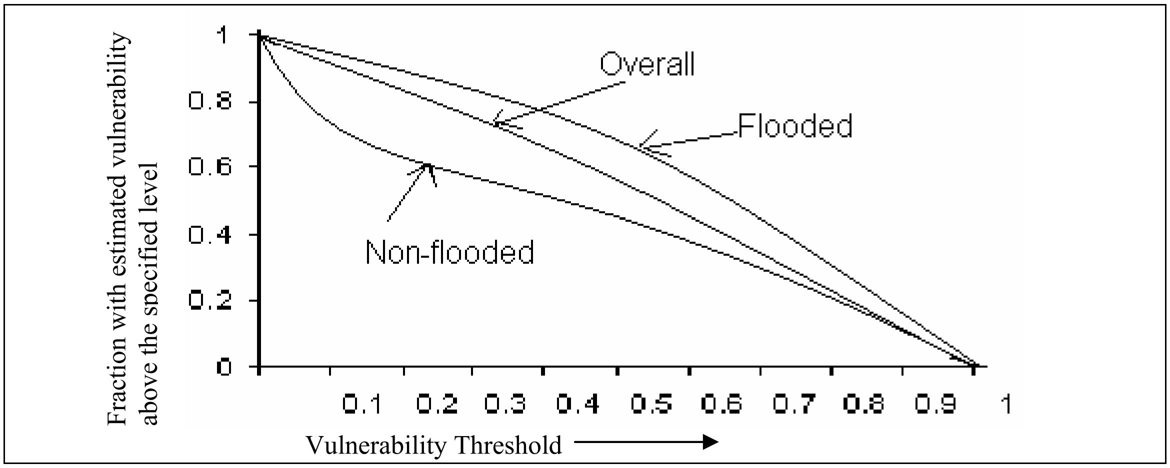
Table 5.7: Vulnerability estimates by the VEP approach

Sample	Districts	Poverty before flood	Poverty after flood	Vulnerability		
				Overall	Idiosyncratic	Covariate
Overall		55.1		62.5	63.4	64.1
Non flooded		51.6		58.8	58.2	51.1
Flooded	Total	57.8	74.8	67.0	66.9	77.2
	Sirajganj	47.1	66.0	60.1	65.5	18.9
	Jamalpur	58.8	88.5	68.2	50.3	15.6
	Sunamganj	53.4	57.5	58.2	57.1	27.8
	Nilphamari	72.3	87.2	78.6	76.4	87.9

Note: Vulnerability threshold point is 0.5, figures are showing percentages
Source: Author's own compilation from survey data

The overall vulnerability rate is about 7 percent higher than before flood poverty, so that such proportion of households will fall under the poverty line in the near future. So, the fixed characteristics and shock variables have some noteworthy effects by pushing down households' wellbeing. Non-flooded households are also vulnerable to poverty, but the disparity between vulnerability and the before flood poverty level is higher for flooded households (about 9%). For the overall sample and for non-flooded households only, it was not possible to evaluate the after flood poverty levels due to shortcomings of data. The estimated vulnerability for flooded households is a bit lower than the actual after flood poverty level. Among the districts, Sirajganj shows the highest fluctuation in vulnerability to poverty rates. Households from Nilphamari district, who faced the flash flood in the year 2005, have the highest poverty and vulnerability rates. Idiosyncratic and covariate vulnerabilities are also estimated through the VEP methodology. Idiosyncratic or household specific vulnerability estimation incorporates only socio-demographic and shock variables described in chapter three, whereas covariate or aggregate vulnerability estimation includes shock and community variables. Households facing flash flood are very vulnerable to both idiosyncratic and covariate characteristics, as they are not prepared for the sudden floods. On average households facing a monsoon flood are more vulnerable to idiosyncratic shocks, as their household specific variables play a major role in mitigating income shocks due to monsoon flood.

Figure 5.2: Estimated vulnerability by the VEP approach



Source: Author’s own compilation from survey data

The above figure further decomposes the vulnerability estimates by VEP approach. Flooded households’ vulnerability levels are higher than the overall and the non-flooded households estimated vulnerabilities. The figure shows a smoothing curve from the histograms corner points.

This study also examines vulnerabilities according to income sources. The following table (5.8) shows that farmers are the most vulnerable to flood disasters, followed by day laborers. However, day laborers show the highest poverty levels before flood, while for farmers, crop damages during floods result in sharp declines of households’ income. Actual poverty levels deteriorate among agriculture based households by 25 percent, followed by dairy and poultry based households (23%). About 32 percent more vulnerability counts for flooded farmers than for non-flooded ones. The least vulnerable flooded households are those whose major source of income is remittance (about 27%), followed by service holders. For non-flooded households, service holders show the lowest poverty and vulnerability levels.

Table 5.8: Major sources of income and vulnerability by the VEP approach

Major source of income	**Flooded**				**Non-flooded**	
	Poverty before flood	*Poverty after flood*	*Change in poverty*	*Vulnerability*	*Poverty*	*Vulnerability*
	(1)	*(2)*	*(2) - (1)*			
Agriculture	61.1	85.7	24.6	93.8	51.3	61.8
Service	30.8	41.0	10.2	39.5	17.2	24.2
Business	38.8	53.8	15.0	45.8	48.4	51.0
Day labor	72.3	87.0	14.7	90.0	59.5	74.7
Dairy and Poultry	30.8	53.8	23.0	50.0	20.0	39.5
Remittance	56.9	62.7	5.8	26.7	58.8	24.8
Boatman and Fisherman	52.8	69.8	17.0	61.5	58.6	60.7

Note: Figures are showing percentages
Source: Author's own compilation from survey data

A careful scrutiny of the above table shows that vulnerabilities estimated through the VEP approach are much higher for flooded households for each source of income than the non-flooded counterparts except for businessmen. The reason may be that businessmen are always in risk cycle whether flooded or non-flooded. This is the only methodology out of four used in this study that could estimate households vulnerability from cross-sectional data and thereby non-flooded households' vulnerability is possible to be estimated only in this section.

5.3.3 Vulnerability to Expected Utility Estimates

The data from flooded households are used in this vulnerability to expected utility (VEU) methodology, introduced by Ligon and Schechter (2003). Out of the 1039 sampled households from flooded and non-flooded areas, 595 households are flooded. Information on flooded households' income and on a few other characteristics was collected from the cross-sectional survey, by asking the respondents about their before and after flood status. So, the data contain a very small type of panel over two periods. The questionnaires include idiosyncratic and aggregate characteristics of the households and their communities. The estimation procedure of households' vulnerability by the VEU approach includes some fixed household criteria such as age, gender, and education; some inter-household variables (for idiosyncratic risk) such as monthly income, non-food expenditure, asset value, number of meals taken, cost to reach market place for both before and after flood; some inter-community variables (for covariate or aggregate risk) such as, availability of primary and secondary schools, public hospital and electricity etc.

Missing values are imputed using regression over the reported information on a set of household characteristics. As Ligon and Schechter (2003) defined their utility function, the utility from perfect equality in a no-risk society is equal to 1. So, the percentage welfare loss from vulnerability is equal to the size of vulnerability. After estimating vulnerability according to the steps described in section 3.3.3, the percentage of welfare loss can be divided for each element of vulnerability, such as poverty, aggregate risk, idiosyncratic risk and measurement error. To look at the correlates of these elements, some fixed household characteristics are regressed over each element and bootstrap standard errors for the coefficients are also measured. A summary of variables used in this approach is given in the appendix 5.5. Estimated vulnerability is regressed on the average year of education for household's working members, dummy variable for gender of household head (1=male, 0= otherwise), age and square of age of household head, cultivable land per capita, ownership of the dwelling place and number of household members. Linear relationship is assumed and OLS estimates of coefficients are given in the appendix 5.6. Now, this study checks whether the omitted variables are significant or not by the Ramsey RESET test using powers of the fitted values of vulnerability (Gujarati, 2003, p.521) with the null hypothesis (H_0) that the model has no omitted variables. As the estimated statistic of the Ramsey test shows, F (3, 592) = 2.40 and Probability > F = 0.671. So, the conclusion would be that the null hypothesis cannot be rejected at a 5% level of significance. The next step is to test for heteroscedasticity because the survey was cross-sectional. The Breusch-Pagan-Godfrey test (Gujarati, 2003, p.411) for heteroscedasticity is applied with the null hypothesis (H_0) that the error variances are constant. The chi-square test statistic results as 331.01 with Probability>chi-square = 0.0000. From the test result, it is depicted that there is heteroscedasticity in the error variance. The next step would be to regress vulnerability and its elements on the fixed set of households' characteristics resolving the heteroscedasticity problem. This analysis performs the regression with robustness and detects the bootstrap standard errors with 500 replications. The results are given in appendix 5.7. The following table accumulates the overall information on the correlates of vulnerability and each of the elements, such as poverty, aggregate risk, idiosyncratic risk and unexplained risk of flooding with the remedial test for heteroscedasticity and bootstrapping.

Table 5.9: Decomposition of vulnerability to poverty and risks by VEU approach

	Vulnerability	**Poverty**	**Aggregate Risk**	**Idiosyncratic Risk**	**Unexplained Risk**
Variables	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
Education	-23.821***	-11.800***	-7.891***	-0.313***	-3.817
	(5.086)	(1.744)	(1.334)	(0.049)	(4.239)
Male	35.803	-13.631	14.855	-2.012**	35.015
	(52.250)	(20.660)	(16.716)	(0.897)	(44.638)
Age	-3.031	2.150	-1.641	0.146**	-3.686
	(6.748)	(2.239)	(1.582)	(0.062)	(4.994)
Age squared	0.008	-0.029	0.021	-0.001*	0.001
	(0.0643)	(0.023)	(0.016)	(0.001)	(0.046)
Cultivable Land per capita	-24.115	-48.335*	-23.222**	-0.294	47.736
	(38.117)	(25.441)	(11.255)	(0.471)	(48.348)
Ownership of house	-80.390**	-33.485***	-24.920***	-1.208***	-20.778**
	(40.805)	(10.454)	(7.970)	(0.399)	(10.520)
Family size	10.681*	5.861**	4.108**	-0.170*	0.882
	(6.055)	(2.681)	(1.991)	(0.095)	(5.560)
R^2	.636	.584	.597	.740	.311

Note: Numbers in parenthesis are bootstrapped standard errors, ***=at 1%, **=at 5% level, *=at 10% level
Source: Author's own compilation from survey data

It is depicted that the correlates of flood vulnerability are apparently similar to the correlates of poverty (for significant variables) which is also a noteworthy factor for defining vulnerability. Additionally, the significant variables in poverty and aggregate risks share the same sign of coefficients. Aggregate shocks from flood are the same for all households, so the poor households may experience a greater impact on their utility from this part of risk. The household's idiosyncratic (individual) risk is measured by three observed factors from two periods (before and after flood), such as: asset value, number of meals taken and cost to reach market place. To assess the aggregate (common) risk, some community-based variables are used, such as: availability of primary and secondary schools, public hospitals, electricity and flood shelter.

Education is the most significant variable to define vulnerability. The households with higher educated members are found to be less vulnerable which is similar to the result of Ligon and Schechter (2003). The increase of one unit educational year of household's earners decreases vulnerability to flood by 24 units. Most of this reduction will appear in poverty, but idiosyncratic and aggregate risks also decrease substantially. The gender of the household head has no significant effect on vulnerability, but reduces the idiosyncratic risk significantly. The reason may be that male-headed households acquire better intra-household resource allocation than the female-headed households. Households with older heads face higher idiosyncratic vulnerability but after a certain point their experience helps them to reduce such kind of vulnerability (negative coefficient for age squared). Arable land holding shows significant relationship with poverty and aggregate risk. Perhaps more availability of land leads the households to rotate and diversify their crop choice, hence reducing poverty and the aggregate risk. Ownership of a dwelling place has a significant negative relation with vulnerability and risks, even reducing unexplained risk considerably. With the increase of the family size, distribution of the household income and resources would be lower to each member. Thus vulnerability, poverty and aggregate risk may be aggravated significantly, but the goods of common share may help to minimize idiosyncratic risk.

Table 5.10: Correlations among the elements of vulnerability

	Poverty	**Aggregate Risk**	**Idiosyncratic Risk**	**Unexplained Risk**
Poverty	1.00			
Aggregate Risk	0.747***	1.00		
Idiosyncratic Risk	0.388***	-0.291	1.00	
Unexplained Risk	0.042	0.018	-0.148*	1.00

Note: Spearman rank correlations technique is chosen for above table. ***=at 1%, **=at 5%, *= at 10% level
Source: Author's own compilation from survey data

Poverty and aggregate risk due to flood have a strong positive correlation. It can be described by the diminishing marginal utility principle that the poor are mostly affected by the aggregate flood risk, which is uniformly distributed to the utility of income of the households. Poverty and idiosyncratic risk are positively correlated and highly significant. The poor have less assets and selective ways of earning. If a flood ruins their crops or hinders their way of earning, then households would live even more in poverty and may fall into the vicious cycle of debt.

5.3.4 Vulnerability Estimates from Monte Carlo Bootstrap Approach

For a better understanding of the vulnerability estimates for flooded households by the Monte Carlo Bootstrap approach, as suggested by Kamanou and Morduch (2002), the changes in normalized poverty gaps and squared poverty gaps for floods are shown in the following (table 5.11).

Table 5.11: Changes in poverty gaps for flooded households

Indicators	Before flood	After flood
Normalized poverty gap	0.182	0.447
Squared poverty gap	0.077	0.336
Average income per capita (in Taka)	650.37	545.45

Note: 595 flooded households, Poverty measures are measured through Foster et al. (1984)
Source: Author's own compilation from survey data

From the above table, it is depicted that the headcount poverty rate is worsened by 17 percent for flooded households in four districts. The normalized poverty gap measures the average distance of the poverty line from the households below the poverty line (594.60 Taka per capita per month), thus indicating the depth of poverty. Flood has been found to cause a deterioration of the poverty depth by one and a half. The squared poverty gap measures the severity of poverty among households where the poorest of the poor households get the highest weight, thus showing the inequality among the poor households. Poorest households are experiencing larger inequality from a flood disaster. The mean per capita income also decreases after flood and falls even below the poverty line.

Measurement error creates a serious challenge for the analysis of vulnerability (Baulch and Hoddinott 2000). This error can come in several ways. First, errors in forming measures of income aggregates for households; second, inappropriate price and household size deflations; third, errors in matching households in panel data. This study incorporates the income from different sources for each of the household member and then sums up the income to get the aggregate income for that household. The prices of commonly consumed food items (rice, wheat, vegetable) are checked to consider inflation or deflation of real income. However, district wise mean prices of the three items do not show any significant variation when comparing before and after flood markets. The survey is cross sectional two weeks after floods and information about the before flood condition is enumerated by recall memory method, so that change in family size and matching of households does not occur in this data set. If there is misreporting in the households' income, it is likely to be under-reported which in turn shows the under-estimation of vulnerability to flood shock but not its exaggeration. The changes in income appear to be systematically related to human capital variables, district wise differences and household composition, suggesting that income variation is not mainly due to measurement error. The quality control of this survey is ensured by cross-checking of field supervisors and quality controllers.

The mean and standard deviation of changes in the per capita income and adult equivalence income for before and after flood periods are delineated in appendices 5.8 and 5.9, respectively. The scale difference (per capita to adult equivalence) does not change the picture very much. The data are disaggregated within districts by income quartiles. The appendices show that variations in the households' average income between before and after flood periods are large in Jamalpur district; the richest groups have the highest variations amongst the quartiles and also possess the largest standard deviations. Sunamganj district shows the least income variations among the four districts. Appendix 5.10 shows that the poorest quartiles from four districts have faced a disproportionately large income shock caused by flood. Downward variability is somewhat less for the richer households than the poorer. Within districts, Jamalpur shows the largest proportional income change compared to others for both mean and standard deviation. In Sunamganj and Jamalpur districts, the poorest households are facing the larger downward income changes regarding their before flood income (on average 0.073 and 0.692, respectively). Nilphamari district's richest households show proportionately greater standard deviation in income change. Albeit the absolute change of income was higher for the richest quartile, the proportionate changes show the different views. The figure in the appendix 5.11 represents the values from the above table in a graphical way. Households in Sunamganj district have the flattest line graph compared with others. Households in Jamalpur district show a higher magnitude of income changes. Households in Sirajganj and Nilphamari districts have somewhat similar patterns, with the poorest being less affected, then the downward stream of income starting to increase and the richer households facing again less income fluctuations. It is hypothesized that the households in the poorest quartiles of the four districts would be mostly affected by floods. The change in the squared poverty gap (also indicating inequality) in appendix 5.12 supports the hypothesis. Among the districts, poorest households have increased their inequality level, except for Nilphamari. Some households in the second quartiles escaped from their poverty status during flood in both Jamalpur and Sunamganj districts; an investigation shows that those households are fishermen or boatmen. Jamalpur district shows the largest deterioration of income due to flood (inequality ranges from 0.29 to 0.59), whereas Sunamganj district shows the least downward income shock (inequality ranges from 0.01 to 0.07).

One simple method to estimate vulnerability may be to compare standard deviations of income or consumption changes, meaning that households or communities are more vulnerable if standard deviations of past consumption changes are higher. This method is associated with variability to estimate vulnerability, but it requires long term panel data. The standard deviation could be estimated from the cross sectional variation that picks up the dispersion of shocks and not their average strength. A strong homogeneity assumption on shock must be made in order to be able to interpret the results of vulnerability. All the households observed in the cross section are assumed to be a sample drawn from the same distribution of consumption changes. The measures of dispersion of changes will then indicate the degree of exposure to risks. Another problem can arise when standard deviation is taken as a measure of vulnerability, then downside risk is weighed the same as upside risk. A five percent upward shock affects the standard deviation identically to a five percent downward shock. Coefficient of variation could help in this regard except for zero means. Another remedial to avoid the problems of standard deviation is to use the Monte Carlo bootstrap method. According to the steps described in section 3.3.4, the following vulnerability estimates are evaluated.

Table 5.12: Estimates of vulnerability by the Monte Carlo Bootstrap simulation

Districts	**Before flood observed headcount**	**After flood observed headcount**	**After flood bootstrap headcount**	**Change in observed headcount**	**Vulnerability index**
	(1)	*(2)*	*(3)*	*(4)=(2)-(1)*	*(5)=(3)-(1)*
Overall	0.578	0.748	0.778	0.170	0.200
Sirajganj	0.471	0.660	0.660	0.189	0.189
Jamalpur	0.588	0.885	0.906	0.297	0.318
Sunamganj	0.534	0.575	0.605	0.041	0.071
Nilphamari	0.723	0.872	0.847	0.149	0.124

Note: Change in observed headcount poverty (column 4) rate indicates the difference between column (2) and column (1), vulnerability index (column 5) is counted as column (3) minus column (1), and positive values indicate a worsening of conditions. N = 595 flooded households
Source: Author's own compilation from survey data

For the overall flooded households, the observed change in the headcount is smaller (0.170) than the vulnerability index (0.2). The table 5.12 shows that many more households are vulnerable than actually become poor after floods (Jamalpur and Sunamganj districts), so a shock like the flood in the year 2005 could play a significant role to the economy, pushing the richer households below the poverty line and the observed poor become poorer.

5.3.5 Comparing Vulnerability Estimates from Four Methodologies

In this section, the estimated households' vulnerability within the different segments of the sample and household's characteristics are stated to facilitate comparisons among the four methodologies used in this study. Since only the VEP approach allows to estimate non-flooded households' vulnerability, table 5.13 focuses on comparing enumerated poverty and estimated vulnerability levels of flooded households.

Table 5.13: Comparison of vulnerability estimates from the four methodologies

Indicators	Variables	Pov. before flood	Pov. after flood	Vul. by VPL	Vul. by VEP	Vul. by VEU	Vul. by Monte Carlo Bootstrap
Overall		57.8	74.8	65.5	67.0	73.9	77.8
District	Sirajganj	47.1	66.0	60.8	60.1	65.3	66.0
	Jamalpur	58.8	88.5	62.0	68.2	81.9	90.6
	Sunamganj	53.4	57.5	74.0	58.2	57.0	60.5
	Nilphamari	72.3	87.2	72.7	78.6	89.4	84.7
Types of floods	Monsoon	53.1	70.7	65.6	62.2	68.1	72.4
	Flash	72.3	87.2	72.7	78.6	89.4	84.7
Gender of Household head	Male	58.1	75.5	68.2	66.3	73.6	83.2
	Female	55.4	69.2	60.0	68.1	60.0	77.8
Education of earners	primary	64.3	80.9	77.1	70.9	83.1	84.3
	secondary	33.3	53.7	60.2	61.5	59.6	76.5
	Above secondary	31.2	37.5	31.8	49.7	40.2	58.3
Major source of income	Agriculture	61.1	85.7	88.3	93.8	81.0	79.0
	Service	30.8	41.0	29.0	39.5	34.7	45.3
	Business	38.8	53.8	48.3	45.8	56.5	54.9
	Day labor	72.3	87.0	78.9	90.0	79.2	85.0
	Dairy and Poultry	30.8	53.8	44.4	50.0	51.3	66.7
	Remittance	56.9	62.7	53.5	26.7	58.9	34.8
	Boatman and Fisherman	52.8	69.8	44.7	61.5	66.8	73.0
Land ownership	Landless	61.1	73.5	78.1	78.3	72.7	67.9
	Landowner	50.8	77.5	55.7	81.4	69.5	83.5
Ownership of dwelling place	No	60.3	76.2	66.1	69.4	77.0	83.6
	Yes	55.7	73.6	68.4	53.9	69.8	68.2
Have loan	No	46.3	66.3	60.1	60.1	67.4	57.7
	Yes	60.0	76.4	68.4	67.7	78.4	89.0
Have savings	No	61.4	77.2	75.0	86.4	73.3	80.0
	Yes	53.8	72.0	58.0	69.0	69.9	68.4

Note: Pov. indicates poverty and Vul. indicates vulnerability, Only for flooded households, Figures are showing percentages
Source: Author's own compilation from survey data

This study hypothesized in chapter three that the VEU approach would better fit the surveyed data than any of the other three methodologies. The logic behind this hypothesis is that the environment before and after flood periods is assumed to be stationary with measurement error and heterogeneity in the household's income data. Households' vulnerability to floods is estimated in this study based on the strong assumption that households' mean income level would remain the same in absence of flooding. In other words, the future income, consumption and utility levels of households are subject to change due to floods only, and otherwise the environment of households' livelihoods would be the same as before. The income and utility levels are assumed to change across households, and some extent of heterogeneity may exist which is the usual phenomena of cross-sectional survey data. Table 5.13 depicts that households' vulnerability levels estimated by the VEU approach across different characteristics are indeed much closer to actual after flood poverty levels as compared to VPL, VEP and Monte Carlo Bootstrap approaches.

5.4 Summary

This chapter starts with econometric models to determine significant factors for households' income and prediction. Then some estimation procedures on households' poverty and vulnerability levels are incorporated. A multinomial logit model, fitted to the flooded data set, shows that flood height, flood duration, loss of crops, loss of working days, coping amount from loan and selling assets are significantly and positively related with the after flood poverty of the poor households. Flood duration, loss of assets, cost of disease during flood and coping from savings and selling assets have positive and significant effects on the non-poor households' welfare.

The results from the VPL approach show that even though the poverty level is lower for the female headed households than their male counterpart (about 3 percent), the ratio of vulnerability to poverty is slightly higher for male ones (1.1 for female and 1.2 for male). It is depicted that the increase of average educational years would decrease households' poverty and vulnerability. The rural households who have cultivable land show a higher mean of the per capita income and a lower vulnerability rate than the rural landless. Flooded households have a higher vulnerability (8%) than the non-flooded counterparts, as estimated by the VEP approach. Another important finding from this methodology is that households facing a monsoon flood are more vulnerable to idiosyncratic shocks, whereas a flash flood would cause fatal covariate shocks. Farmers are found to be the most vulnerable due to flood disasters, followed by day laborers and the least vulnerable flooded households are remittance holders. Out of the four methodologies used in this study to estimate vulnerability, only the VEP approach is appropriate for cross-sectional data. Since this study only has one period (before flood) information for non-flooded households, vulnerability of the non-flooded households is estimated through the VEP approach. From the VEU approach, it is depicted that the correlates of flood vulnerability are similar to the correlates of poverty. Education is found to be the most significant variable to define vulnerability. The households with higher educated members are less vulnerable. Arable land holding shows a significant relationship with poverty and aggregate risk. Poverty and aggregate risk due to flood show a strong positive correlation in the VEU approach. Estimates from the Monte Carlo Bootstrap approach show that vulnerability levels are higher in proportion than the actual poverty levels after floods. Therefore, a shock like a flood in the year 2005 plays a significant role to the economy, pushing the richer households below the poverty line and the observed poor become poorer. However, households' vulnerability levels estimated by the VEU approach across different characteristics are much closer to actual after flood poverty levels compared to VPL, VEP and Monte Carlo Bootstrap approaches.

Chapter Six

6. Coping with Floods

The Oxford English Dictionary defines 'cope' as 'to manage successfully'. The coping strategies are fallback mechanisms for when habitual means of meeting needs are disrupted (Frankenberger 1992). If households suffer from a shock like a flood, they utilize the resources and options they have to survive. The actions for survival strategies are mentioned as coping strategies. Initially, households try to minimize risks and maintain some minimal level of sustenance. Gradually the households start the disposal of assets in several phases as a coping strategy. This chapter focuses on the descriptive statistics and econometric analyses of coping strategies of flooded households.

6.1 Coping Strategies of Flooded Households

In the empirical study conducted after the floods, households' representatives were asked about the coping strategies they followed during and after flood periods. Out of 595 flooded households, all of them followed at least one strategy to cope with flood and aftermath. Some of the households followed more than one coping strategy.

Table 6.1 shows that flooded households have multiple responses for coping with floods, 2005. The highest frequency (193 households) is observed for borrowing goods and cash from the nearby shop or pharmacy. The coping strategies are classified into six broader groups, namely borrowing, using savings, selling items, changing habits, taking aids and others. The empirical results in table 6.1 show that flooded households relied more on taking loan from different sectors compared to the other five general classifications. Among 23 different sources, the highest amount used for coping with flood and aftermath is Taka 293,956 which was borrowed from neighbors or relatives with interest (2.32%). Only 33 households responded about having received aid from Government or NGO sectors and the amount (Taka 3674) was significantly lower than from borrowing loan or selling of assets. Some households (20 in numbers) also consume or use their savings to cope with flood. 154 flooded households reported that they reduced their number of meals and amount of consumption in a day, or sometimes bought cheap food items to cope with flood and aftermath.

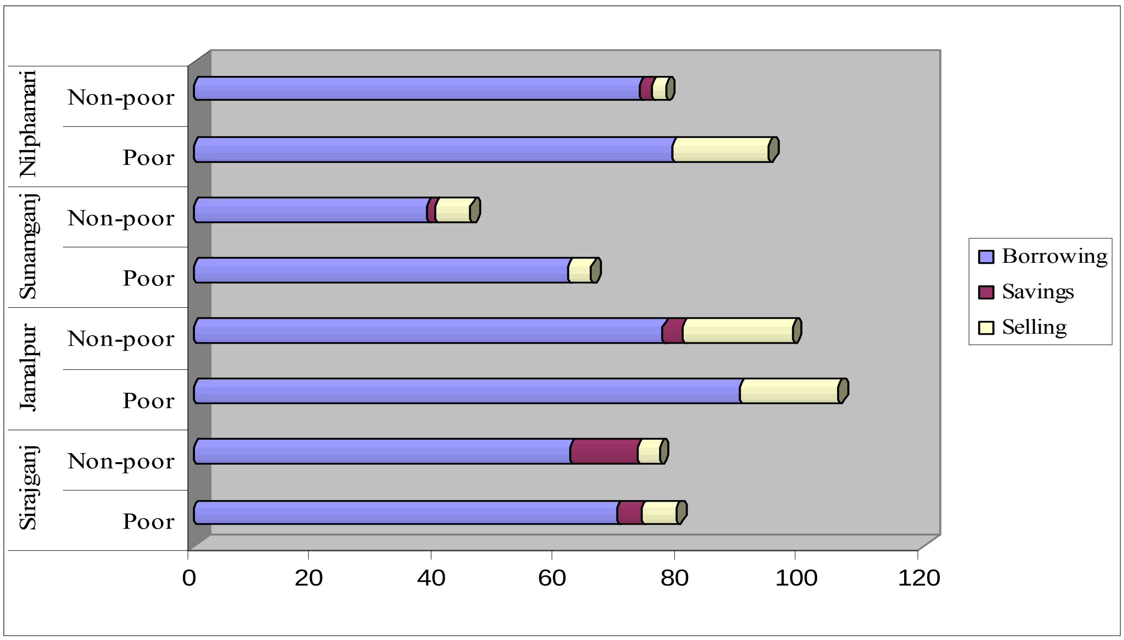
Table 6.1: Types of coping strategies and frequency of flooded households

	Type of coping	Number of household	Amount (in Taka)
Borrowing/ taking loan	Loan from neighbors/relatives (with interest)	119	293,956
	Loan from bank	12	64,000
	Loan from NGO	23	107,000
	Loan from employer/master	3	6000
	Loan from money lender	57	154,200
	Loan from neighbors/relatives (without interest)	115	240,870
	Loan food grain from kin	47	49,572
	Loan from nearby shop/pharmacy	193	157,413
Use savings	Use/consume savings	20	62,800
Selling	Sell home/homestead/cultivable land	2	5700
	Sell domestic assets (furniture, utensils, clothing, means of transport)	3	6450
	Sell livestock (cattle, buffalo, chicken, ducks, hens)	42	73,400
	Sell jewelry	1	2000
	Sell agricultural products in advance at lower price	1	2400
	Sell trees	2	5000
	Sell rice stocks	15	31,580
Changing habits	Change frequency of meals, food items and reduce consumption	154	
	Change occupation or working pattern	8	
Taking aid	Aid from Government or NGO	33	3674
	Aid from any organization	1	3000
	Aid from neighbors/relatives	4	1500
Others	Begging	3	1300
	Mortgage land	1	5200

Source: Author's own compilation from survey data

While the frequency of households and amount of coping are illustrated in the above table, it is worthwhile to know about the percentage distribution of rural households using coping strategies against floods in the year 2005 among different districts and poverty levels. Figure 6.1 shows that borrowing plays a major role for both poor and non-poor households in each district. The highest proportion of borrowing is taken by the poor households (89.7%) in Jamalpur district and the same group of people sells their assets at a high proportion (16.1%) for coping after monsoon flood. The flash flood in Nilphamari district also forces people, especially the poor households, to take loan (78.5%) and sell their assets (15.9%) at high proportion.

Figure 6.1: Percentage distribution of households' coping strategies among districts and poverty levels



Source: Author's own compilation from survey data

The figure 6.1 shows the categories and frequency distribution of coping from borrowing or taking loans. About 32 percent of flooded households reported to borrow money or essential goods from a nearby shop or pharmacy. Households also coped by taking loan from neighbors or relatives with and without interest by 20 percent and 19 percent, respectively. In total Taka, borrowing from neighbors or relatives with interest was the highest source of coping. Total amount of loan taken by flooded households was Taka 1,073,011. It also depicts from the empirical analysis that out of the 595 flooded households, 413 households (about 69%) mentioned to cope with borrowing or taking loans from any of the eight different sources. It appears from the table 6.1 that informal sources of credit were more effective than traditional micro-credit programs (as noted in Zaman 1999 and Ninno et al. 2001). Appendix 6.1 shows average monthly interest rates mentioned by the flooded households who borrowed money or goods from different sources. The highest interest rate (8.25%) is taken by the money lenders. The average weekly interest rate taken by Government or private banks (1.4%) is much lower than those taken by NGOs or money lenders (7.5%), but rural people have limited access to claim for the loan during and aftermath of flood. From focus group discussion, it is depicted that people take loans from NGOs or money lenders despite high interest rates at an emergency basis. The finding of this study on interest rates taken by NGOs contradicts with the result of Ninno et al. (2001), who found from the flood survey in Bangladesh that NGOs took the lowest interest rates.

Appendix 6.2 depicts the frequency of households taking loans for coping during and aftermath of flood and the amount of loans in different poverty groups among the four districts. It is apparent that poor households depended more on borrowing than the non-poor households in all districts except for Sirajganj. Appendix 6.3 delineates households' distribution and their amount of money used as a coping strategy from borrowing by different income quartiles and districts. In Sirajganj district, frequency and amount of money borrowed by the richest quartile are higher than for the other three quartiles. Households who coped with borrowing in Jamalpur district are higher in numbers in the third quartile, but the poorest quartile took more loans (Taka 124,725) than the other three groups. For Sunamganj district, households in the third quartile took the highest amount of loans among the four quartiles. Flooded households in Nilphamari district who belong to the poorest quartile show the highest amount and frequency of borrowing. It is depicted in appendix 6.4 that farmers in flooded areas borrowed the highest amount of loan for coping (Taka 406536 in total). In frequency, day laborers borrowed at a higher rate (137 households) than the other income sources. Only 46 households with business as major income source took loan for coping, but illustrated the highest amount of borrowing per household (Taka 4005 per household) amongst all income sources.

Table 6.2: Utilization of loans and savings by flooded households

Sectors	Coping with borrowing/loan		Coping with savings	
	Number of households	*Percentage of total amount of loan spent*	*Number of households*	*Percentage of total amount spent from savings*
Agriculture/ farming	230	20.4	8	14.64
Business	45	18.9	2	12.72
Health/Education	161	7.1	8	08.84
Food	322	25	15	32.69
Housing (repairing)	79	18	2	11.21
Marriage/dowry	27	6	4	17.55
Others	24	4.6	3	2.35

Source: Author's own compilation from survey data

About 78 percent of the households used the loan for buying food that amounts to 25 percent of the total loan (Taka 1,073,011). Ninno et al. (2001) also found a similar kind of result from the flood survey in 1998, that a high percentage of flooded households took loan especially for food consumption. 230 households spent the borrowing money for farming which was 20 percent of the total amount of loan. About 19 and 18 percent of the total loan were used for business and house repair after flood respectively. In rural areas spending for marriage ceremony and paying dowry are customary events. 6 percent of the total loan was used for marriage disbursement. The category 'others' stands for spending money on judiciary cases, transition cost of temporary migration, or repaying loans. Among flooded households (595), only 20 households responded to use their savings for coping with flood. Table 6.2 depicts that 75 percent of households, out of 20 households who used savings for coping, utilize their money for food. About 33 percent of the total amount is spent on food items. About 18 percent of savings is used for repaying loans, and about 15 percent of savings is utilized for the agriculture sector.

There are multiple coping strategies that are simultaneously determined by the flooded households. As not all coping mechanisms are chosen by each of the flooded households, this study uses some reduced form of regression analyses to identify the determinants for borrowing, savings and selling assets. The regression models suitable for this type of truncated sample, where there are significant zero values in the dependent variable (for households who did not use any coping amount from borrowing, savings or selling items), is known as the censored regression model or tobit model (Greene 2003, p.764), proposed by Tobin (1958). The general formulation is given in terms of an index function

(1) $y_i^* = x_i'\beta + \varepsilon_i$

where $y_i = 0$ if $y_i^* \leq 0$

and $y_i = y_i^*$ if $y_i^* > 0$

The random variable y_i is transformed from the original dependent variable y_i^*, x_i is denoting the exogenous variables and ε_i is the error term. For the standard case with censoring at zero (households do not cope with borrowing, savings or selling assets) and normally distributed error terms, coefficients would be estimated as

(2) $\dfrac{\partial E[y_i|x_i]}{\partial x_i} = \beta\Phi\left(\dfrac{\beta' x_i}{\sigma}\right)$

where Φ (.) denotes the cumulative density of the standard normal distribution. From the above equation, it is depicted that least square estimates of the coefficients in a tobit model usually resemble the MLE (Maximum Likelihood Estimate) times the proportion of non-limited observations in the sample. Factors and variables that are significant determinants for coping with borrowing money, spending from savings and selling assets are depicted in appendices 6.5, 6.6 and 6.7, respectively. Assessing the difference in proportions of households choosing three main coping strategies among districts in figure 6.1, the tobit model estimates include the district dummies as community factor. Three different models are chosen for estimating the significant factors for each of the three main coping strategies: the first model includes only shock variables to measure whether the shock factors alone could explain the variation of borrowing amount sufficiently; the second model includes demographic factors in addition to shock variables; and the third model considers all shock, demographic, economic and community factors. However, for all three coping strategies (borrowing, savings and selling assets), the model with all four factors (model 3) shows the highest log likelihood values. This means that the third model for each coping strategy is predicting the outcome variable more accurately with highly significant probability values. Table 6.3 shows the estimated results using tobit models (the best predicted models detected from appendices 6.5, 6.6 and 6.7) for the three main coping strategies using MLE.

Table 6.3: Determinants of coping strategies: tobit model estimates

Factors Variables	Borrowing	Savings	Selling assets
	Coefficients	*Coefficients*	*Coefficients*
Shock factors:			
Flood height	164.51 (53.06)**	-766.97 (572.37)	88.14 (116.41)
Flood duration	1.08 (7.28)	127.93 (67.89)**	25.99 (8.16)***
Loss of crops	0.006 (0.003)**	0.36 (0.39)	0.07 (0.06)
Loss of assets	0.60 (0.11)***	0.72 (0.83)	0.25 (0.15)*
Loss of working days	8.72 (4.67)*	73.39 (38.39)*	8.40 (9.62)
Demographic factors:			
Household size	-39.88 (17.37)**	-25.62 (151.91)	-34.20 (32.59)
Dependency ratio	12.25 (39.26)	209.96 (122.06)*	3.50 (0.54)***
Age of household head	-4.80 (2.58)*	-2.47 (26.22)	-8.05 (5.55)
Average education of working members	-2.96 (13.82)	-120.03 (70.19)*	-23.44 (31.11)
Gender of household head (male=1)	209.64 (116.19)*	159.13 (152.15)	-39.51 (49.56)
Occupation (agriculture=1)	111.52 (63.09)*	476.37 (975.09)	73.95 (70.20)
Economic and community factors:			
Per capita income before flood	-0.12 (0.04)**	1.73 (0.52)**	-0.34 (0.25)
Membership in cooperatives	51.63 (68.89)	761.37 (688.72)	12.54 (6.53)**
District dummy 1(Sirajganj=1)	-117.54 (127.10)	713.58 (628.68)	-12.99 (55.88)
District dummy 2(Jamalpur=1)	184.14 (107.86)	192.11 (279.50)	249.20 (205.42)
District dummy 3(Sunamganj=1)	-133.66 (128.09)	-258.40 (238.06)	-122.43 (175.13)
Number of uncensored observations	413	20	57
Log likelihood	-89.55	-116.99	-149.14
LR chi-square	112.72	35.29	22.24
Probability>chi-square	0.000	0.008	0.001
Pseudo R^2	0.577	0.382	0.413

Note: Dependent variables: amount of borrowing, savings and selling assets (truncated from the lower limit zero, i.e. zero amount of borrowing, spending from savings or selling assets), robust standard errors are in parentheses, values are statistically significant at ***=at 1%, **=at 5%, *=at 10% level, All the models include constant terms not reported in the table

Source: Author's own compilation from survey data

A household's decision to borrow as coping strategy has a positive and statistically significant relationship with the height of flood; if the flood height increases by one foot then households would borrow on average Taka 165 more. Male headed households would borrow more than their female counterparts. Interestingly, the amount of borrowing is negatively correlated with household size but positively correlated with the dependency ratio that means the more active members a household has the less amount they borrow for coping. The loss of assets is positively related to the amount of borrowing but households with more income are less likely to borrow. Amount of savings spent by the households shows a significant positive relation with duration of floods, that is if flood water stays at their homestead one more day then the average spending from savings would increase by Taka 128. Dependency ratio and loss of working days are also positively interacted with the money spent from savings. Households with higher income are supposed to have higher savings and can afford to spend from savings in crisis time. Data of this study illustrate a similar pattern. Amount of selling assets is highly significant and positively correlated with flood duration and dependency ratio. Any membership of households in the local cooperatives would help to sell their assets during floods. In the table 6.3, it is depicted that households start borrowing when they realize that a flood shock is taking place. Gradually they instigate spending money from savings and selling assets with the extended period of flood.

Some *specification* issues may arise in tobit estimates, namely heteroscedasticity and non-normality. As heteroscedasticity $\{\mathrm{var}(\varepsilon) \neq \sigma^2\}$ emerges as a serious problem for MLEs, this study measures tobit estimates with robust standard error for each of the coping strategies and finds that the significance levels of the independent factors are not changed from the estimated models with normal standard errors. Therefore, MLEs from the three models (in appendices 6.5, 6.6, 6.7) do not suffer from heteroscedasticity problems. Then, the next step is to check the normality assumption of the estimated error terms of the models. Skewness-kurtosis tests are performed for the error terms estimated from each of the model with the three dependent variables amount of borrowing, spending from savings and selling items. At 1% level of significance, all the three models show that normality assumptions hold for the disturbance terms.

6.2 Diversification as Coping Strategy

Diversification of agricultural activities is commonly used by the households facing flood risks. The idea is to reduce the dispersion of the overall return by selecting a mixture of activities that have net returns with low or negative correlations (Alderman and Paxson 1992; Reardon et al. 2000). Moreover, the target is to find the risk-efficient combinations of activities, not only one crop that simply minimizes variance, but which focuses on the characteristics of increasing the level of risk aversion of the farmers. Such diversification could be costly if the households aim to take the advantages of specialization that confers to acquire superior technologies for the needs of specific markets. The new technology requires farmers to invest more levels of inputs to gain higher potential returns. Even risk averse poor households may have been willing to accept this risk and the greater volatility in return for the prospect of potential gains, while the potential gains in risk efficiency from agricultural diversification are often lower than what was imagined. Agriculture based families, in a less developed country like Bangladesh, often diversify income sources. Several ways of diversification are possible, such as engaging in non-farm activities as handicraft production, poultry rearing, running small scale business.

6.2.1 Crop Diversification

Analyses of this section show the crop diversification impact and households' vulnerability to floods. Households living in the same district may have different magnitude of vulnerability from the flood 2005 for their variation of crop choice. From the descriptive analyses, it is depicted that close to one-third of the households are farmers and as table 5.8 has shown, households' in this income group are the most vulnerable (about 94%). That is why this section mainly focuses on crop diversification and vulnerability differentials.

The first step is taken by measuring district wise percentages of farmers from the flooded sample. Percentages of farmers for Sirajganj, Jamalpur, Sunamganj and Nilphamari districts are 6.5, 63.3, 4.1 and 43.9, respectively. So, only farmers from Jamalpur and Nilphamari districts are considered for econometric analyses due to larger sample sizes. In Jamalpur district 53 percent farmers reported to produce jute (cash crop) as major crop and 42 percent produce paddy (staple crop) as major crop. Some farmers produce both crops but the major crop is defined by the response of the surveyed households in terms of land, labor allocations and input price. The households' expected (normal) production of jute and paddy was asked and subtracted from their actual amount of crop yields after flood, 2005. The total yield loss of cash crop (jute) was higher in proportion (86%) than that of the staple crop. The proportion of yield damage in staple crop (paddy) was reported as 54 percent. Jamalpur district was affected by monsoon flood (caused by monsoon rain or torrential rain) during August to mid-September and the field survey was held during September 20th to October 15th. The average duration of flood was 7 days reported by the affected households, and average flood water height was 1 feet in the homestead. The sowing and harvesting period of paddy and jute is given in appendix 6.8, based on information from the BBS (2005:1).

The farmers' households in Jamalpur district who reported paddy as their major crop, mainly produce Aus[11] paddy. The flood during August to September affected the late harvested Aus paddy and the seeds of transplanted Aman[12] paddy, but the inundation of flood during that period mostly affected the jute production because of the harvesting time. The farmers already invested all their input money to the jute crop but could not get the output value from the yields. Some of the households lost their whole jute production. Table 6.4 shows the socioeconomic and vulnerability differentials of the Jamalpur farmers between those households who produce jute and paddy as the major crops. Then diversification of the crop pattern between the staple and cash crops to reduce risk from future flood is suggested, because the sowing and harvesting time of the two crops are almost the same regardless of the productivity, input price and profitability.

Table 6.4: Vulnerability differentials for different crop producers in Jamalpur

District	Crop	Yield loss (due to flood) in kilo per house hold	Value (yield* market price) loss (due to flood) in Taka	Asset value in Taka	land hold-ing in acre	Poverty before flood (%)	Vulner-ability (%)	Vulner-ability to Poverty ratio
Jamalpur		(1)	(2)	(3)	(4)	(5)	(6)	(6)
	Jute (cash)	59.12	866.04	3584.16	0.142	61.92	73.54	1.19
	Paddy (staple)	98.87	844.51	3327.74	0.133	63.81	69.03	1.08

Note: Column 1, 2, 3 and 4 represent the mean values; Vulnerability is measured by Chaudhuri et al. 2002; number of households for jute = 39 and for paddy = 50
Source: Author's own compilation from survey data

Vulnerability estimates (Chaudhuri et al. 2002) include the before flood per capita income as dependent variable; household member, dependency ratio, age and gender of household head, educational year of highest educated member, ownership of dwelling

[11] Special type of paddy produced in Bangladesh
[12] Special type of paddy produced in Bangladesh

place, per capita asset value, per capita arable landholding are included as independent variables. The additional variables, yield and value (yield*market price) loss in crops are included for estimating the error term (to catch the inter temporal income variability). From the above table 6.4, it is depicted that households possessing larger assets and arable land area, go for profitable cash crop production (value per kilo jute is 18.12 Taka, whereas value of per kilo paddy is 11.05 Taka). But in case of flood inundation, cash crop is more vulnerable in terms of value loss. The results support the hypothesis that poorer households, in imperfect insurance markets, prefer to cultivate traditional or staple crop over riskier cash crop like jute or more profitable new varieties (Morduch 1994). The average yield loss for jute is 40 percent lower than that for paddy, but the average value loss is higher in nominal value terms than from the staple crop. The poverty rate is 2 percent higher in paddy cultivated households but the vulnerability to poverty ratio is lower than for the cash crop producers. It could be better for jute producers to cultivate mix crops (jute and paddy) to minimize the vulnerability or future risk.

Nilphamari district data show that 66 percent of the farmers cultivated paddy (staple) as major crop and 32 percent produce nut (cash crop) as major crop. The yield loss of staple crop (paddy) was higher in proportion (95 percent) than for the cash crop. The proportion of yield damage in cash (nut) crop was reported as 84 percent. Nilphamari district was affected by flash flood (caused by unexpected rain and sudden overflow of river basin) in early November and field survey was held during November 25th to December 5th. The average duration of the flood was 3 days, and average flood water height was 0.78 feet in the homestead as reported by the affected households. Most of the farmers have faced the adverse effect of flood and crop damage. The households reported about their damage of paddy, mostly plough the Aman paddy and the flood inundation occurred just before their harvesting time. Nut producers also face the disastrous effect of flood but less than the paddy producers. According to the farmers' report, nut and Aman paddy both share a similar pattern of sowing and harvesting times, so the vulnerability and socioeconomic differentials of those two groups of farmers in Nilphamari district may lead to some interesting findings and future policy recommendations despite of the variability of productivity and profitability.

Table 6.5: Vulnerability differentials for different crop producers in Nilphamari

District	Crop	Yield loss (due to flood) in kilo per household	Value (yield* market price) loss (due to flood) in Taka	Asset value in Taka	land hold-ing in acre	Poverty before flood (%)	Vulner-ability (%)	Vulner-ability to Poverty ratio
Nilphamari		(1)	(2)	(3)	(4)	(5)	(6)	(6)
	Nut (cash)	35.67	1557.60	2619.06	0.156	66.71	68.38	1.03
	Paddy (staple)	85.25	827.20	1175.65	0.096	70.0	78.41	1.12

Note: Column 1, 2, 3 and 4 represent the mean values; Vulnerability is measured by Chaudhuri et al. 2002; number of households for nut = 21, and for paddy = 44
Source: Author's own compilation from survey data

In Nilphamari district, the pattern of crop loss in yield and values for staple and cash crops are similar to that of Jamalpur district. The cash (nut) crop takes the larger loss in values than the staple one but mean loss in yield is lower. Households with greater asset values and arable land area prefer to cultivate nut more than paddy. From the sample survey, the average value of per kilo paddy is calculated as 11.05 Taka and per kilo nut is evaluated with 39.57 Taka. The well-off households have the option and ability to spend more money for profitable crops like nuts, and are found to be less vulnerable for flash flood inundation. Comparatively poorer households have fewer options in terms of crop diversification and they rather prefer to grow staple crops due to the low input cost. However, staple crop producers are found to be more vulnerable to flash flood in Nilphamari district. From the above table 6.5, it might be concluded that non-poor households may allocate their land, and share some joint farming with poor farmers for mix crop cultivation. Poorer households may also think of cash crop cultivation, which could be more profitable and less prone to losses due to floods than the staple crop.

6.2.2 Income Diversification

To compare the relative variability of two or more distributions, such as income differentials during flood (between before and after flood income) of different quartiles of sample, the coefficient of variation is a commonly used statistical measure. It can be calculated by dividing the standard deviation (positive square root of variance) by the mean. The coefficient of variation specifies the relative dispersion of the distribution relative to the mean. The quartile group of each district which has the most income variability due to flood is shown in the appendices 6.9 and 6.10. The quartiles in the appendix 6.9 are defined from the before flood per capita income. First the range was selected from the lowest to the highest income, and then it is spitted into four groups. The difference of the before flood and after flood income is calculated and the sample mean is evaluated. The coefficient of per capita income variation is measured to get a standardized comparable value relative to the mean. The quartiles from each district show the highest values of coefficient of variations are selected. For ensuring the robustness of the selected quartiles, this analysis also applies the adult equivalence scale (Ligon and Schechter 2002, Townsend 1994) in appendix 6.10 instead of the per capita measure. Both the appendices 6.9 and 6.10 show the similar quartile from each district having the highest coefficient of variation value. For Jamalpur and Sunamganj districts the poorest quartiles possess the largest variation in income due to flood and for the Sirajganj and Nilphamari districts interestingly the richest quartiles have the highest variations with respect to the means. The most important sources of income are identified for each of the selected quartiles. An income correlation matrix is drawn to search for the sources which are negatively (significantly at 5 percent level) correlated with the major income groups from the specified quartiles.

In the surveyed sample, the richest quartile in Sirajganj district consists of 40 households, out of which 14 (main earner) are working in the service sector (Government and NGO, educational institutes, monthly wage labor in shops) and 13 households earned from business activities (small and large scales). The other 10 percent of the quartile households' main earning source was agriculture and 15 percent are getting remittance. In Jamalpur district, the poorest quartile has the highest coefficient of variation of income. Out of 37 households, 70 percent are farmers, about 14 percent are lay laborers and 15 percent are getting remittances. For the poorest quartile of Sunamganj district, out of 30 households, 12 households' main earners are day laborers and 11 (about 37%) households' main income earners are either fishermen or boatmen. Again in Nilphamari district the richest quartile shows the highest income variation relative to the mean, and among 37 households 46 percent (17 households) are farmers, about 22 percent (8 households) are earning from the dairy and poultry sector and 4 households (about 11%) are getting remittance.

Table 6.6: Income correlation matrix by sources of income

District	**Quartile with the highest coefficient of variation**	**Source of income with the highest coefficient of variation from income difference**	**Most negatively related (with column 3) source of income**	**Correlation coefficient^**
(1)	(2)	(3)	(4)	(5)
Sirajganj	Richest (4th)	Business	Remittance	-0.615*
Jamalpur	Poorest (1st)	Agriculture	Remittance	-0.558*
Sunamganj	Poorest (1st)	Day labor	Fishing and Boating	-0.811**
Nilphamari	Richest (4th)	Agriculture	Dairy and Poultry	-0.887*

Note: ^Pearson correlation coefficient, * =at 10 percent, ** = at 5 percent level, parenthesis indicates the column number
Source: Author's own compilation from survey data

The above table 6.6 allows to derive some policy implications. Column two shows the quartiles with the highest coefficient of variation in difference between before and after flood per capita income. Column three shows the major sources of income from the selected quartiles. The next step is to find out the negatively correlated sources of income in terms of the income sources found in column three. There are several sources which are negatively correlated, so only the most negatively correlated sources are taken for comparison to see the diversification. For Sirajganj and Jamalpur districts, remittance comes out as the diversification source of income to reduce risk compared to business and agriculture activities respectively. Business and agriculture sectors accordingly from the first two districts were found to be mostly affected by flood (largest coefficient of variation of income difference). The households from these two districts could mitigate risk for future flood or cope with such natural disaster by investing some money to allow household members to migrate into nearby cities for better jobs. In Sunamganj district the poorest quartile has a volatile and susceptible income because most of the households are day laborers; they could earn some more money during flood season if they had boating or fishing materials. Proportion of farmers in Nilphamari district is high and has the largest variation of income due to flood. These agriculture based households could mitigate risk by managing some small scale dairy or poultry farms.

6.3 Migration as Coping Strategy

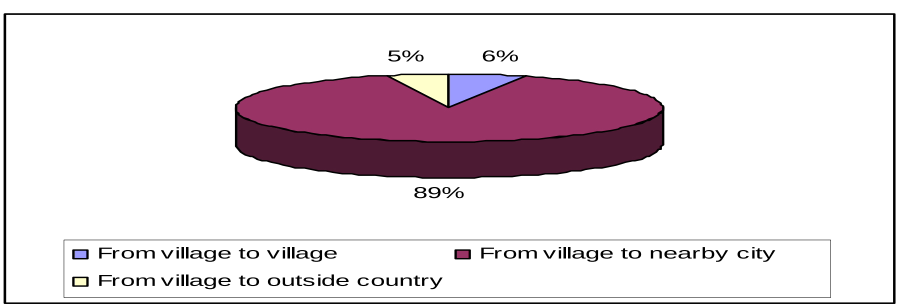
The frequent cases of floods and river-bank erosions are found as significant causes for homelessness, landlessness and consequent migration for many thousand people every year (Lewis 1999). Migration is denoted as a component of people's livelihood strategies in Bangladesh. Natural disasters play a part in forcing people to migrate in order to cope with shocks. Rural-urban migration is playing a significant role in this process. The net migration (migrants/1000 population) increased dramatically from 1.2 to 16.4 in urban areas between 1984 and 1998 (Afsar 2005). A study by Rahman et al. (1996), accumulating the information from 62 randomly selected villages in Bangladesh, shows that nearly two-thirds of the emigration from rural areas was to urban areas.

The following parts delineate the empirical results from the field survey and relate these to some literature review and theoretical point of views. It will be first investigated what types of migration occur in Bangladesh due to floods, and how these different types relate to poverty and vulnerability of households.

6.3.1 Synopsis of Migrants

The interview was conducted by asking the respective household head or a representative. All members sharing the same kitchen were defined as belonging to the household; any member who lives outside the residence but who contributes to the household's resources is denoted as migrant. Out of 595 rural households, 168 (28%) households indicated that they have at least one migrant. 79 percent of these 168 households have only one migrant, others have more than one. The following figure 6.2 shows different types of migration of the flooded households.

Figure 6.2: Types of migration for flooded households



Note: Total migrant households = 168. Source: Author's own compilation from survey data

From the above figure, it is depicted that most of the migrated households (89 percent) migrate from rural to urban areas. Only 6 percent of the households move to another village, while 5 percent decide to move to another country. Now, the general question arises why 89 percent of migrant households choose a nearby city?

This study starts searching for an answer on the basis of the theoretical literature which offers two models in this context. The Harris-Todaro (1970) model is based on a neo-classical response to urban-rural wage differentials, while the Massey-Parrado (1994) model is from the new economic theory of migration which anticipates migration from areas with limited credit and capital markets. The first neo-classical model only focuses on the migration's role in generating a labor market equilibrium; furthermore the return of remittance in origin areas and the migrants' knowledge of expected returns are considered. The Harris-Todaro model predicts that migration is more likely if an individual's expected income in the destination area, arising from the expected wage times the probability of employment, is higher than income from the current origin area. Asking about reasons for migration, it is found that 83 percent of the migrants' households see unemployment and deficiency of capital market formation due to frequent floods as the main reasons for migration. 5 percent of the head of the households with emigrants gave wage differentials as a cause. Only 3 percent of respondents indicate education as a main reason for migrating, and the remaining 9 percent of households with migrants said that better employment and higher wages in nearby cities as well as loan repayment impelled the migrated members to move, although they were employed in the rural areas but only with low wages.

As an agro-based country, the majority of households in Bangladesh depend on underwater cultivation of rice during the flood season (June-September) as a primary staple crop. Small landholders overcome flood-season deficits by taking loans in terms of high, pre-harvesting grain prices and repaying the loans with lower, post-harvest prices (Jensen 1987). This type of yearly cycle of debt dependence often leads small landholders to default, land mortgage, and foreclosure (Kuhn 2002a). Remittances paid by the emigrants to origin places, like rural areas, would reduce the need to incur debt. The results demonstrate inclination to the Massey-Parrado model of limited credit and capital markets. However, the two models are not mutually exclusive; some justifications for the wage differentials are also found from the data set.

6.3.2 Social Network and Migration

This study also focuses on the role of village-based social networks in perpetuating the flow of rural-urban migration. According to Kuhn (2002a, p.1), *"The decision to migrate is often guided by a desire to restore or replenish a family's agricultural tradition and resources, yet ironically the success of migration is often determined by the extent of a family's resources. And more often than not, the opportunity to migrate is determined by social linkages based in the village."*

About 79 percent of migrant households said they had known someone in the destination place. In the context of migration, networks function as a form of credit and information source for the potential migrants. This study examines the strength of weak ties for rural-urban linkage. Weak ties are defined as being less likely socially involved with one another compared with strong ties arising from close relatives. According to the Granovetter (1983, p. 202, 205), *"...individuals with few weak ties will be deprived of information from distant parts of the social system and will be confined to the provincial news and views of their close friends. ... the weak ties have a special role in a person's opportunity for mobility."*

Empirical work also supports the above stated theory of networks and weak ties for enhancing rural-urban migration. About 72 percent of the households reported that rural-urban migration was motivated by friends already living in the destination places. Those who migrated received the information from former village friends or neighbors in urban areas, which indicates the strength of weak ties. 26 percent of households indicated that their migrated members shifted to urban places with the help of close relatives (strong ties), and the remaining 2 percent was based on organizational links and networks.

6.3.3 Vulnerability and Consequences of Migration

A more detailed analysis aims at finding out which groups of households are more vulnerable to floods depending on the source of income, including remittances. Households whose major sources of income are remittances from urban migrants are found to be the least vulnerable in appendix 6.11. If households suffer from a shock like a flood, they utilize the resources and options they have to survive on. The actions for survival strategies are considered as coping strategies. The coping strategies are fallback mechanisms for when habitual means of meeting needs are disrupted (Frankenberger 1992). Initially, households try to minimize risks and maintain some minimal level of sustenance. Gradually, the households start the disposal of assets as a coping strategy. Several phases can be distinguished: first, the liquid assets are disposed of, then jewelry, and finally, the productive assets. After the disposal of assets, individual or family migration is chosen as a survival strategy. The household heads were asked about the effects of migration in origin places. As an illustration from the appendix 6.12, it is apparent that 80 percent of the households with migrants receive financial help. 12 percent of the migrants' households respond not to get any remittances but their social prestige increases; inhabitants from surrounding places come and ask them about the way to migrate and give them importance in social gatherings. Only 8 percent of the households responded that they spent higher transition cost for migrants than the remittances they are getting back. Therefore, the people from rural areas are often denoting the investment costs of migration as financial loss. Households were also asked about the utilization of remittances from emigrants. The analyses of data show that the highest amount of remittance was used for buying food items in both before and during flood periods. Remittances are also used for repairing houses after floods.

6.4 Summary

Flooded households have multiple responses for coping with floods in the year 2005 with the highest frequency of households borrowing goods and cash from a nearby shop or pharmacy. The highest proportion of borrowing is taken by the poor households of Jamalpur district affected by monsoon flood. About 78 percent household used the borrowing for buying food that amount to 25 percent of the total borrowing. One-fourth of flooded households reported that they reduced their number of meals and amount of consumption in a day, or sometimes bought cheap food items to cope with flood and aftermath. From tobit model estimates, it is revealed that households start borrowing when they realized that a flood shock is taking place; gradually, they instigate spending money from savings and selling assets with the extended period of flood. The results from vulnerability estimates following the VEP method support the hypothesis that poorer households prefer to cultivate traditional or staple crops over riskier (cash crop like jute) or more profitable new varieties. From two different districts (Jamalpur and Nilphamari), econometric results show that farmers who plough either cash or staple crop may be vulnerable due to the downside effects of monsoon or flash flood. Thus this study suggests a share or mix cropping system in rural Bangladesh that would minimize households' vulnerability to floods. For Sirajganj and Jamalpur districts, remittance is found to be the less risky source of income with compared to business and agriculture respectively. In Sunamganj district, the poorest quartile has the most volatile and susceptible income because most of the households are day laborers. Households depending on farming in Nilphamari district could minimize risks of floods by expanding their activities towards some small scale dairy or poultry farming. Empirical work also supports that networks and weak ties enhance rural-urban migration that reduces rural households' vulnerability to floods.

Chapter Seven

7. Summary and Conclusion

The combination of its geography, population density, and extreme poverty makes Bangladesh very vulnerable to disasters. Floodplains occupy about 80 percent of the land area of Bangladesh. During the monsoon season (June to September) each year heavy rainfall across the country causes floods, especially in the catchments of the rivers. Since its independence in 1971, serious floods occurred in 1971, 1974, 1980, 1984, 1987, 1988, 1998, 2004 and 2007 as disastrous events. Therefore, this study is set forth to examine the relationships between socioeconomic conditions and vulnerability to flood hazards. The concrete objectives of this research are to search (i) who are the most vulnerable to monsoon and flash floods and how vulnerable are they? (ii) what are the significant factors of vulnerability to floods in rural Bangladesh? (iii) what coping strategies are followed by the flooded households and why? (iv) which methodology is suitable to estimate household vulnerability to floods in Bangladesh? and (v) which types of interventions are most likely to reduce vulnerability in rural Bangladesh?

Researchers from different disciplines conceptualize vulnerability in multifaceted terms. Papers from the disaster management literature tend to evaluate the probabilities and damages associated with specific physical disasters. Sometimes vulnerability is related to weather-related crop failures. Sociologists assess poverty and vulnerability in non-monetary terms, introducing entitlement, defenselessness, social exclusion, gender and race discrimination, social violence and corruption. Economists define vulnerability as the probability of income or consumption expenditures to fall below the poverty line. This is also the approach which is chosen for this study. It reflects a narrow concept but allows quantification of households' vulnerability, in contrast to the concepts of many other disciplines.

Papers dealing with vulnerability and risk in Bangladesh have not scrutinized households' vulnerability to a particular flood shock that might be the principal concern of policy making. Sen (1999) examines vulnerability as the variability of poverty levels from a panel survey of 62 villages in Bangladesh during the years 1989 and 1994. Amin et al. (1999) show in their study on Bangladesh that female headed households are still vulnerable to poverty despite being a member of a micro credit program. Siddiqui (2004) depicts that people of Bangladesh involved with different types of migration are vulnerable to situations that expose them to contract HIV/AIDS; especially women are vulnerable who may be infected by their emigrant worker husbands. Skoufias and Quisumbing (2003) evaluate some vulnerability due to loss of livestock. Ninno et al. (2001) focus only on the coping strategies during and after floods in the year 1998 without any perception of vulnerability to floods. Therefore, this study is set forth to examine households' vulnerability to floods in the year 2005.

The working concept of vulnerability used in this study is as follows:
"A household is said to be vulnerable if any downside risk, e.g. flood in rural Bangladesh during the year 2005, causes loss of welfare below some socially accepted benchmark. The degree of vulnerability depends on the frequency and magnitude of the risk and the household's ability to respond to risk. The ability to respond to risk relies on household characteristics. A socially accepted benchmark refers to a poverty line."

Downside risks are defined here as the estimated potential that security, income, expenditure or overall livelihoods might decline in real value if the area is flooded. These may be occurred if the distribution of actual outcomes is negatively skewed. Floods in rural Bangladesh occur almost each and every year but at different scales. The ability to respond to such downside flood risks also differs among households. This study considers the monsoon and flash floods during the year 2005 as downside risks that may cause idiosyncratic (household specific) and covariate (community level) vulnerabilities.

The vulnerability framework for this study begins with a notion that individuals, households, communities or nations may face multiple risks from floods in Bangladesh. Households use formal and informal risk management instruments depending on their access to these instruments. Risk management strategies involve ex ante and ex post actions. Ex ante actions may be introduced before the next flood risks take place, and ex post risk management are generally taken after households have already been flooded (e.g. coping). Thus, risk reduction and lowering risk exposure strategies can be generated from vulnerability estimates. A risk reduction strategy may involve building dams and canals, or migration to upland areas to lower the exposure to flood risks. Vulnerability measures can also help people to take risk mitigation strategies that include formal and informal responses to expected losses such as self-insurance (e.g. precautionary savings) and building social networks. Coping strategies after floods may comprise selling assets, borrowing money for food, changing agriculture and livestock practices, changing employment or working patterns, changing consumption habits, or migration of selected family members or even begging.

In the year 2005, Bangladesh was affected by two types of floods, once in mid August to September by a monsoon flood in some floodplains and then in November, a flash flood occurred in some parts of northern areas. A cross sectional household survey was carried out after the floods. Three districts, Jamalpur, Sirajganj and Sunamganj, were randomly chosen after the monsoon flood, and Nilphamari district was surveyed after the flash flood. The total number of rural households from different regions amounted to 1050, with 600 households belonging to the flooded sample and 450 households to the non-flooded sample. The outliers are detected by the box plot and Cook's distance approaches. In total eleven outliers are deleted from the overall sample, so that the working sample finally consists of 1039 households, with 595 households being from flooded and 444 households from non-flooded areas.

Some descriptive statistics are shown from the survey areas. The poverty line used in this study for the rural areas is Taka 594.60 per person per month (BBS 2004). The average per capita income per month of sample households is about 673 Taka, only 78 Taka more than the poverty line. The difference between mean income of flooded and non-flooded households is 52 Taka. The highest average income is revealed from Sirajganj district households (804 Taka) and the lowest from Nilphamari district (534 Taka). In terms of the per capita asset value, households of Sunamganj district have the lowest amount (2924 Taka) compared to the other three districts. On average, the per capita savings are the highest in Sirajganj district (1351 Taka) and the lowest in Nilphamari district (430 Taka), while per capita loans are the highest for Jamalpur district (about 2143 Taka) and the lowest for Nilphamari district (1184 Taka). When comparing the socioeconomic profiles of flooded with non-flooded households, the average family size is higher in flooded than non-flooded households. On average, per capita income, per adult equivalence income and per capita asset values are higher for non-flooded households than the flooded households. At 5 percent level of significance, the two-sample t test result shows that there is no statistically significant difference between flooded and non-flooded households' per capita and per adult equivalence scale income before flood.

Households in Jamalpur and Nilphamari districts depend on agriculture to a larger extent than in the other two districts. Day laborers are playing a major role in Sirajganj and Sunamganj districts as main income earners. 14 percent of the households responded that migrants are the main earners in Nilphamari district. One-fourth of the households in Sunamganj district are Boatmen and Fishermen. Households in Sirajganj district were the most affected in terms of inundation days and height of flood water at the homestead. Overall, 17 percent of the flooded households fell into poverty after flood, whereas about 42 percent of the non-poor households fell into poverty after flood. Nilphamary district shows the largest poverty rate and over half of the non-poor households have fallen into poverty due to a flash flood. About three-fourth of non-poor households in Jamalpur district have fallen under the poverty line due to monsoon flood damage. Illustrating a noteworthy impact of floods on poverty levels, this study proceeds with econometric analyses to determine significant and influential factors of households' income. Then the next step is to check whether some socioeconomic factors besides floods have any causal effect on households' downside poverty levels.

A multivariate regression of log per capita income before flood on household's demographic, economic and community characteristics is performed to determine the factors which significantly affect households' income. Family size is significantly and negatively related to the log per capita income, so that the addition of one person to the household membership would cause 12 Taka decrease in income on average. But if the member is a male adult, then the average income will increase; this is also verified by the negative but insignificant coefficient of the variable dependency ratio. Average educational years of earners, arable land holding, asset value and savings are highly significant and positively related with the household income level. The more distant the markets, the lower the income of households; owners of dwelling places earn higher income compared to non-owners. The statistical test (p-value<0.01) shows that floods have highly significant effects on the households' income after flood. This stresses the importance of examining the poverty and vulnerability due to floods in the rural Bangladesh.

After investigating the determinants of income before floods and the significant downside effect on after floods income, this study aims to scrutinize the determinants of poverty after floods in rural sample households. A multinomial logit model is chosen because the dependent variable is discrete with three distinct choices that are not orderly assigned. Among the shock variables, flood height, flood duration, loss of crops, loss of working days, coping amount from loan, and selling assets are significantly and positively related with the after flood poverty of the poor households. The variables which have positive and significant effects on the non-poor households' welfare are: flood duration, loss of assets, cost of disease during flood, coping from savings, and selling assets. If the flood duration is one day longer, then the log-odds between after flood poverty from poor households and after flood non-poor households would increase by 0.04 and the log-odds between after flood poverty from non-poor households and after flood non-poor households would increase by 0.05. Among the economic factors, arable land holding, possession of assets and savings show statistically significant and negative effects of floods as the unit of economic variables increase. Especially for the non-poor households, one unit increase of asset value and savings would minimize the log-odds of after flood poor from non-poor status before flood to after flood non-poor by 0.01 and 0.007 units respectively.

One of the major research questions of this study is, ‘who are the most vulnerable to monsoon and flash floods and how vulnerable are they?’ Therefore, four different types of methodologies are applied in this study, which are suitable for cross-sectional and short panel survey data, to estimate vulnerability to floods in rural Bangladesh. Chaudhuri et al. (2002) and Chaudhuri (2003) use the vulnerability to expected poverty (VEP) method which is generalized from expected headcount measure of poverty. It is estimated by the VEP approach that flooded households have a higher vulnerability (8%) than the non-flooded counterparts. Another important finding from this methodology is that households facing a monsoon flood are more vulnerable to idiosyncratic shocks, whereas a flash flood would cause downside covariate shocks. Farmers are found to be the most vulnerable due to flood disasters, followed by day laborers and the least vulnerable flooded households are remittance holders. Out of the four methodologies used in this study to estimate vulnerability, only the VEP approach is appropriate for cross-sectional data and thus applied to estimate vulnerability of non-flooded households.

Pritchett et al. (2000) calculate vulnerability to poverty line (VPL) which is also the direct analogue of the headcount poverty line. Here another research question of this study, ‘what are the significant factors of vulnerability to floods in rural Bangladesh?’ is addressed. The results from the VPL approach show that even though the poverty level is lower for the female headed households than their male counterparts (about 3 percent), the ratio of vulnerability to poverty is higher for male ones (1.1 for female and 1.2 for male). It is depicted that the increase of average educational years would decrease households’ poverty and vulnerability. The rural households who have cultivable land show a higher mean of the per capita income and a lower vulnerability rate than the rural landless.

The vulnerability to expected utility (VEU) methodology, as suggested by Ligon and Schechter (2003), disaggregates the vulnerability estimates among poverty, idiosyncratic risk, aggregate risk and unexplained risk. From the VEU approach, it is depicted that the correlates of flood vulnerability are similar to the correlates of poverty. Education is found to be the most significant variable to define vulnerability. The households with higher educated members are less vulnerable. Arable land holding shows a significant relationship with poverty and aggregate risk. Poverty and aggregate risk due to floods show a strong positive correlation.

Kamanou and Morduch (2002) introduce the Monte Carlo Bootstrap method to overcome the shortcomings of using standard deviation. Estimates from the Monte Carlo Bootstrap approach show that vulnerability levels are higher in proportion than the actual poverty levels after floods. Therefore, a shock like a flood in the year 2005 plays a significant role to the economy, pushing the richer households below the poverty line and the observed poor become poorer.

Ligon and Schechter (2004) conduct Monte Carlo experiments to explore the performance of different estimators proposed by different authors, under different assumptions and economic environments. They find that if the environment is stationary, but consumption expenditures are enumerated with measurement errors, then the estimator based on the Ligon and Schechter (2003) approach performs the best. When the distribution of consumption is non-stationary, then the estimator from the Pritchett et al. (2000) approach is suitable. This study considers a stationary environment before and after flood periods but with measurement error and heterogeneity in the household's income data. Therefore, households' vulnerability levels estimated by the VEU approach across different characteristics are closer to actual after flood poverty levels compared to VPL, VEP and Monte Carlo Bootstrap approaches. The solution of another research question, 'which methodology is suitable to estimate household vulnerability to floods in Bangladesh?', is that the VEU approach fits best with this study data set.

Flooded households were asked about the coping strategies they followed during and after flood periods. The highest frequency (193 households) is observed for borrowing goods and cash from the nearby shop or pharmacy. Borrowing plays a major role for both poor and non-poor households in each district. The highest proportion of borrowing is found for the poor households (89.7%) in Jamalpur district and the same group of people sells their assets at a high proportion (16.1%) for coping after monsoon flood. The flash flood in Nilphamari district also forces people, especially the poor households, to take loan (78.5%) and sell their assets (15.9%) at high proportion. About 78 percent of the households used the loan for buying food. About 75 percent of households, out of 20 households who used savings for coping, utilize their money for food. This study uses tobit model estimates to identify the determinants for borrowing, savings and selling assets. The estimates show that a household's decision to borrow as coping strategy has a positive and statistically significant relationship with the height of flood. Male headed households would borrow more than their female counterparts. Interestingly, the amount of borrowing is negatively correlated with household size but positively correlated with the dependency ratio that means the more active members a household has the less amount they borrow for coping. The loss of assets is positively related with the amount of borrowing but households with more income are less likely to borrow. The amount of savings spent by the households shows a significant positive relation with duration of floods. Dependency ratio and loss of working days are also positively interacted with the money spent from savings. Amount of selling assets is highly significant and positively correlated with flood duration and dependency ratio. Any membership of households in the local cooperatives would help to sell their assets during floods. It is depicted from tobit model estimates that households start borrowing when they realized that a flood shock is taking place. Gradually they start spending money from savings and selling assets with the extended period of flood.

This study also focuses on the diversification issues in cropping pattern and income sources of flooded households to mitigate the future flood risks. Agriculture is the major source of livelihood in the rural areas of Bangladesh, where about 77 percent of the population live. The agriculture sector contributes about 22 percent to the national GDP, about 51 percent of the labor force in the crop sector alone (BBS 2003). There are ample opportunities to mitigate flood risk, disasters and aftermaths by crop diversification. From the results of empirical analyses, it is depicted that non-poor households might introduce some sharecropping with poor farmers, which in turn could reduce their future poverty. For Sirajganj and Jamalpur districts, remittance comes out as the diversification source of income to reduce risks compared to business and agriculture activities, respectively. In Sunamganj district, day laborers could benefit if they transferred to boating or fishing occupation. Farmers in Nilphamari district could mitigate risk by expanding their activities towards some small scale dairy or poultry farming.

It is depicted from the vulnerability estimates (using the VEP approach) that households whose major source of income are remittances from urban migrants are the least vulnerable compared to the other income groups. Empirical research also justifies the strength of weak ties; about 72 percent of the households reported that rural-urban migration was motivated by acquaintances and lose friends living in destination places, which indicate that weak ties are very effective for the surveyed households.

7.1 Policy Recommendation

This study describes the extent of damage caused by the flood 2005 in rural Bangladesh to crop production, households' assets, income, expenditure as well as coping strategies of flooded people. Many households lost their minimal standard of living during floods. People's income and wealth were affected enormously. Income losses were rooted from the loss of agricultural production and lack of jobs during the flood. The deterioration in the economic situation had a negative impact on food and non-food consumption, physical and mental health, agricultural and non-agricultural income, durable and productive assets, as well as on social life. The flood aid programs could intend to reach the transient poor and provide opportunities not only to the current or chronic poor but to those households who have experienced flood disasters. Social protection, social insurance or micro credit schemes for the landless households may motivate them to start small-scale businesses or farming. Food for education policy, as already initiated in Bangladesh, is expected to enhance the education level of households to increase their ability to cope with floods.

A major proportion of households have been found to borrow money or resources from informal sources, such as nearby shops or the pharmacy, friends or relatives, or local money lenders, to buy food items and other essentials. This finding indicates that better access to financial services like banks or micro-credit programs with low rates of interest could enhance households' ability to cope with the floods and help them to recover from the debt cycle. More targeted credit programs would be useful where formal bank credit programs are limited in scope.

Both short-term and long-term policies could play major roles to reduce households' and communities' vulnerability to floods in rural Bangladesh. Government's flood aid programs should be better targeted towards severely affected flood victims. Government or NGOs could carefully expand the food grain distribution for the most vulnerable group. More research needs to be done to detect the loopholes of the disaster management policies by the Bangladesh Government. It is necessary to improve the availability and quality of information and interventions, so as to provide food, shelter and security at the time of the flood disasters and its immediate aftermath.

As the study has shown, floods in Bangladesh lead rural households to slide even deeper into poverty and vulnerability. Households living under or just above the poverty level often suffer from food insecurity, own only marginal land and usually live in flood prone areas. Recurrent flood damages result in low productivity and deceasing income levels of poor households, and lead them to suffer from lingering effects of debt. As a consequence, people move from rural to urban areas for finding better employment opportunities. That again creates high population density and pressure in urban areas. Therefore, Governmental policies should aim at fostering economic growth and increasing agricultural productivity in rural areas of Bangladesh. Providing access to income-generating sources for the most vulnerable households can both help to reduce poverty as well as increase the capacity of households to resist future flood disasters.

7.2 Scope for Further Research

The randomized cross-sectional data of this study contains some shortcomings. Firstly, this data set is not nationally representative, only four districts were chosen out of 64. Secondly, the survey was conducted just after the flood and information was collected by asking the respondents on their present and before flood status, so that it leads to large variability in survey data. Another reason is that some information are gathered by recall method, such as income, food and non-food expenditure, value of crops and assets, though the non-response and measurement errors are adjusted in the questionnaires by cross-checking, repeated asking and spending much time with respondents. Thirdly, the data did not consider seasonal variations with respect to crop diversification. Fourthly, the data used in this study are cross-sectional; it would be more robust and econometrically sound if long period panel data were used. Per capita income was utilized as a proxy of welfare measure for households, so if consumption expenditure was used rather than income, like it is being done in many other economic papers, then this study would be more accurate. Dynamic modeling of vulnerability (Elbers and Gunning 2003) needs a long panel data, that is why this study only used static measures of vulnerability (Chaudhuri et al. 2002, Ligon and Schechter 2003, Pritchett et al. 2000, Kamanou and Morduch 2002).

Vulnerability to floods is not only a quantitative measurement based on income and expenditure survey. This study excludes the sociological and anthropological perspectives of vulnerability during floods. The distress of flooded people cannot be explicitly measured in only econometric terms. Vulnerability of gender hierarchies is not clearly shown in this study, as women in Bangladesh may experience marginalization and discrimination of intra-household resource allocation compared to men during floods.

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Appendices

Appendix 4.1: Frequency distribution of flooded and non-flooded households among four districts

District	flooded status	N
Overall	Non-flooded	444
	Flooded	595
	Total	1039
Sirajganj	Non-flooded	148
	Flooded	153
	Total	301
Jamalpur	Non-flooded	147
	Flooded	148
	Total	295
Sunamganj	Non-flooded	149
	Flooded	146
	Total	295
Nilphamari	Flooded	148
	Total	148

Note: N denotes number of households
Source: Author's own compilation from survey data

Appendix 4.2: Cross tabulation of districts and income sources

District	Income sources						
	Agriculture	*Service*	*Business*	*Day labor*	*Dairy and Poultry*	*Remittance*	*Boatmen and Fishermen*
Sirajganj	7.0	14.3	23.3	46.2	1.7	6.6	1.0
Jamalpur	41.4	3.1	19.3	29.2	1.4	5.4	0.3
Sunamganj	14.2	6.1	13.6	35.3	0.7	4.4	25.8
Nilphamari	43.9	1.4	4.1	31.8	4.7	14.2	0
Total	24.1	6.9	16.7	36.2	1.7	6.7	7.7

Note: Figures are showing percentages
Source: Author's own compilation from survey data

Appendix 4.3: Cross tabulation of district level households' poverty and income sources

District	Poverty status before flood	Income sources						
		Agriculture	*Service*	*Business*	*Day labor*	*Dairy and Poultry*	*Remittance*	*Boatmen and Fishermen*
Sirajganj	Poor	4.4	6.6	19.0	62.8	1.5	5.1	0.7
	Non-poor	9.1	20.7	26.8	32.3	1.8	7.9	1.2
Jamalpur	Poor	45.1	0.6	16.6	30.9	1.1	5.7	0
	Non-poor	35.8	6.7	23.3	26.7	1.7	5.0	0.8
Sunamganj	Poor	8.4	5.2	11.7	42.2	0.6	2.6	29.2
	Non-poor	20.6	7.1	15.6	27.7	0.7	6.4	22.0
Nilphamari	Poor	43.0	0	2.8	38.3	0	15.9	0
	Non-poor	46.3	4.9	7.3	14.6	17.1	9.8	0

Note: percentage distribution for total sample, 1039 households
Source: Author's own compilation from survey data

Appendix 4.4: Cross tabulation of district level poverty and income sources for flooded households

District	Poverty status before flood	Income sources						
		Agriculture	*Service*	*Business*	*Day labor*	*Dairy and Poultry*	*Remittance*	*Boatmen and Fishermen*
Sirajganj	Poor	4.2	9.7	13.9	62.5	2.8	6.9	0
	Non-poor	8.6	24.7	25.9	24.7	1.2	13.6	1.2
Jamalpur	Poor	64.4	0	8.0	21.8	2.3	3.4	0
	Non-poor	62.3	3.3	14.8	9.8	1.6	6.6	1.6
Sunamganj	Poor	2.6	6.4	14.1	35.9	0	3.8	37.2
	Non-poor	5.9	4.4	23.5	27.9	0	8.8	29.4
Nilphamari	Poor	43.0	0	2.8	38.3	0	15.9	0
	Non-poor	46.3	4.9	7.3	14.6	17.1	9.8	0

Note: percentage distribution for flooded sample, 595 households
Source: Author's own compilation from survey data

Appendix 4.5: Cross tabulation of district level poverty and income sources for non-flooded households

District	Poverty status before flood	Income sources						
		Agriculture	*Service*	*Business*	*Day labor*	*Dairy and Poultry*	*Remittance*	*Boatmen and Fishermen*
Sirajganj	Poor	4.6	3.1	24.6	63.1	0	3.1	1.5
	Non-poor	9.6	16.9	27.7	39.8	2.4	2.4	1.2
Jamalpur	Poor	26.1	1.1	25.0	39.8	0	8.0	0
	Non-poor	8.5	10.2	32.2	44.1	1.7	3.4	0
Sunamganj	Poor	14.5	3.9	9.2	48.7	1.3	1.3	21.1
	Non-poor	34.2	9.6	8.2	27.4	1.4	4.1	15.1

Note: percentage distribution for non-flooded sample, 444 households
Source: Author's own compilation from survey data

Appendix 4.6: Cross tabulation of income sources of households and before flood quartiles

Quartile	Income sources						
	Agriculture	*Service*	*Business*	*Day labor*	*Dairy and Poultry*	*Remittance*	*Boatmen and Fishermen*
Poorest quartile	56 (33.5)	5 (3)	8 (4.8)	65 (38.9)	1 (0.6)	21 (12.6)	11 (6.6)
2nd quartile	34 (26)	7 (5.3)	16 (12.2)	54 (41.2)	2 (1.5)	7 (5.3)	11 (8.4)
3rd quartile	38 (25.3)	7 (4.7)	19 (12.7)	54 (36)	3 (2)	8 (5.3)	21 (14)
Richest quartile	47 (32)	20 (13.6)	37 (25.2)	11 (7.5)	7 (4.8)	17 (11.6)	8 (5.4)

Note: Figures in parentheses are denoting percentages for flooded households
Source: Author's own compilation from survey data

Appendix 4.7: Poverty status before flood by districts

Sample	Flood status	Poverty status		Total
		Poor	*Non-poor*	
Overall	Flooded	344	251	595
		(57.8)	(42.2)	(100)
	Non-flooded	229	215	444
		(51.6)	(48.4)	(100)
	Total	573	466	1039
		(55.1)	(44.9)	(100)
Sirajganj	Flooded	72	81	153
		(47.1)	(52.9)	(100)
	Non-flooded	65	83	148
		(43.9)	(56.1)	(100)
	Total	137	164	301
		(45.5)	(54.5)	(100)
Jamalpur	Flooded	87	61	148
		(58.8)	(41.2)	(100)
	Non-flooded	88	59	147
		(59.9)	(40.1)	(100)
	Total	175	120	295
		(59.3)	(40.7)	(100)
Sunamganj	Flooded	78	68	146
		(53.4)	(46.6)	(100)
	Non-flooded	76	73	149
		(51.0)	(49.0)	(100)
	Total	154	141	295
		(52.2)	(47.8)	(100)
Nilphamari	Flooded	107	41	148
		(72.3)	(27.7)	(100)
	Total	107	41	148
		(72.3)	(27.7)	(100)

Note: Figures in parentheses are denoting percentages
Source: Author’s own compilation from survey data

Appendix 4.8: Transition of poverty status of flooded households

Area	Poverty before flood	Poverty after flood		N
		Poor	*Non-poor*	
Overall	Poor	340 (98.8)	4 (1.2)	344
	Non-poor	105 (41.8)	146 (58.2)	251
Sirajganj	Poor	72 (100)	0	72
	Non-poor	29 (35.8)	52 (64.2)	81
Jamalpur	Poor	86 (98.9)	1 (1.1)	87
	Non-poor	45 (73.8)	16 (26.2)	61
Sunamganj	Poor	75 (96.2)	3 (3.8)	78
	Non-poor	9 (13.2)	59 (86.8)	68
Nilphamari	Poor	107 (100)	0	107
	Non-poor	22 (53.7)	19 (46.3)	41

Note: Figures in parentheses are indicating percentages
Source: Author's own compilation from survey data

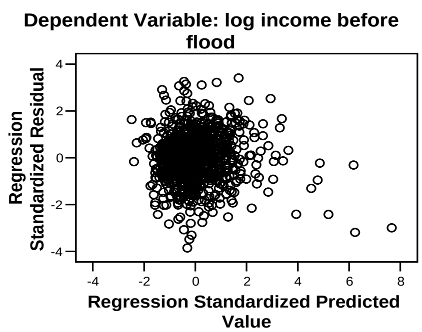
Appendix 5.1: List of variables according to household's characteristics

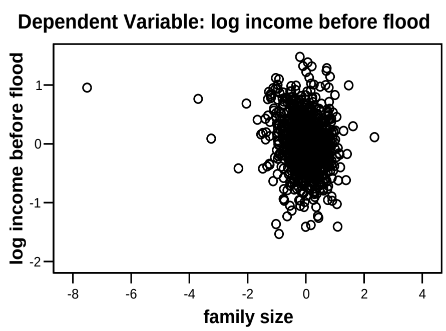
Classification	Variable	Type	Description	Expected sign
Demographic Characteristics	Family size	Numeric	Number of household members in a household	+/-
	Family size squared	Numeric	Square of family size	-/+
	Dependency ratio	Numeric	Ratio of the number of household members 0-14 years and 60 years and over to the number of members 15-59 years	-/+
	No. of adult males	Numeric	Number of household males over 18 years old	+
	No. of adult females	Numeric	Number of household females over 18 years old	+/-
	Age of household head	Numeric	In years	+/-
	Age square of household head	Numeric	Square of household head's age in years	-/+
	Average education of household earners	Numeric	In years, over 8 years and contribute to household income	+
	Gender of household head	Dummy	=1, if male =0, if female	+/-
	Years of staying		Years of staying in the dwelling place	+/-
Economic Characteristics	*Major sources of income:* agriculture	Dummy	(contribute major portion of household's income) =1, if agriculture =0, otherwise	+/-
	Service	Dummy	=1, if service =0, otherwise	+
	Business	Dummy	=1, if business =0, otherwise	+
	Dairy & Poultry	Dummy	=1, if dairy & poultry =0, otherwise	+/-
	Remittance	Dummy	=1, if remittance =0, otherwise	+
	Boating & Fishing	Dummy	=1, if boating & fishing =0, otherwise	+/-
	Day labor	Dummy	Reference category	
	Arable land	Numeric	Per capita arable land holding in acre	+
	Asset value	Numeric	Per capita asset value: durable assets (poultry, animal, tree), household items in Taka	+
	Distance to market	Numeric	In kilometers	-/+
	Cost to reach market	Numeric	In Taka	-/+
	Access to media	Dummy	=1, if owner of radio =0, otherwise	+/-
	Ownership of dwelling place	Dummy	=1, if owner of the dwelling place =0, otherwise	+/-
	Housing materials	Dummy	=1, if walls are made of raw materials =0, if cement/brick made	-/+
	Loan	Numeric	Per capita loan in Taka	-
	Savings	Numeric	Per capita savings in Taka	+

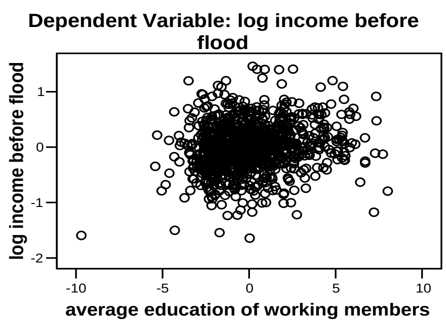
	Membership of cooperatives	Dummy	=1, if member of NGO, Grameen bank, local cooperatives =0, otherwise	+/-
Community characteristics	Electricity	Dummy	=1, have electricity =0, otherwise	+
	Primary school	Dummy	=1, if any primary school in Mouza =0, otherwise	+/-
	Public hospital	Dummy	=1, if any public hospital in Mouza =0, otherwise	+/-

Source: Author's own compilation

Appendix 5.2: Graphical presentation of heteroscedastic pattern of sample data







Source: Author's own compilation from survey data

Appendix 5.3: Description of flood shock variables

Classification	Variable	Type	Description	Expected sign
Flood (shock) related characteristics	Coping from loan	Numeric	Per capita loan for coping during/after flood in Taka	-/+
	Coping from savings	Numeric	Per capita savings withdrawal for coping during/after flood in Taka	-/+
	Coping from selling	Numeric	Per capita selling price of assets for coping during/after flood in Taka	-/+
	Flood height	Numeric	Height of flood water at the homestead in feet	-/+
	Flood duration	Numeric	Duration of flood at homestead in days	-/+
	Loss working days	Numeric	Loss of working days for flood in days	-/+
	Loss of asset	Numeric	Per capita loss of asset value for flood in Taka	-/+
	Cost of disease	Numeric	Per capita cost of treatment for the disease during flood	-/+
	Flood shelter	Dummy	=1, if there is any permanent flood shelter =0, otherwise	+/-

Source: Author's own compilation

Appendix 5.4: Estimation of measurement error using estimates of the non-food share

	Monthly income per capita (before flood)	
	OLS	*IV*
Constant	-0.193	-2.466
	(-0.65)	(-2.93)
Log income	0.856	1.215
	(18.44)	(9.13)
R-square	0.403	0.333
N	595	595
Ratio of OLS to IV estimate	0.705	
Estimate of measurement error to total variance ratio	30%	

Note: Dependent variable is log (monthly income per capita), t-statistics are in parentheses, Instruments for income are asset per capita (before flood), education, gender dummy, ownership of house, housing condition variables

Source: Author's own compilation from survey data

Appendix 5.5: Summary of variables for flooded households

Variables	Value
Monthly income per capita before flood (mean) in Taka*	650.37
Gini coefficient for income before flood	.396
Monthly income per capita after flood (mean) in Taka	545.45
Gini coefficient for income after flood	.596
Educational year of working members (mean)	2.68
Male headed households (percentage)	89%
Age of household head (mean)	43.60
Cultivated land per capita in acres (mean)	0.078
Ownership of house (percentage)	53.57%
Family size (mean)	5.22

Note: *80 Taka =1 Euro (at field survey time, 2005)
Source: Author's own compilation from survey data

Appendix 5.6: Correlates of vulnerability in income

Covariates	Coefficient	Standard Error	t-statistic	P>t	[95% Confidence Interval]	
Education of earners	-23.82	5.04	-4.72	0	-33.73	-13.90
Male headed	35.80	61.94	0.58	0.56	-85.84	157.45
Age	-3.03	7.25	-0.42	0.67	-17.27	11.20
Age squared	0.008	0.07	0.11	0.91	-0.13	0.15
Arable land per capita	-24.11	71.83	-0.34	0.73	-165.21	116.96
Ownership of house	-80.39	37.74	-2.13	0.03	-154.52	-6.26
Family size	10.68	8.74	1.22	0.22	-6.50	27.86

Source: Author's own compilation from survey data

Appendix 5.7: Correlates of vulnerability in income with bootstrap standard errors and robust estimates

Covariates	Observed Coefficient	Bootstrap Standard Error	z-statistic	P>z	Normal-based [95% Confidence Interval]	
Education of earners	-23.82	5.08	-4.68	0	-33.78	-13.85
Male headed	35.80	52.25	0.69	0.49	-66.60	138.21
Age	-3.03	6.74	-0.45	0.65	-16.25	10.19
Age squared	0.008	0.06	0.12	0.90	-0.11	0.13
Arable land per capita	-24.11	38.11	-0.63	0.52	-98.82	50.59
Ownership of house	-80.39	40.80	-1.97	0.04	-160.78	-0.41
Family size	10.68	6.05	1.76	0.07	-1.18	22.55

Source: Author's own compilation from survey data

Appendix 5.8: Changes in income (per capita) in Taka: Means and Standard Deviations

Districts	Quartiles	Mean			Standard Deviation	
		Before flood	*After flood*	*Variation (Before – After)*	*Before flood*	*After flood*
Sirajganj	1st quartile (poorest)	356.38	202.49	153.89	69.11	124.69
	2nd quartile	537.06	336.28	200.78	51.27	147.23
	3rd quartile	754.81	518.82	235.99	86.45	274.85
	4th quartile (richest)	1576.82	1296.31	280.51	715.33	767.46
Jamalpur	1st quartile (poorest)	322.45	94.21	228.24	64.50	111.33
	2nd quartile	473.39	145.22	328.17	38.03	156.72
	3rd quartile	618.21	234.29	383.92	46.58	221.38
	4th quartile (richest)	1052.47	508.79	543.68	345.67	423.76
Sunamganj	1st quartile (poorest)	337.21	308.22	28.99	74.60	117.74
	2nd quartile	502.64	489.33	13.31	37.92	65.77
	3rd quartile	653.27	609.83	43.44	54.12	147.43
	4th quartile (richest)	1302.64	1236.71	65.93	839.67	821.01
Nilphamari	1st quartile (poorest)	239.62	116.39	123.23	59.22	90.11
	2nd quartile	376.52	197.18	179.34	31.91	125.66
	3rd quartile	516.83	258.13	258.7	59.53	175.44
	4th quartile (richest)	1072.66	633.86	438.8	270.89	471.76

Note: Quartiles are detected from before flood income
Source: Author's own compilation from survey data

Appendix 5.9: Changes in income (per adult equivalent) in Taka: Means and Standard Deviations

Districts	Quartiles	Mean			Standard Deviation	
		Before flood	*After flood*	*Variation (Before – After)*	*Before flood*	*After flood*
Sirajganj	1st quartile (poorest)	458.69	279.11	179.58	94.58	155.47
	2nd quartile	674.06	381.14	292.92	61.82	226.50
	3rd quartile	954.04	665.24	288.8	107.86	305.76
	4th quartile (richest)	1957.47	1596.06	361.41	812.50	925.44
Jamalpur	1st quartile (poorest)	428.45	126.28	302.17	83.63	153.83
	2nd quartile	616.65	214.85	401.8	53.14	210.25
	3rd quartile	810.49	269.0	541.49	60.78	264.84
	4th quartile (richest)	1347.05	665.35	681.7	496.92	615.06
Sunamganj	1st quartile (poorest)	473.32	432.74	40.58	110.96	163.16
	2nd quartile	697.28	673.69	23.59	44.42	86.90
	3rd quartile	875.80	829.79	46.01	63.63	183.72
	4th quartile (richest)	1629.29	1541.57	87.72	974.38	954.69
Nilphamari	1st quartile (poorest)	335.29	155.59	179.7	91.68	129.44
	2nd quartile	532.65	246.28	286.37	42.02	178.96
	3rd quartile	703.71	378.21	325.5	74.05	225.66
	4th quartile (richest)	1329.53	814.19	515.34	338.89	568.66

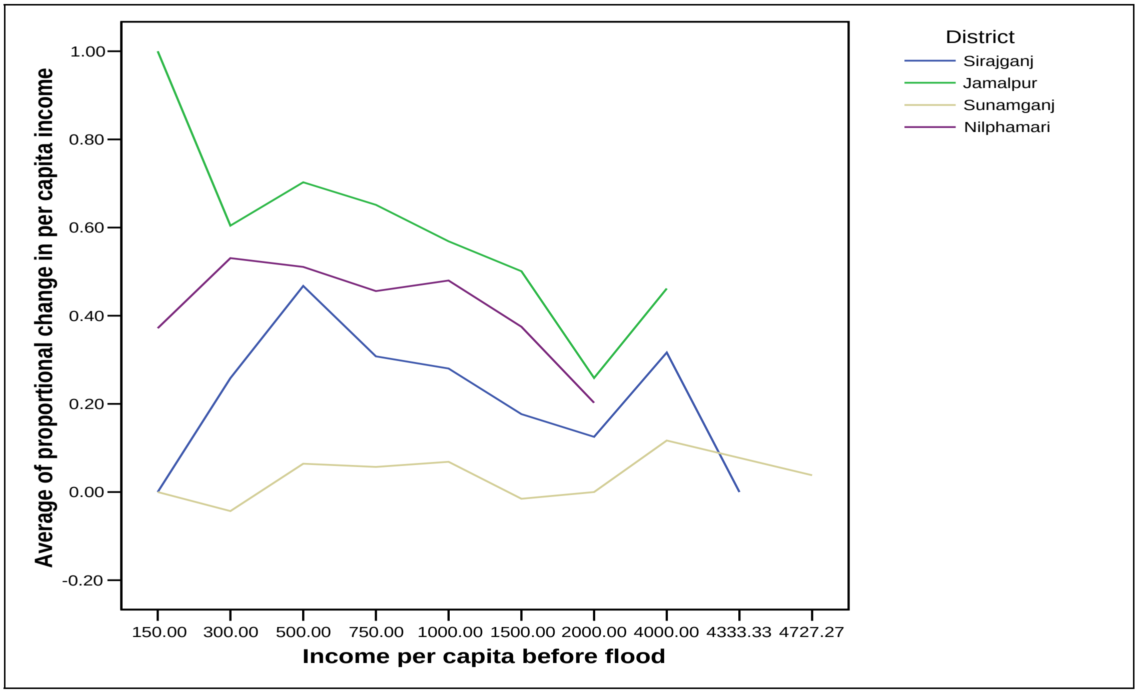
Note: Measure of per adult equivalent income assigns the values from Ligon and Schechter (2003)
Source: Author's own compilation from survey data

Appendix 5.10: Proportional changes in income by per capita and adult equivalence scale: Means and Standard Deviations

Districts	Quartiles	Per capita		Per adult equivalence scale	
		Mean	*Standard deviation*	*Mean*	*Standard deviation*
Sirajganj	1st quartile (poorest)	0.421	0.339	0.378	0.323
	2nd quartile	0.379	0.254	0.440	0.315
	3rd quartile	0.314	0.348	0.300	0.313
	4th quartile (richest)	0.180	0.275	0.194	0.292
Jamalpur	1st quartile (poorest)	0.692	0.401	0.685	0.418
	2nd quartile	0.694	0.328	0.647	0.351
	3rd quartile	0.615	0.364	0.672	0.317
	4th quartile (richest)	0.553	0.311	0.558	0.331
Sunamganj	1st quartile (poorest)	0.073	0.290	0.071	0.279
	2nd quartile	0.026	0.106	0.034	0.104
	3rd quartile	0.066	0.204	0.053	0.193
	4th quartile (richest)	0.051	0.191	0.053	0.203
Nilphamari	1st quartile (poorest)	0.504	0.344	0.520	0.351
	2nd quartile	0.469	0.338	0.534	0.340
	3rd quartile	0.511	0.318	0.463	0.313
	4th quartile (richest)	0.430	0.374	0.397	0.359

Note: Proportional changes in income = [(before flood income-after flood income)/before flood income)]
Positive values (mean) indicate the condition from before to after flood incomes are deteriorating
Source: Author's own compilation from survey data

Appendix 5.11: Proportional change in per capita income among districts



Source: Author's own compilation from survey data

Appendix 5.12: Observed changes in measured poverty in per capita income

Districts	Quartiles	Headcount index before flood	Change in headcount index	Change in squared poverty gap	Sample size
Sirajganj	1st quartile (poorest)	1.0	0	0.30	50
	2nd quartile	0.73	0.20	0.23	30
	3rd quartile	0	0.61	0.17	33
	4th quartile (richest)	0	0.75	0.06	40
Jamalpur	1st quartile (poorest)	1.0	0	0.52	36
	2nd quartile	1.0	-0.03	0.59	38
	3rd quartile	0.33	0.62	0.50	39
	4th quartile (richest)	0	0.58	0.29	36
Sunamganj	1st quartile (poorest)	1.0	0	0.07	30
	2nd quartile	1.0	-0.07	0.01	44
	3rd quartile	0.10	0.20	0.04	40
	4th quartile (richest)	0	0.03	0.03	33
Nilphamari	1st quartile (poorest)	1.0	0	0.30	37
	2nd quartile	1.0	0	0.35	38
	3rd quartile	0.84	0.16	0.37	38
	4th quartile (richest)	0	0.43	0.26	37

Note: Poverty rate in after flood period less the rate in the before flood period, positive numbers reflect a worsening of condition, through Foster et al. (1984)
Source: Author's own compilation from survey data

Appendix 6.1: Monthly interest rates among borrowing categories

Types of loan	Average weekly interest rate
Loan from neighbors/relatives (with interest)	2.32
Loan from bank (Government or private)	1.38
Loan from NGO	7.54
Loan from money lender/employer/master	8.25
Loan from neighbors/relatives (without interest)	0
Loan from nearby shop/pharmacy/ grain from kin	0.28

Note: Figures are in percentages, Source: Author’s own compilation from survey data

Appendix 6.2: Classification of borrowing by districts and poverty status

District	Poverty status	Number of households who borrowed	Total amount borrowed in Taka
Sirajganj	Poor	50	1,23,065
	Non-poor	50	2,02,680
Jamalpur	Poor	78	2,27,685
	Non-poor	47	1,53,419
Sunamganj	Poor	48	94,700
	Non-poor	26	60,150
Nilphamari	Poor	84	1,51,882
	Non-poor	30	59,430

Source: Author’s own compilation from survey data

Appendix 6.3: Classification of borrowing by districts and income quartiles

District	Income quartiles	Number of households borrowed	Total amount borrowed in Taka
Sirajganj	Poorest quartile	26	62365
	2nd quartile	22	53900
	3rd quartile	19	49100
	Richest quartile	33	160380
Jamalpur	Poorest quartile	33	124725
	2nd quartile	33	70230
	3rd quartile	39	108856
	Richest quartile	20	77293
Sunamganj	Poorest quartile	17	43400
	2nd quartile	19	29200
	3rd quartile	28	62550
	Richest quartile	10	19700
Nilphamari	Poorest quartile	51	93232
	2nd quartile	25	44950
	3rd quartile	16	24380
	Richest quartile	22	48750

Source: Author's own compilation from survey data

Appendix 6.4: Income sources, amount of borrowing and households' frequency

Quartile	Income sources						
	Agriculture	Service	Business	Day labor	Dairy and Poultry	Remittance	Boat-men and Fisher-men
Poorest quartile	153632 (47)	16500 (3)	9950 (5)	102765 (49)	2300 (1)	22075 (13)	16500 (9)
2nd quartile	67680 (30)	11800 (4)	27450 (10)	74800 (43)	250 (1)	12100 (6)	4200 (5)
3rd quartile	82771 (30)	10490 (2)	22950 (13)	103850 (38)	3300 (1)	3625 (3)	18000 (15)
Richest quartile	102453 (28)	34000 (12)	123900 (18)	12700 (7)	14900 (6)	11370 (10)	6800 (4)
Total	406536 (135)	72790 (21)	184250 (46)	294115 (137)	20750 (9)	49070 (32)	45500 (33)

Note: Figures in parentheses are containing frequency of households
Source: Author's own compilation from survey data

Appendix 6.5: Determinants of borrowing as a coping strategy: tobit model estimate

Factors Variables	Model 1	Model 2	Model 3
	Coefficients	*Coefficients*	*Coefficients*
Shock factors:			
Flood height	191.81 (52.39)***	175.04 (52.56)**	164.51 (53.06)**
Flood duration	-2.26 (7.07)	-0.18 (7.21)	1.08 (7.28)
Loss of crops	0.02 (0.02)	0.002 (0.03)	0.006 (0.003)**
Loss of assets	0.63 (0.11)***	0.59 (0.11)***	0.60 (0.11)***
Loss of working days	11.22 (4.56)**	9.53 (4.64)**	8.72 (4.67)*
Demographic factors:			
Household size		-37.13 (17.17)**	-39.88 (17.37)**
Dependency ratio		5.31 (38.90)	12.25 (39.26)
Age of household head		-5.14 (2.56)**	-4.80 (2.58)*
Average education of working members		-0.91 (12.59)	-2.96 (13.82)
Gender of household head (male=1)		203.79 (116.02)*	209.64 (116.19)*
Occupation (agriculture=1)		130.28 (85.26)	111.52 (63.09)*
Economic and community factors:			
Per capita income before flood			-0.12 (0.04)**
Membership in cooperatives (yes=1)			51.63 (68.89)
District dummy 1 (Sirajganj=1)			-117.54 (127.10)
District dummy 2 (Jamalpur=1)			184.14 (107.86)
District dummy 3 (Sunamganj=1)			-133.66 (128.09)
Number of uncensored observations	413	413	413
Log likelihood	-461.27	-252.73	-89.55
LR chi-square	75.29	90.36	112.72
Probability>chi-square	0.000	0.000	0.000
Pseudo R^2	0.011	0.271	0.577

Note: Dependent variable: amount of borrowing (truncated from the lower limit zero), robust standard errors are in parentheses, values are statistically significant at ***1%, **5%, *10% level, All the models include constant terms not reported in the table

Source: Author’s own compilation from survey data

Appendix 6.6: Determinants of savings as a coping strategy: tobit model estimate

Factors	Variables	Model 1	Model 2	Model 3
		Coefficients	*Coefficients*	*Coefficients*
Shock factors:				
	Flood height	-938.43 (681.50)	-1151 (720)	-766.97 (572.37)
	Flood duration	174.65 (79.96)**	174.09 (85.43)**	127.93 (67.89)**
	Loss of crops	-0.14 (0.35)	-0.30 (0.46)	-0.36 (0.39)
	Loss of assets	0.90 (1.08)	0.53 (1.07)	0.72 (0.83)
	Loss of working days	74.93 (46.24)	80.83 (48.72)*	73.39 (38.39)*
Demographic factors:				
	Household size		-163.99 (206.11)	-25.62 (151.91)
	Dependency ratio		147.85 (82.04)*	209.96 (122.06)*
	Age of household head		-18.22 (30.94)	-2.47 (26.22)
	Average education of working members		-91.20 (138.37)	-120.03 (126.61)
	Gender of household head (male=1)		114.89 (167.25)	159.13 (152.15)
	Occupation (agriculture=1)		225.92 (1181.60)	476.37 (975.09)
Economic and community factors:				
	Per capita income before flood			1.73 (0.52)**
	Membership in cooperatives			761.37 (688.72)
	District dummy 1 (Sirajganj=1)			713.58 (628.68)
	District dummy 2 (Jamalpur=1)			192.11 (279.50)
	District dummy 3 (Sunamganj=1)			-258.40 (238.06)
Number of uncensored observations		20	20	20
Log likelihood		-209.16	-203.96	-116.99
LR chi-square		12.94	23.34	35.29
Probability>chi-square		0.023	0.015	0.008
Pseudo R^2		0.030	0.054	0.382

Note: Dependent variable: amount of savings (truncated from the lower limit zero), robust standard errors are in parentheses, values are statistically significant at ***1%, **5%, *10% level, All the models include constant terms not reported in the table

Source: Author's own compilation from survey data

Appendix 6.7: Determinants of selling assets as a coping strategy: tobit model estimate

Factors Variables	**Model 1**	**Model 2**	**Model 3**
	Coefficients	*Coefficients*	*Coefficients*
Shock factors:			
Flood height	117.66 (109.93)	109.84 (116.36)	88.14 (116.41)
Flood duration	36.50 (17.62)**	29.44 (8.27)***	25.99 (8.16)***
Loss of crops	0.09 (0.05)	0.05 (0.06)	0.07 (0.06)
Loss of assets	0.46 (0.24)**	0.51 (0.25)**	0.25 (0.15)*
Loss of working days	10.09 (9.20)	9.86 (9.57)	8.40 (9.62)
Demographic factors:			
Household size		-34.18 (32.70)	-34.20 (32.59)
Dependency ratio		22.60 (7.10)***	3.50 (0.54)***
Age of household head		-8.87 (5.56)	-8.05 (5.55)
Average education of working members		-40.70 (29.16)	-23.44 (31.11)
Gender of household head (male=1)		-15.30 (249.95)	-39.51 (49.56)
Occupation (agriculture=1)		309.32 (169.49)	73.95 (70.20)
Economic and community factors:			
Per capita income before flood			-0.34 (0.25)
Membership in cooperatives			12.54 (6.53)**
District dummy 1 (Sirajganj=1)			-12.99 (55.88)
District dummy 2 (Jamalpur=1)			249.20 (205.42)
District dummy 3 (Sunamganj=1)			-122.43 (175.13)
Number of uncensored observations	57	57	57
Log likelihood	-584.86	-372.34	-149.14
LR chi-square	10.80	19.83	22.24
Probability>chi-square	0.055	0.047	0.001
Pseudo R^2	0.009	0.016	0.413

Note: Dependent variable: amount of selling assets (truncated from the lower limit zero), robust standard errors are in parentheses, values are statistically significant at ***1%, **5%, *10% level, All the models include constant terms not reported in the table

Source: Author's own compilation from survey data

Appendix 6.8: Crops in Bangladesh and cultivation periods

Name of crop	Sowing period	Harvesting period
Aus paddy	Mid March to Mid April	Mid July to Early August
Broadcast Aman paddy	Mid March to Mid April	Mid November to Mid December
Transplanted Aman paddy	End June to Early September	December to Early January
Local Boro paddy	Mid November to Mid January	April to May
High yielding Boro paddy	December to Mid February	Mid April to June
White Jute	Early March to Mid April	July to August
Tossa Jute	Mid April to Early May	August to September

Source: BBS 2005:1

Appendix 6.9: Coefficient of variation in quartiles for each district (per capita)

District	Quartile per capita income	Mean of income difference (in Taka)	Standard deviation	Coefficient of variation
Sirajganj	1st (poorest)	154.29	128.16	0.830644
	2nd	200.78	132.02	0.657536
	3rd	235.99	263.76	1.117674
	4th(richest)	280.51	476.81	1.699797
Jamalpur	1st (poorest)	176.36	339.03	1.922375
	2nd	328.18	156.67	0.47739
	3rd	383.91	230.95	0.601573
	4th(richest)	543.68	285.88	0.525824
Sunamganj	1st (poorest)	28.98	106.69	3.681504
	2nd	-144.77	860.89	-5.9466
	3rd	43.44	136.38	3.139503
	4th(richest)	62.16	217.02	3.491313
Nilphamari	1st (poorest)	123.23	93.25	0.756715
	2nd	179.33	133.18	0.742653
	3rd	258.70	155.16	0.599768
	4th(richest)	438.79	403.04	0.918526

Note: Per capita income and only for flooded households
Source: Author's own compilation from survey data

Appendix 6.10: Coefficient of variation in quartile for each district (per adult equivalent scale)

District	Quartile per adult equivalence income	Mean of income difference (in Taka)	Standard deviation	Coefficient of variation
Sirajganj	1st (poorest)	179.58	159.62	0.888852
	2nd	292.92	213.06	0.727366
	3rd	288.79	307.83	1.06593
	4th(richest)	361.42	603.98	1.671131
Jamalpur	1st (poorest)	227.89	457.94	2.009478
	2nd	401.80	219.47	0.546217
	3rd	541.48	255.68	0.472187
	4th(richest)	681.71	355.25	0.521116
Sunamganj	1st (poorest)	40.58	150.81	3.716362
	2nd	-208.04	1429.68	-6.87214
	3rd	46.00	170.61	3.708913
	4th(richest)	82.41	292.03	3.543623
Nilphamari	1st (poorest)	179.69	136.02	0.75697
	2nd	286.37	184.24	0.643363
	3rd	325.49	221.02	0.679038
	4th(richest)	515.34	524.47	1.017716

Note: Per adult equivalence income and only for flooded households
Source: Author's own compilation from survey data

Appendix 6.11: Sources of income and vulnerability

Source of income of main earner	Distribution of households in frequency	Flood vulnerability
Agriculture	29.4	93.79
Service	6.6	39.5
Business	13.4	45.78
Day labor	30.9	90
Dairy & Poultry	2.2	50
Fishing & Boating	8.6	61.53
Remittances from urban migration	6.8	23.71
Remittances from village and out-country migration	2.1	29.66

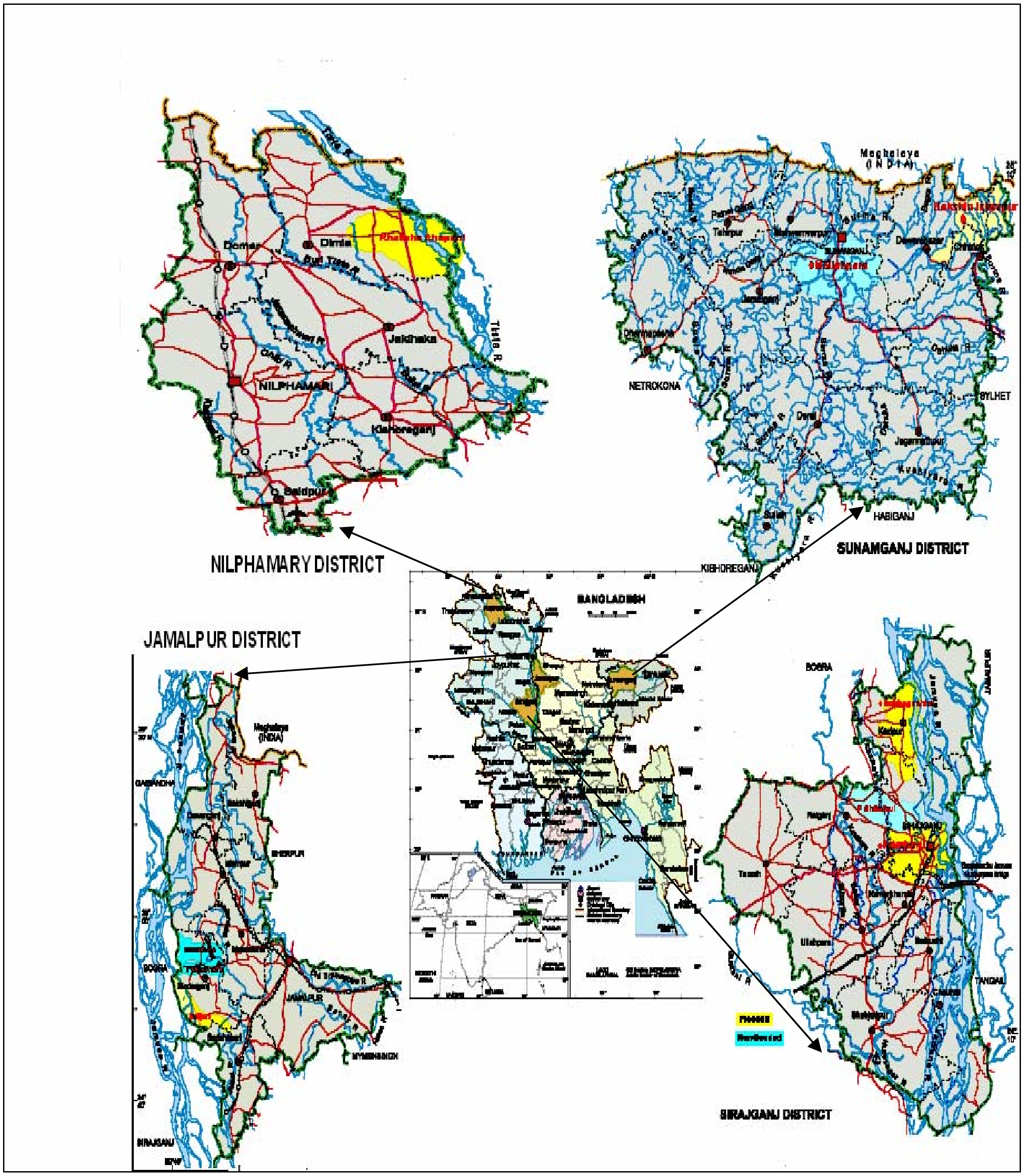
Source: Author's own compilation from survey data following Chaudhuri et al. (2002)

Appendix 6.12: Impacts of migration

Category	Frequency	Percentage
Financial help from migrants	100	60
Improvement of social value (without any financial help)	21	12
Financial help and social value	33	20
Financial loss for migrants	14	8

Source: Author's own compilation from survey data

Appendix A: Flooded and non-flooded survey areas in four districts



Note: Yellow shaded areas are flooded and blue shaded areas are non-flooded survey areas

Appendix B: Questionnaire of field survey for this study

Applicable only for research works Sample number

Questionnaire: Assessing household vulnerability and coping strategies to flood: A comparative study in flood and non-flood prone areas of Bangladesh

[This Survey should be conducted with the Heads/Representative of households and filled out by the interviewer]

[***** signed questions should be applied for flooded areas only, **M** signed questions can include multiple answers, last/this flood means flood in 2005]

Objective: This survey is the part of a Ph.D. thesis. The frequent occurrence of flood events amounts to losses in both human life and property values in Bangladesh. This study thus is set forth to examine the household vulnerability to flood and socioeconomic conditions for determining significant coping strategies, such examination will be instructive for both the short term and long term flood management in Bangladesh.

Part-A
(Data Entry Record)

01. Questionnaire No. (Interviewer will fill it)

02. Date of Interview D D M M 2 0 0 5

03. Area Identification

A)	Village	....	B)	Mouza	....
C)	Union	....	D)	Upazila	....
E)	Zila	....	F)	Division	....

04. Identification of Household head

A) Name ....

B) Fathers/Husband's name ....

C) Name of Respondent ....

D) Relation with Household head

01=self, 02=Husband/Wife, 03=Son, 04=Daughter, 05=Son's wife, 06=Grand-son/daughter, 07=Brother/Sister, 08=Father/Mother, 09=Others

Name of interviewer ....

Signature ....

Part-B
(Socio-Demographic Information)

Q05. Household Information

Serial no.	Name of household (HH) members	Relation with HH head	Sex M=1, F=2	Religion	Age		Education (completed class)	Marital Status	Occupation	
					Year	Month			Primary	Secondary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
01		01								
02										
03										
04										
05										
06										
07										
08										
09										
10										

(2) **Relation with HH head**
01=own
02=Husband/Wife
03=Son
04=Daughter
05=Son's wife
06=Grand son/daughter
07=Brother/sister
08=Father/Mother
09=Others

(4) **Religion**
01=Muslim
02=Hindu
03=Buddhist
04=Christian
05=Others

(7) **Education**
00=<Class 1
01=Class 1
02= Class 2
03= Class 3
04= Class 4
05= Class 5
06= Class 6
07= Class 7
08= Class 8
09= Class 9
10= Class 10 or Equivalent
11=Class 12 or Equivalent
12=Graduation or Equivalent
13=Post-Graduation/ Equivalent
14=Doctor or Engineer
15=Diploma
16=Vocational
55=Can sign
66=Non-institutional
77=Illiterate
88=Not Applicable (<5 years children)

(8) **Marital Status**
01=Married
02=Un-married
03=Widowed
04= Separated
05= Divorced
88=Not Applicable (<12 years HH)

(9)- (10) **Occupation**
01= Agriculture (own)
02= Agriculture (Share)
03=Agriculture (Fishing/Poultry/ Domestic animals)
04=Day labor
05= Potter
06=NGO worker
07=Salaried employee
08=House helper/maid
09= Chief-labor
10=Fisherman
11=Boatman
12= Blacksmith
13= Cobbler
14= Rickshaw/van puller
15=Driver
16=Large-scale business
17=Imam
18=Barber
19=Student
20= Retired person
21=Contract labor
22=Beggar
23=Inefficient (old aged)
24=Artist
25=Agriculture day-labor
26=Mechanic
27=Village doctor
28=Permanent labor
29=Laundry
30= Sewing
31=Don't know
32=Small-scale business
33= Carpenter
34= Teacher
35=Un-employed
36=Others
88=Not Applicable (<6 years children)

Q06. Structure of Dwelling House

	Elements	Floor	Wall	Roof
		(1)	(2)	(3)
a	Soil			
b	Bamboo			
c	Tin/Wood			
d	Cement			
e	Others			

Q07. How many years have you been living here? [ ] 97=since fatherhood 98=since grand-fatherhood or earlier

***Q08.** Was the home/homestead affected by last flood?

Yes	no
1	2

If 2 then skip to Q09

		Height of flood water (in feet)	Duration of inundation(in days)
		(1)	(2)
a	Home		
b	Homestead		

Q09. Ownership of house [ ]
1= Own, 2= Father's/Mother's/Husband's/Wife's, 3= Government, 4= Rented, 5= Rent free, 6=Others, 7=Don't know

Q10. Water Source and Use **(M)**

Types of use	Before flood	*During flood	*After flood
	(1)	(2)	(3)
Drinking water			
Cooking water			
Water for bath & wash cloths			
Water for dish wash			

1= Tube well, 2= Well, 3= Pond/River/Canals, 4= Tap, 5= Boiling water from Pond/River/Canals, 6=Flood water, 7= Others

Educational Institutions:

Q11. Do you have the opportunity to get service from following educational institutions?

Type of institution		yes=1, no=2	Distance in kilometer (nearest one) (Put 00 for <1 kilometer)	Conveyance (during flood/within one month) in Taka	*Affected by flood 1=yes, 2=no, 3=don't know
	(1)	(2)	(3)	(4)	(5)
1.	Primary school	1 2			1 2 3
2.	Secondary school	1 2			1 2 3
3.	Higher-secondary school	1 2			1 2 3
4.	Madrasa	1 2			1 2 3
5.	Others------------	1 2			1 2 3

Medical/Health Care Centre:

Q12. Do you have the opportunity to get service from following Hospital/Health care centre?

	Hospital/Health care center	Yes=1 No=2	Distance in kilometer (nearest one) (Put 00 for <1 kilometer)	*Affected by flood 1=yes, 2=no, 3=don't know	*Service rendered during flood 1=yes, 2=no, 3=don't know	Conveyance (during flood/ within one month) in Taka	Conveyance (after flood) in Taka
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a	Public hospital	1 2		1 2 3	1 2 3		
b	Private hospital	1 2		1 2 3	1 2 3		
c	NGO health care	1 2		1 2 3	1 2 3		
d	Pharmecy	1 2		1 2 3	1 2 3		
e	Others	1 2		1 2 3	1 2 3		

Market Place :

Q13a. How far the nearest market from your home? ☐ In Kilometer (put 00 for <1 kilometer)

Q13b. How can you reach there usually? **(M)**

Walking ☐ Vehicle ☐ (if walking then skip to Q13d)

1=Rickshaw/van, 2=Cycle, 3=hand-van, 4=Motor-cycle, 5=Boat, 6=Bus, 7=Lori, 8=Others…………..

Q13c. (before flood) how much it cost (daily in Taka)?

1. .... 2. .... 3. ....

Q13d. Was the market affected in this flood?

Yes	no
1	2

If 2 then skip to Q14

Q13e. If affected

[ ] 1=partially, 2=completely

***Q13f.** How could you manage to reach your market place during flood? **(M)**

[ ] If 8 then skip to Q14a

1=Rickshaw/van, 2=Cycle, 3=hand-van, 4=Motor-cycle, 5=Boat, 6=Bus, 7=Lori, 8=Walking, 9=Others…………..

***Q13g.** How much it cost to reach in market place during flood (daily)? [ ] (taka)

Roads:

***Q14a.** Was your nearby road affected by flood?

Yes	no
1	2

If no then skip to Q14c

***Q14b.** (If yes) how much was it affected?

[ ] 1=Partially, 2=Completely

Q14c. What is the road condition from your home to market? **(M)**

[ ]

1=Raw, 2=Pitch road, 3=Soling road, 4=Others……………………..

Public Services:

Q15. Are these following public services available in your village?

	Type of service	Before flood/within 1 month		*During flood		*After flood	
		Yes	No	Yes	No	Yes	no
		(1)		(2)		(3)	
a	Electricity						
b	Vehicles**(M)**						
c	Flood shelter ( )						
d	Canal						
e	Others						

(b): 1=Rickshaw/van, 2=Cycle, 3=hand-van, 4=Motor-cycle, 5=Boat, 6=Bus, 7=Lori, 8=Walking, 9=Others…………..

Q15a. (If electricity is available) monthly expenditure (Taka) [ ]

Part-C
(Information Related to Damages and Shock of the Household)

Q16. Was your home affected by flood in the following years?

Yes	no
1	2

1988 [ ] 1998 [ ] 2004 [ ] *****2005 [ ]

***Q17.** In which month (including duration) the flood was occurred this year? (in Bengali)

Month [ ][ ]

1	4	1	2

***Q18.** What was the loss in the following sectors during flood?

Sector		Didn't affect	Affected		Amount of loss (Taka)
			Partially	Completely	
		(1)	(2)	(3)	(4)
1	Furniture of home				
2	Households health				
3	Home				
4	Food/food grain				
5	Appliances for work				
6	Domestic animals				
7	Others……………..				
8	Others………………				
				Total	

Part-D
(Coping Strategies at Crisis)

Q19. What were the coping strategies in this flood/within 1 month? **(M)**

Serial no.	Type of coping	Yes=1, 2=no	Amount in Taka (if possible)
		(1)	(2)
01	Loan from neighbors/relatives	1 2	
02	Loan from Money Lender	1 2	
03	Loan from NGO	1 2	
04	Grain loan from kin	1 2	
05	Cash loan from merchants	1 2	
06	Loan from bank (mention bank name)	1 2	
07	Adjustment to Meals	1 2	
08	Cereal loan from merchants	1 2	
09	Farmland mortgage out	1 2	
10	Farmland leased out	1 2	
11	Used savings	1 2	
12	Loan without interest	1 2	
13	Sold trees	1 2	
14	Sold Jewelry	1 2	
15	Sold cows/bullock and other domestic animals	1 2	
16	Sold standing crop	1 2	
17	Sold fish in advance at a lower price	1 2	
18	Sold agricultural products at a low price	1 2	
19	Sold fruits in advance	1 2	
20	Sold men/women labor	1 2	
21	Sold household utensils	1 2	
22	Sold poultry/birds	1 2	
23	Sold home/homestead land	1 2	
24	Sold farmland	1 2	
25	Sold child labor	1 2	
26	Occupation change	1 2	
27	Migrated to sale labor	1 2	
28	Taken relief	1 2	
29	Begging	1 2	
30	Debit from nearby shop/pharmacy	1 2	
31	Help from any institution	1 2	
32	Others………………………………….	1 2	
33	Others…………………………………..	1 2	

Q20. What do you and your family need most at this moment (after flood/within 1 month) **(M)**

01.	Money to buy food	
02.	Financial aid to start a business	
03.	Support in finding a job	
04.	Clothes	
05.	Medical service	

06.	Spiritual aid	
07.	Be part of an organization to defend your rights	
08.	Children programs	
09.	House plot	
10.	Construction material	
11.	Others……………………………………	

Q21. Did your family receive any kind of support/aid during this flood/within 1 month?

Yes	no
1	2

If 2, in flooded area skip to Q22, non-flooded area skip to Q24

Q21a. (If yes) What kind of support did you receive and when did you receive it?

Types of aid		*Within 1 week After flood	Within 1 month (after flood/non-flooded)	Amount (Taka) (if possible)	Helping organization (**M**)
		(1)	(2)	(3)	(4)
01.	Financial aid				
02.	Subsidized loans/credits				
03.	Tents				
04.	Transport				
05.	Food/food grain				
06.	Health Service				
07.	Education				
08.	Child and Youth Programs				
09.	Tools				
10.	Training/ technical assistance				
11.	Construction material				
12.	Donations (blankets, pots, etc.)				
13.	Allocation of land				
14.	Others……………..				

(4): 1= Red Crescent, 2=Government organization, 3=NGO, 4=Family members/friends, 5=Any reputed person, 6=Others…….., 7=Don't know

***Q22.** Do you have any early warning system for flood in your village?

Yes	no
1	2

If 2 then skip to Q22c

***Q22a.** (If yes) What is it?

Describe:

………

***Q22b.** Was there any effect of the warning system?

Yes	no
1	2

***Q22c.** Did you guess any sign before this flood?

Yes	No
1	2

If 2 then skip to Q23

***Q22d.** (If yes) How was that?

Describe...

***Q23.** Did your family have access to the following information media before flood? (It is not necessary for you to own these information media by yourselves, you might as well use them at friends' and family houses, or elsewhere.)

Media		opinion	
		Yes	no
		(1)	
1.	Radio		
2.	Television		
3.	Newspaper		
4.	Telephone		

Q24. Do you expect that an early-warning system for floods will be implemented in your place of origin?

Yes	No
1	2

If 2/don't know then skip to Q25

(If yes) How quickly do you think this will happen?

1.	Within 1 year	
2.	Within few years	
3.	It will take many years	

Part-E
(Socio-Economic Information of the Household)

Q25. Household Productive Assets:

	Type	Quantity (local unit)	Quantity (standard unit)	Current value (Taka)	*Affected by flood			*Quantity of loss (Taka)
					Not	Partially	totally	
		(1)	(2)	(3)	(4)			(5)
a	Home							
b	Homestead							
c	Cultivable land							
d	Non-cultivable land							
e	Garden							
	Total							

Crops and Production:

Q26. Was there any crop damaged during this flood/within 1 month?

Yes	No
1	2

If 2/not applicable then skip to Q27

Q26a.

Name of the crop	Normal yield (in kilo.)	Market price (Taka)	*Yield after flood (in kilo.)	*Market price after flood (Taka)	Amount of loss (Taka)
	(1)	(2)	(3)	(4)	(5)
1.					
2.					
3.					
4.					
5.					

Q27. Consumer Durable Assets:

	Type	Quantity (in kilo.)	Market price (Taka)	*Affected during flood			Amount of loss during flood/within 1 month (Taka)
				Not	Partially	totally	
		(1)	(2)	(3)			(4)
Animal							
01	Cow						
02	Buffalo						
03	Goat						
04	Sheep						
05	Others						

Poultry							
11	Chicken/hen						
12	Duck						
13	Others						
Trees							
16	Fruits						
17	Wood tree						
18	Bamboo						
19	Others						
Others							
31	Rickshaw/van						
32	Tractor						
33	Power tiller						
34	Trawler						
35	Boat						
36	Hand-van						
37	Tube well						
38	Shallow-tube well						
39	Shallow machine						
40	Fishing net						
41	Sewing machine (small)						
42	Sewing machine (large)						
43	Mike						
44	Spade						
45	Weed cutter						
46	Lever						
47	Others						
Household Item							
61	Wrist watch/wall clock						
62	Radio						
63	Television						
64	Bicycle						
65	Motor cycle						
66	Fan						
67	Jewelry (Gold) (in ana) 1/16 of a bhory						
68	Jewelry (Silver) (in ana) 1/16 of a bhory						
69	Bed						
70	Chair/Table						
71	Almira						
72	Bench						
73	Ware drop						
74	Meet safe						
75	Others						

Q28. Household Income (per month) (Taka)

	Source of income	Before flood/Usually	*During flood	*Amount loss for flood	*Loss of working day
		(1)	(2)	(3)	(4)
01	Agriculture (yearly divided by 12)				
02	Service (Government/NGO)				
03	Business				
04	Day labor/Wage labor				
05	Poultry rearing				
06	Dairy rearing				
07	Rickshaw/van puller				
08	Remittance				
09	Others……………				
	Total				

Q29. Household Expenditure (monthly) on Non-food Items (Taka)

	Source	Before flood/within 1 month	*During flood	*Amount of loss
		(1)	(2)	(3)
01	Education (tuition, exam fee/book, pencils)			
02	Health care			
03	Repay debit (except from savings)			
04	Clothes (yearly)		///////////////	///////////////////
05	Livestock/Poultry			
06	Agricultural equipments			
07	Social/Religious work			
09	Housing (yearly)		///////////////	///////////////////
10	Housing utensils (yearly)		///////////////	///////////////////
11	Conveyance			
12	Bribery/punishment fees/Cost of trial (yearly)		///////////////	//////////////////
13	Cooking materials			
14	Recreation (picnic, fair) (yearly)		///////////////	//////////////////
15	Make-up (soap, oil, powder)			
16	Others…………			
17	Others………………..			

Savings:

Q30. Do you have any savings?

Yes	No
1	2

If 2 then skip to Q31

Q30a. Have you spent the money during flood/within 1 month from your savings?

Yes	No
1	2

If 2 then skip to Q30c

Q30b. Where have you used the saving money during flood/within 1 month?

Sector		Yes=1, no=2		Taka (if possible)
		(1)		(2)
01.	Education	1	2	
02.	Health	1	2	
03.	Loan repayment	1	2	
04.	Agriculture input/equipment purchase/fishing instrument	1	2	
05.	Housing	1	2	
06.	Clothes	1	2	
07.	Paying dowry	1	2	
08.	Festivals/social obligations	1	2	
09.	Buying food items	1	2	
10.	Business	1	2	
11.	Livestock/poultry	1	2	
12.	Buying seeds for plants	1	2	
13.	Helping relatives/ friends	1	2	
14.	Installment for Samity	1	2	
15.	Others……………………………………….	1	2	

Q30c. How much money have you been saved (till the date of interview)? ______ Taka

Loan/Debt:

Q31. Do you have any loan (till the date of interview)?

Yes	No
1	2

If 2 then skip to Q32

Q31a. (If yes) How much? ______ Taka

Q31b. What are the sources of loan?

Source		Amount of Taka	Interest rate
		(1)	(2)
1.	Mohajan/Money lender		
2.	NGOs		
3.	Friends/relatives		
4.	Bank		
5.	Nearby shop/pharmacy		
6.	Others………………		
Total			

Q31c. Did you spend money from loan?

Yes	No
1	2

If 2 then skip to Q32

Q31d. For which sector you used the loan?

Sector		Amount of money (Taka)
	(1)	(2)
01.	Farming	
02.	Small scale works (sewing, gardening)	
03.	Health	
04.	Housing	
05.	Social/Religious/Marriage ceremony/Paying dowry	
06.	Food consumption	
07.	Dairy/Poultry/Fishing	
08.	Business	
09.	Given credit to others	
10.	Land purchase/Repay loan for land	
11.	Buying seeds of plants	
12.	Buying agricultural/business tools	
13.	Savings for future risk	
14.	Others……………………………….	
15.		

Q32. Do you/your family members have any membership in the local institution?

Yes	No
1	2

If 2 then skip to Q34

Q33. (If yes) Which of the following?

Name of institution		Yes	No	Inclusion	
		(1)		(2)	
				Male=1, Female=2	
01	Political party	1	2	1	2
02	Union Parishad	1	2	1	2
03	Village leadership	1	2	1	2
04	Committees of school/madrasa/market/mosque	1	2	1	2
05	Borrower of Bank	1	2	1	2
06	Grameen Bank	1	2	1	2
07	Club	1	2	1	2
08	NGOs group	1	2	1	2
09	Participation in community festivals	1	2	1	2
10	VGF Card/Old age pension membership	1	2	1	2
11	Other associations (rickshaw driver, labor, fishermen, irrigation group, etc.)	1	2	1	2
12	Member of different govt. organizations	1	2	1	2
13	Others……………………………………	1	2	1	2

Part-F
Food Consumption and Expenditure

Q34. How many times you/your family members take the meals in a day?

Before flood	*During flood	*After flood
(1)	(2)	(3)

Q35. Food intakes and expenditure

Code	Items	Quantity consumed in the normal day before interview		Market price per kilo.	Daily expenditure (Taka)	Source **(M)**
		Number	Gm/liter			
		(1)	(2)	(3)	(4)	(5)
Cereals						
01	Rice	//////////////////				
02	Wheat	//////////////////				
03	Wheat flour (Ata)	//////////////////				
04	Flour refined (Moyda)	//////////////////				
05	Others---------------					
Pulses						
06	Lentil	//////////////////				
07	Black gram dhal	//////////////////				
08	Khesari dhal	//////////////////				
09	Green gram dhal	//////////////////				
10	Others-------------					
Edible oils						
11	Soybean	//////////////////				
12	Mustard	//////////////////				
13	Others---------------					
Non-leafy Vegetables						
14	Potato					
15	Bean					
16	Parwar					
17	Balsam apple					
18	Lady's finger					
19	Brinjal					
20	Tomato					
21	Pumpkin					
22	Sweet pumpkin					
23	Bottle gourd					
24	Carrot					
25	Radish					
26	Onion stalks					
27	Banana green					
28	Papaya					
29	Colocasia tuber					

30	Bean (barbati)					
31	Others………..					
Leafy Vegetables						
32	Pui leaves					
33	Amaranthus leaves, red					
34	Badha copy					
35	Amaranthus leaves					
36	Ipomoea leaves					
37	Colocasia leaves green					
38	Bottle gourd leaves					
39	Coriander leaves					
40	Spinach					
41	Onion leaves					
42	Radish leaves					
43	Others………					
Fish, Meat and Egg						
44	Beef					
45	Mutton					
46	Chicken/Duck					
47	Pigeon's meat					
48	Egg					
49	Milk					
50	Large fish					
51	Small fish					
52	Dry fish					
53	Others……..					
Fruits						
54	Banana					
55	Papaya					
56	Orange					
57	Apple					
58	Lemon					
59	Guava					
60	Others……….					
Sweet						
61	Sweet in shop					
62	Sweet (red)					
63	Sugar					
64	Others…….					
Spices						
65	Salt					
66	Onion					
67	Turmeric					
68	Chili (raw)					
69	Chili (dry)					
70	Garlic					
71	Ginger					

72	Jira					
73	Masala					
74	Others………					
Tobacco, Tea						
75	Cigarette					
76	Betel leaf					
77	Tea					
78	Others………….					

(5):1=Purchase, 2=As payment, 3=Home-made, 4=Gifted, 5=Others……………………………………

Part-G
(Health)

Q36a. Did any of your family members suffer from disease during this flood/within 1 month?

Yes	No
1	2

If 2 the skip Q37

Q36b. (If yes) How many members? [ ]

Q36c. **(Please fill up each row for individuals)**

HH serial no.	Disease **(M)**	Duration of suffering (day)	Any treatment? **If no then skip to 10th column** 1=yes, 2=no	Whose suggestion was taken? **(M)**	Any Medicine? **If no then skip to 8th column** 1=yes, 2=no	Which medicine? **(M)**	Any test? 1=yes, 2=no	Total cost (conveyance, medicine, test, fee in hospital cabin, fee for doctor) in Taka	Why didn't take any treatment? **(M)**	Amount of loss due to illness
1	2	3	4	5	6	7	8	9	10	11

(2): <u>Disease code:</u> 01=Diarrhea 02=Dysentery 03=Influenza 04=Ear disease 05=Teeth disease 06=Skin disease 07=pain in joints 08=Rheumatic fever 09=Fever 10=Malaria 11=Cold 12=Headache 13=Pain in belly 14=Anemia 15=Cough	16=Tiphoid 17=Collera 18=Chickenpox 19=Hum 20=Titanus 21=Moums 22=Unusual breathing 23=Others pain 24=Mental illness 25=Snake bite 26=Problem in pregnancy 27=Others......	**(5): <u>Physician code</u>** 01=Paramedics 02=Allopathic doctor 03=Non-professional doctor 04=Homeopath doctor 05=Kobiraj 06=Dhatri 07=Pir/Fakir 08=Hospital 09=Pharmecy 10=Own/no one 11= Others……..	**(7): <u>Medicine code</u>** 1=Allopathic 2=Homeopathic 3=Iurbedi 4=Kobiraj 5=Pir/Fakir 6=Others……..	**(10): <u>Reason for no treatment</u>** 01=Financial problem 02=Casualness 03=Illiteracy 04=Less access to treatment 05=Problem in communication 06=Improper treatment 07=No company 08=Thought unnecessary 09=Others……….

Part-H
(Women Status)

Q37. Is any of your HH female member go out of home for work?

Yes	No
1	2

If 2 then skip to Q38

Q37a. (If yes) In which sector she/they is/are working?

Sector		Before flood/within 1month	Income	*After flood	*Income
		(1)	(2)	(3)	(4)
01.	Agriculture				
02.	Day/wage labor				
03.	Fishing				
04.	Sewing				
05.	Small scale business/handicraft				
06.	Servant				
07.	Selling things				
08.	Carrying water				
09.	Working in NGO				
10.	Social/Religious works				
11.	Garments industry				
12.	Baby care				
13.	Plantation				
14.	Rearing livestock/poultry				
15.	Teaching				
16.	Others……..				
17.	Others…………………				

Part-I
(Migration Information of the Household)

Q38. Did any of your household members migrate into a different region?

Yes	no
1	2

If 2 then skip to Q39

Q38a. How many members in your family already migrated?

Q38b. Which of the following kinds? **(M)**

1. From own village to another village
2. From own village to another city
3. From own village to another country
4. Another place in own village

Q38c. What was the reason? **(M)**
1=flood 2=unemployment 3=wage differentials 4=motivated by other migrants 5= insecurity 6=reimburse debt 7=others………………..

Q38d. (If migrated) Address of destination place:

i ______________________________

ii ______________________________

iii ______________________________

Q38e. Was there any network in destination place?

Yes	No
1	2

If 2 then skip to Q38g

Q38f. (If yes) What kind of network (relation) was it? **(M)**
1=relative 2=friends 3=neighbors 4=organization 5=others……………………..

Q38g. Is there any impact of migration in your current status?

Yes	No
1	2

If 2 then skip to Q39

Q38h. (If yes) What kind of impact is it? **(M)**

If 2/3 code is used then skip to Q39

1=Monetary, 2=Social status, 3= Others…………………

Q38i. How much money do you get from each migrant per month? (in Taka)

1 ______ 2 ______ 3 ______

Q38j. How are you investing the remittances? (Monthly in Taka)

Serial no.	Sectors	During flood/Usually (1)	*After flood (2)
01.	Farming		
02.	Health		
03.	Marriage		
04.	Housing		
05.	Paying dowry		
06.	Consumption for food		
07.	Consumption for non-food		
08.	Fishing		
09.	Poultry and Livestock		
10.	Given credit to others		
11.	Buying productive assets		
12.	Loan repayment		
13.	Savings		
14.	Land purchase		
15.	Others………………………		

Q39. Are you planning to migrate?

Yes	No
1	2

If 2, in flooded area skip to Q42, non-flooded area skip to Q47

Q39a. (If yes) What are the reasons for this decision? **(M)**
1=flood 2=unemployment 3=wage differentials 4=motivated by other migrants 5= insecurity 6=others………

Q40. Where will you go?

(i) Another village 1
(ii) Another city 2
(iii) Another country 3
(iv) Other place within this village 4

Q40a. How far it will be?

(i) Near this village 1
(ii) Far away from this village 2

Q40b. Will the destination place be a part of resettlement project?

(i) Yes 1
(ii) No 2
(iii) Don't know 3

Q40c. Did you get any offer from resettlement project?

Yes	no
1	2

Q40d. Do you have relatives and / or friends living there?

Yes	no
1	2

Q40e. Do you expect any chance of finding a job in the destination place?

Yes	No
1	2

If 2 then skip to Q40g

Q40f. (If yes) How do you estimate your chance of finding a job there?

(i)	Convinced to be able to find a job	1
(ii)	Probably able to find a job.	2
(iii)	Difficult to find a job.	3
(iv)	Unlikely to find a job.	4
(v)	Never thought about it	5

Q40g. Which of the following public services would you expect to find available to your household in that destination place?

Serial no.	Service	Accessible=1 Not accessible=2	
01.	Electricity	1	2
02.	Water pipe	1	2
03.	Gas pipe	1	2
04.	Canalization	1	2
05.	Transport	1	2
06.	Health service	1	2
07.	School	1	2
08.	Market	1	2
09.	Others………………………..		

Q41. Would you receive anything for your house plot if you decided to leave?

No compensation	1
Financial compensation	2
Others…………………………………………	3

***Q42.** Did you observe any of your neighborhoods migrate due to flood?

Yes	no
1	2

***Q43.** Was any of your HH member goes to another area for work during daytime but remain in home during night due to flood?

Yes	no
1	2

Part-J
(Miscellaneous)

***Q44.** What precautionary flood control measures did you implement before this flood?

1. ....
2. ....
3. ....

***Q45.** What kind of precautions do you have for next flood hazards?

1. ....
2. ....
3. ....

***Q46.** What are the major obstacles to flood prevention in the communities?

1. ....
2. ....
3. ....

Q47. How much dowry did you receive/give in the last marriage ceremony?

Received	
Given	
Not applicable	88

Q48. Was there any death case in your house during this flood?

Yes	no
1	2

<u>Sanitation (Toilet):</u>

Q49. What type of sanitation is your HH member using? (It should be checked by interviewer) [ ]
1=Water sealed, 2=Fixed pit, 3=Hanging, 4=Open space

***Q49a.** Was your sanitation affected by this flood? [ ] (1=yes, 2=no) If 2 then skip the next question

***Q49b.** (If yes) What have you done during flood to manage the sanitation procedure? **(M)** [ ]
1=Other's toilet, 2=High places, 3=In flood water, 4=Others…………………………

Comment of the interviewer about overall interview

I confirm that I completed the survey according to the Instructions and personal interview method, and with the respondent chosen according to the Instructions.

Signature of interviewer__________________________

Name of Supervisor: ____________________________________

Date & Signature ________________