Chapter 5
Which Household Characteristics Help Mitigate the Effects of Extreme Weather Events? Evidence from the 1998 Floods in Bangladesh

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Abstract Climate change is predicted to increase the frequency and intensity of natural disasters. Bangladesh is a vulnerable country due to its geography, topography, poverty and low adaptive capacity. This chapter focuses on the potential for household characteristics to mitigate the effects of natural shocks. Using a panel dataset of the 1998 floods from the International Food Policy Research Institute, an econometric methodology was developed using three ordinary least squares (OLS) models. This approach helped identify the effects of the floods and to assess which characteristics influenced household welfare outcomes. The primary focus was on household calorie consumption but we also reflected on local migration (as both a dependent and independent variable). However, limitations in the dataset restricted a full investigation of migration.

Keywords 1998 floods • Adaptation • Bangladesh • Household characteristics • Interaction effects

5.1 Introduction[1]

Global climate change (GCC) is one of the most significant challenges facing the world today. GCC refers to the long-term change in the statistical distribution of weather patterns over periods of time that range from decades to millions of years

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(IPCC 2007a).[2] In practical terms, GCC is understood as the change in average weather conditions such as temperature, precipitation and wind as well as a change in the frequency of events such as more or fewer extreme weather events (EWE). The worldwide impacts of climate change are increasingly evident through the extensive record of devastating natural disasters in the past few decades. There is now a global consensus that climate change poses a serious threat to the social and economic well-being of people in both developed and developing countries (World Bank 2010).[3] GCC is predicted to increase the intensity and frequency of natural disasters, which will result in significant economic and social ramifications globally. For underdeveloped countries that already face considerable economic and social challenges, climate change will further compound their ability to develop (Mirza 2003). Specifically, the most threatened societies are those that engage in a mixture of subsistence farming and agricultural production for domestic use.

This chapter studies the case of severe flooding because this is the most recurrent and widespread type of natural disaster in Bangladesh. Whilst long-term climatic change is difficult to study, the onset of natural disasters provides some insights into such phenomena. The 1998 floods affected households in two main ways: households incurred substantial damage to crops and assets as a direct result of floodwaters and were also indirectly affected by higher prices and lower wages. Subsequently, households experienced lower calorie consumption, while income and the general nutrition of adults and children declined greatly (Del Ninno et al. 2001). Meanwhile, livestock assets, female education and credit (to varying degrees) were found to have positive associated benefits in limiting the fall in household calorie consumption.

5.2 Literature Review

5.2.1 Climatic Change and Natural Disasters

According to the IPCC (2007a) there have been large shifts in long-term temperatures, rainfall averages, sea levels as well as the frequency and intensity of droughts and floods. Changes in climate are expected to result in greater intensity and frequency of EWEs and natural disasters (Mirza 2003). Scientific evidence indicates that increased sea surface temperature will subsequently intensify

[2] The classical length of time is considered to be 30 years by the world meteorological organisation (WMO) (as cited in Dasgupta et al. 2010).

[3] Unless specified otherwise, the World Bank classifications are based on the World Bank Atlas Method which groups countries as: low income, US$995 or less and lower middle income, US$3,945–$12,195 (developing) and high income, US$12,196 or more (developed) (see World Bank 2011).

cyclone activity and heighten storm surges all over the world (Dasgupta et al. 2010).[4] Subsequently, storm surges can create damaging flood conditions in coastal zones and adjoining low-lying areas.[5] According to Nicholls (2003) (as cited in Dasgupta et al. 2010), in the past 200 years, 2.6 million people may have drowned during storm surge events. The international workshop on tropical cyclones (IWTC) has noted that the vulnerability to flooding from tropical cyclones would increase if global warming causes a projected rise in sea levels (IWTC 2006, as cited in Dasgupta et al. 2010). The destruction caused by tropical cyclone Sidr[6] in Bangladesh (November 2007) and cyclone Nargis[7] in the Irrawaddy Delta of Myanmar (May 2008) provide recent examples of devastating storm-surge impacts in vulnerable developing countries such as Bangladesh. Additionally, the intensity and frequency of extreme precipitation events are likely to increase resulting in more numerous floods and mudslides (IPCC 2007a). Recent examples of this phenomenon were the devastating Pakistani floods in 2010 and 2011. As a result, Bangladesh is an important case study because of the intensity and frequency of numerous natural factors ranging from heavy monsoonal rains, coastal cyclones and storm-surge related activities.

5.2.2 The 1998 Bangladesh Floods and Impacts

The 1998 flood event that swept through Bangladesh in late summer was dubbed the ‘flood of the century’ because of its prolonged duration and the depth of water. At its peak in early September, the floods had covered two-thirds of Bangladesh. This caused severe damage to the *aman* monsoon rice crop, which was due to be harvested in November/December.[8] Consequently, the total rice production losses exceeded 2.2 million tons which was equivalent to about 10 % of the annual rice consumption in Bangladesh (Del Ninno et al. 2001). The situation threatened the food security of tens of millions of households. The unusually long duration of

[4] A sea-temperature of 28 °C is considered an important threshold for the development of major hurricanes of categories three, four and five (Michaels, Knappenberger, and Davis 2005 and Knutson and Tuleya 2004, as cited in Dasgupta et al. 2010).

[5] Storm surge refers to the temporary increase, at a particular locality, in the height of the sea due to extreme meteorological conditions: Low atmospheric pressure and/or strong winds (IPCC 2007a).

[6] According to Bangladesh Disaster Management Information Centre (report dated 26 November 2007) 3,243 people were reported to have died and the livelihoods of seven million people were affected by Sidr.

[7] In Myanmar, 1,00,000 people were reported to have died and the livelihoods of 1.5 million people were affected by Cyclone Nargis.

[8] The three crops of rice that are cultivated in Bangladesh are: *aman*, typically transplanted during the monsoon season in June-July and harvested in November–December; *boro*, transplanted in December–January and harvested in May–June; and *aus*, often directly sown in March–April and harvested in April–August.

the flood forestalled any possibility of re-planting rice seedlings which were destroyed in the standing water. The unusually high floodwaters resulted in substantial crop losses: 69 % of *aus* production, 82 % of deep water *aman* and 91 % of transplanted *aman* (Del Ninno et al. 2001). Due to losses of 24 % of the total value of anticipated agricultural production, the prolonged adverse effects of the flood proceeded long after the floodwaters had receded.

5.2.3 Departure from Existing Literature: The Role of Household Characteristics as Mitigating Factors

Previous studies of the 1998 Bangladesh floods have not specifically considered household characteristics as a potential source for the mitigation of the effects of floods. Although incomplete, existing literature provides useful starting points for further research. For instance, Skoufias (2003a) has explained that floods can both directly destroy crops and assets as well as create additional suffering due to the resulting higher prices and lower wages. He also documents examples of how ex-ante preparations for EWEs are more effective than ex-post responses. Khandker (2007) identified that 60 % of all households adopted one of several different coping mechanisms including borrowing, skipping meals or selling assets. Although outside the scope of his study, Khandker (2007) did not undertake econometric testing of the ability of characteristics to directly mitigate the effects of flooding.

This chapter attempts to extend the existing analysis by considering various household characteristics with respect to flood mitigation. In addition to identifying beneficial household characteristics, the research investigates whether the effectiveness of these characteristics varies depending on the level of flood exposure. The IPCC (2007b) has stressed that households can play a major role in adapting to GCC and mitigating some of the adverse effects of GCC and EWEs. Various researchers have also identified the mechanisms through which households overcome the advent of a natural shock. These include accumulation of human capital (Baez and Santos 2007; Gitter and Barham 2007; and Portner 2008, as cited in van den Berg 2010), access to microcredit (Khandker 2007), livelihood strategies (van den Berg 2010) and asset-smoothing strategies (Hoddinott 2006; Zimmerman and Carter 2003). Consequently, this study will shed light on whether household characteristics assist in mitigating the effects of natural disasters.

5.3 Data

The micro-level analysis for this chapter is based on the IFPRI-FMRSP household survey. The 1998 floods survey was designed to evaluate the impact of the natural disaster. The survey covers a large sample (n = 757) of spatially-dispersed households in seven flood-affected *thanas*.[9] The panel consists of four rounds: (1) November–December 1998 (2) April–May 1999 (3) November–December 1999 and (4) April–May 2004. Only the first three rounds of data were relevant to the scope of this research, because these rounds were recorded within a year of the floods and provided information on the immediate effects of the floods and the role of household characteristics. The survey collected an array of household and community information including demographics, consumption, assets, employment, agricultural production practices and borrowing. A fair representation of different parts of the country was sought using multiple criteria.[10] Furthermore, households were selected using a multiple-stage probability sampling technique (see Del Ninno et al. 2001).

5.4 Conceptual Definitions

5.4.1 Definition of Flood Exposure

A measure of flood exposure is required to ascertain how households experienced the floods. This forms a crucial variable for the analysis that we undertake in this chapter. The survey utilises the Bangladesh Water Development Board's (BWDB) traditional measures of flood impact (see below). Geographical location is often not the best indicator of flood exposure as not all households were exposed to floods to the same extent in any given area. In the 1998 floods, there were varying degrees of flooding in homesteads and some households even had to abandon their houses for days or weeks at the peak of the flooding. To a certain extent, the direct exposure and intensity depended on the height of the homestead and the presence of an embankment or road.

5.4.2 Measuring Flood Impact

As one cannot accurately observe and measure flood exposure, the surveyors created an ordered qualitative index called *FAFFECT* as illustrated in Table 5.1 below. This was in fact a simplified version of a larger qualitative index called *FEINDEX*. Three measures were used to construct the index: the depth of water in the homestead, the depth of water in the home and the number of days that water was in

[9] A *thana* (referred to as *upazila* by the present government) is an administrative unit that is smaller than a sub-district and larger than a village.

[10] The criteria were: the severity of flooding and level of poverty; from the first two criteria, those *thanas* would give a good geographic balance were chosen.

Table 5.1 Formation of flood exposure index

	Original variable		Created category variable	
Variable	Range	Unit of measure	Range	Categories
Depth of water in the homestead	0–12	Feet	0–5	0–4: number of feet 5: more than 4 feet
Depth of water in the home	0–45	Feet	0–6	0–5: number of feet 6: more than 5 feet
Number of days of water in the home	0–120	Days	0–5	0: None 1: $> 0 \leq 1$ week 2: $> 1 \leq 2$ week 3: > 2 weeks ≤ 1 month 4: > 1 month ≤ 2 months 5: > 2
Flood index (*FEINDEX*)			0–16	
Flood-exposed categories (*FAFFECT*)			0	Not exposed
			1–5	Moderate
			6–10	Severe
			11–16	Very severe

the house. The totals for each of these measures were aggregated and threshold categories were created to distinguish levels of flooding. The threshold levels were given categorical values in order to classify households as:

- not exposed to the flood (0)
- moderately exposed to the flood (1)
- severely exposed to the flood (2); or
- very severely exposed to the flood (3).

There are two forms of flood exposure that were utilised in the modelling and analysis.

5.4.2.1 Household-Level Flood Exposure (FVAR)

The formation of the *FAFFECT* index had a degree of arbitrariness in terms of the thresholds for the various measures used as well as the way that it was aggregated. For ease of interpretation, the categorical flood exposure variable (*FAFFECT*) was transformed into a flood exposure dummy (*FVAR*). This approach also avoided the complications with comparing the four categories in the *FAFFECT* index. Households that recorded moderate, severe and very severe exposure (*FAFFECT* = 1, 2 or 3) were considered to be exposed as indicated by FVAR = 1 whilst non-exposed households were indicated by FVAR = 0. This construction was helpful in comparing outcomes between exposed and non-exposed households as well as in determining the positive/negative sign and size of the interaction effects between households with varying levels of exposure and characteristics. As the first round collected survey data within a couple of months of the flood, the *FVAR* was available only for Round 1.

5.4.2.2 Village-Level Flood Exposure (VFVAR)

Additionally, using the village-mean of *FVAR* of all households, a village-level variable of flood exposure (*VFVAR*) was created. In the econometric analysis, *VFVAR* is able to capture village-level unobservable characteristics relating to the flood. For instance, *VFVAR* captures the general equilibrium effects that influence household outcomes. The general equilibrium effects arise due to changing market conditions such as supply constraints (of food) as well as demand constraints (lower wages and disposable income).

5.4.3 Measuring Household Welfare

There is a considerable degree of contention with regard to the measure of household welfare. Nonetheless, it is now considered that income—which has dominated much of poverty and well-being analysis in the past—provides a (limited) one-dimensional view of welfare (Alkire and Foster 2010).[11] In the aftermath of natural disasters, broader definitions of welfare are more appropriate because in such situations consumption, nutrition and health all deteriorate rapidly (Skoufias 2003a). Within welfare literature, various measures have been suggested to evaluate outcomes amongst individuals, households or nations. Anand and Harris (1994) provide five potential indicators of individual welfare.[12] Ultimately they suggest that perhaps the single most important aspect, particularly for developing countries, is calorie intake.[13] In this chapter, adult equivalent

[11] The 'uni-dimensional' method of utilising a single cardinal variable of 'income' aggregates various dimensions of a person's life and develops an aggregate cut-off to determine who is poor. Typically the cut-offs will vary for different dimensions (e.g. health, education, security etc.) and between people and communities (Alkire and Foster 2010).

[12] The five indicators are: household per capita income, household total expenditure per capita, household food expenditure per capita, household calorie intake per capita and household inverse-food share (defined as the ratio of total expenditure to food expenditure).

[13] Whilst calorie consumption is a popular measure in the literature, some caveats need to be noted. According to Skoufias (2003b), there is now a consensus that the total caloric availability provides only limited insights about how the availability within households responds to changes in income and other resources. For example, when household income drops, caloric availability may be maintained more or less constant through substitutions within and between food groups. The outcome could be that whilst caloric consumption is maintained, the consumption of essential micronutrients may fall as households consume less meat, vegetables, egg and milk (Behrman 1995, as cited in Skoufias 2003b).

calorie measure is used to account for the types of occupants so that a more accurate indicator is obtained for the household. After a weather shock, an extreme outcome can be famine and widespread hunger. Often, this is the most crucial issue that needs to be addressed before income and other social measures such as housing and education. Rural citizens in developing countries remain highly vulnerable to fluctuations in the weather which can affect their welfare because a large percentage of their budget is allocated to food (Burgess and Donaldson 2010).

5.5 Conceptual Framework

The central proposition that this research tested is that household welfare is a function of household characteristics. For ease of description, the characteristics are categorised as physical capital (e.g. ownership of various assets), human capital (e.g. education levels) and financial capital (e.g. borrowing). Consequently, the following estimable model of determinants of household welfare can be tested:

$$HW = f\,(PC, HC, FC) \tag{5.1}$$

where, *HW* is household welfare and *PC*, *HC* and *FC* stand for physical, human and financial capital respectively. In the discussion, the physical capital and human capital variables are also referred to as asset and demographic variables. The dependent variables and the explanatory variables are discussed in detail in the following section.

5.5.1 Dependent Variable

The calorie dependent variable is recorded in adult-equivalent calorie consumption (*AECAL*) form. This allows one to account for the composition of adults and children in each household. Moreover, the logarithmic form [*LNAECAL*, or in short notation, ln(c)] was utilised in all of the models because it corresponded better to the data structure in the regression model. The log-form also has the added benefit that it can be interpreted as an elasticity (Wooldridge 2006). An elasticity calculation helps one to easily measure by how much the dependent variable varies for a small change in the dependent variable.

5.5.2 Description of the Explanatory Variables

This section describes the explanatory variables for each category along with the prior expectations (hypotheses) about their relationship with household welfare.

5.5.2.1 Human Capital

Human capital is represented by years of education attained by the household head (*EDUCA*), total education of all females in the household (*FMAXEDUCA*) and age of the household head (*AGEY*). It is widely acknowledged that education plays a crucial role in socio-economic development and growth (see McMahon 2000). Many recent endogenous growth and Solow models now incorporate aspects of human capital (Barro 2007). Education also has significant returns for individuals and the household collectively (Psacharapoulos and Patrinos 2004). Particularly in Bangladesh, returns to education for females are higher than for males (Asadullah 2006). Aggregate female education is also expected to lower the adverse costs of natural disasters (Blankespoor et al. 2010). Thus, this chapter hypothesises that a household with a literate head and with higher aggregated female education will consume more calories, consequently mitigating some of the effects of the flood. This is because they may be more skilled at managing the crisis and seeking sources of support. However, it is also possible that education may not be very beneficial in the aftermath of the floods because the economy was slow to recover (especially for skilled sectors). For instance, employment and wages of salaried workers fell dramatically in affected regions and remained low for a long time (Mueller and Quisumbing 2010).

The relationship between age and calorie consumption cannot be determined a priori. The household head's age can affect calorie consumption through asset accumulation, technology adoption or risk aversion (Demeke et al. 2011). Age can also be considered a proxy for experience of prior natural disasters and knowledge of coping strategies (Glewwe 1991). Behaviourally, individuals who have experience of natural disasters are less likely to experience a negative outcome resulting from that event than individuals without such experience (Halpern-Felsher et al. 2001). However, age could be negatively correlated with calorie consumption as older heads may be less efficient in carrying out demanding activities (e.g. farm operations) resulting in lower production and productivity (Demeke et al. 2011).

5.5.2.2 Additional Demographic Control Variables

Two additional controls that are included in Model 2 and 3 regressions are sex of the household head (*SEX*) and the size of the household (*HHSIZEA*). These are introduced to prevent bias in the ordinary least squares (OLS) estimators. *SEX* has to be controlled because male-headed households are expected to consume more calories than their female-headed counterparts. This inequality is likely since most female-headed households in the Bangladesh rural system are formed as a result of the death of the male household head or divorce. This situation usually leaves women with insufficient resources such as land, livestock and other productive assets (Demeke et al. 2011). *HHSIZEA* has to be controlled because the dependent variable adjusts the household-level calorie consumption through accounting for the composition of members. From preliminary estimation testing, there appears to be a systematic relationship between *AECAL* and *HHSIZEA* which biases the results.

5.5.2.3 Physical Capital

Three asset variables, *LIVESTOCK*, *CONSASSETS* and *HTOTLAND*, are included to provide various measures of household asset ownership and to control for wealth effects which may influence calorie consumption. They are expected to have positive effects on calorie consumption. All of the three assets studied here can be used as collateral or sold to obtain urgent funds to cope with the disaster. Specifically, *LIVESTOCK* is an important physical capital for farming activities in rural Bangladesh. Livestock can be a store of wealth, a source of income and can also be a means to cope with difficult economic times (Hoddinott 2006). Furthermore, landholding (*HTOTLAND*) is a resource to grow food for subsistence and to be sold in the market. It is possible, however, that greater landholding can make households more susceptible to flooding. Where households are dependent on land, they can suffer from crop failure and loss of feed for livestock.

5.5.2.4 Financial Capital

Financial capital is represented by borrowing (*LNLOANTOTAL*) and purchase of food on credit (*FOODCRED*). Borrowing is anticipated to have a positive influence because it enables households to address the immediate damage and costs of the flood (such as repairs). Loans also resolve short term liquidity constraints for households. Thus, inputs can be purchased to continue food production. Borrowing can also be used to smooth consumption in the event of food shortages in the household (Zeller and Sharma 2000). Similarly, the purchase of food on credit represents an ability to maintain consumption through deferring payment. However, loans are expected to provide only temporary benefits as households would soon need to make repayments and could face a severe debt-burden (Del Ninno et al. 2003). If households had access to greater remittances, that could serve as a substitute for borrowing and lower the negative repercussions from indebtedness.

5.5.2.5 Food Prices

Food prices are included in the analysis as additional explanatory variables. The food price variables, as described in Table 5.2, were recorded as the mean village-level per-kilo price. This was calculated by first dividing the total value of purchases of the particular food group by total quantity bought. Thereafter, the mean of all purchases of food within a particular food group was calculated. Finally, the

Table 5.2 Definitions and summary statistics of the variables (panel form)

Variable name[a]	Description	Mean	SD
Dependent variable			
AECAL	Adult equivalent calorie consumption	3,331.881	1,175.361
LNAECAL	Logarithm of *AECAL*	8.049795	0.3579022
Independent variables			
Flood variables			
FVAR	Dummy = 1 if household was moderately, severely or very severely exposed to the flood	0.7133421	0.4524993
VFVAR	Village-level mean of *FVAR* (each household in a village has same value)	0.7133421	0.3645893
Physical capital			
CONSASSETS	Total value of three consumer assets that are measured: wall clock, tv and radio (in 100′s of taka)	1.491986	10.72747
HTOTLAND	Total amount of land owned by the household (including homestead, ponds and farming or other lands) (in 100′s of decimals)[b]	1.266664	1.89445
LIVESTOCK	The number of cows, bullocks and sheep in the household	0.8071334	1.265873
Human capital			
EDUCA	Total years of education attained by the household head	2.607013	3.73519
FMAXEDUCA	Total years of education attained by all females in the household	4.98975	6.544568
AGEY	Age of household head (in 10 s of years). The regression models also include *AGEY2*–age-squared of household head (in 100 s of years)	4.502109	1.249097
Financial capital			
FOODCRED	Total amount of food purchased on credit by household (in 100′s of taka)	2.444551	5.758981
LNLOANTOTAL	Logarithm of total value of outstanding household loans through various lending schemes (microfinance programs, money lenders and personal borrowing)	0.7800688	1.163526

(continued)

Table 5.2 (continued)

Variable name[a]	Description	Mean	SD
Other control variables			
SEX	Dummy, = 1 if the household head is male	0.9590054	0.1980395
HHSIZEA	The number of household members	5.730838	2.198105
Food price variables			
RICEPRICE	Mean village-level per-kilo price of food purchases of all households	15.18259	2.788722
ATTAPRICE	"	11.89998	1.944583
VEGEPRICE	"	16.12201	6.581636

[a]Outliers for the following variables were removed: *AECAL* (>10,000 or <800), *RICEPRICE* (>60 or <3) and *ATTAPRICE* (>100 or <5). Outliers were adjusted because they can adversely influence the OLS estimates (Wooldridge 2006)

[b]An ancient South Asian unit of area measurement (1 decimal ≈ 436 sq. feet)

village-level mean was obtained by taking the average of all households in each village.

5.5.2.6 Excursus on Migration

It was originally intended that this research would also study the relationships between household characteristics and domestic migration. This could have added an interesting dimension to EWE mitigation strategies. However, with little useful data comparing the changes in household size and composition, this line of inquiry could not be pursued adequately.[14] This section discusses some of the ideas linking EWE to migration. In addition, we present a potential methodology to study migration as a strategy to mitigate the effects of EWEs.

With or without climate change, people move for many different reasons. Banerjee writes in this book, based on research from flood-prone Nepal, that migration can be seen as a form of anticipatory behaviour in situations of environmental threat. Previously, Banerjee et al. (2011) explained the use of migration-based remittances as a tool for adaptation. Meanwhile, it can be seen that numerous authors have also questioned the direct linkages between climate change and migration (see Montreux and Barnett 2009). In this book, McLeman makes a stark departure from the dominant perspective of the environmental push. According to his findings, it would be far too simple to assume a direct causal relationship between environmental change and out-migration. Previously, he developed a typology of the complex system in which these and other factors influence one another (see McLeman 2010). Similarly, Gosh (1992) and Lohmann (1994) (as cited in Meze-Hausken 2000) also present a non-uniform typology of migrants based on four root causes of migration which include: survival migration, opportunity-seeking migration, environmental migration and flight due to persecution and conflict. As a result of these studies, the factors that McLeman (2010), Gosh (1992) and Lohmann (1994) (as cited in Meze-Hausken 2000) identify should be taken into consideration when undertaking econometric modelling of migration to avoid potential omitted variable bias[15] and endogeneity issues (e.g. where a factor causing migration is determined within the model).[16]

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[14] When the difference in *HHSIZEA* was compared, both negative and positive values were generated (i.e. some households grew in size whilst others fell). This made it difficult to test the change in *HHSIZEA* as a dependent variable econometrically.

[15] Omitted variable bias is the bias that appears in estimates of parameters in a regression analysis in that the regression omits an independent variable that should be in the model.

[16] Those factors include not just the size of demographic change, but also its composition, its impact on social networks, and the (possibly negative) impact of migration on in situ adaptation options of those left behind.

5.5.2.7 Migration: Dependent Variable

The dependent variable could have been created by taking the physical difference of the household size (*HHSIZE*) between two consecutive rounds. Thus, migration after Round 1 could be measured as:

$$\Delta HHSIZEA = HHSIZEA_{t+1} - HHSIZEA_t \tag{5.2}$$

The change in *HHSIZEA* could have been a useful dependent variable because it measures the population in each community at a particular round. A change in this could reveal whether people moved to another location (after controlling for factors such as death and illness) due to the floods and if other household characteristics could explain that change.

5.5.2.8 Migration: Independent Variable

Additionally, migration could also be considered as an explanatory variable. In this sense, individuals and households migrate in order to mitigate the adverse effects of flooding. One of the strongest reasons that explain why people migrate locally and internationally is the possibility of making remittance payments back 'home'. In the context of least-developed countries (LDCs), Stark and Levhari (1982) have found that remittances can be used as: a tool for risk aversion, a substitute for failing local financial markets and for income diversification. The availability of remittances as another source of income could also limit the requirement for local loans or food credits as well as their associated negative percussions on future welfare through indebtedness. In the context of flood-prone Bangladesh, amongst various reasons, migration could assist in finding higher ground, rescuing farm animals or moving to relatives and friends' houses for shelter and food.

5.5.2.9 Additional Explanatory Variables

When considering migration as either a dependent or independent variable, some additional explanatory variables could strengthen the model. For instance, because remittances are an important feature of migration, it must be included in the model to control for any income effects.[17] Also, when studying changes in income, remittance payments need to be included as a control variable.

Further to the previous discussion linking human capital to household welfare, in terms of migration, there are possibly strong linkages between education and skilled migration. In a recent World Bank report on African migration, Ratha et al. (2011) explain that emigration of skilled workers has several general benefits including remittances, contacts with foreign markets, technology

[17] In economics, income effects refer to the change in consumption that arises from a change in income.

transfer, enhanced skills and perhaps increased demand for education in the origin country. At the same time, the authors also acknowledge some of the disadvantages of this process including the reduction in 'supply of critical services; limiting productivity spill-overs to both high-and low-skilled workers; reducing the potential for innovative and creative activities that are at the core of long-term growth; and limiting contributions to the health of social, political and economic institutions' (Ratha et al. 2011: p. 7). It must also be noted that migration rates can be predicted to vary depending on where wages fall. Wages may fall only in the affected regions or all over the country—the latter through aggregated shocks to the economy. This might lead to an increase in migration to further distances within the country (in the first case) or to a decrease in migration (in the second case).

As a result, any successful modelling strategy needs to address the relationships between education and skilled migration to delineate the benefits and costs of skilled migration. Therefore, it is suggested that the aforementioned approaches (migration as either a dependent or independent variable) could be tested in further research using other datasets that adequately measure changes in household size, remittance payments and changes in these variables across time periods.

5.6 Summary Statistics

The summary statistics (in panel form) for each of the variables used in the analysis are provided in the following Tables (5.3, 5.4, 5.5).

Table 5.3 Summary statistics across rounds: round 1

Variable	N	Mean	Standard deviation
LNAECAL	743	7.972746	0.3743848
FVAR	757	0.7133421	0.4524993
VFVAR	757	0.7133421	0.3645893
CONSASSETS	757	4.055746	17.91208
HTOTLAND	757	1.163405	1.771432
LIVESTOCK	757	0.8956407	1.354375
EDUCA	721	2.676838	3.753832
FMAXEDUCA	757	4.779392	6.434464
AGEY	753	4.502258	1.249705
AGEY2	753	21.83001	12.29169
FOODCRED	757	4.857075	7.802658
LNLOANTOTAL	757	1.156797	1.232893
*HHSIZE*A	757	5.59181	2.107203
SEX	753	0.9561753	0.204841

Table 5.4 Summary statistics across rounds: round 2

Variable	N	Mean	Standard deviation
LNAECAL	743	8.089613	0.3535889
CONSASSETS	757	0.0176354	0.2292646
HTOTLAND	757	1.295518	1.948423
LIVESTOCK	757	0.7886394	1.245193
EDUCA	745	2.565101	3.720239
FMAXEDUCA	753	5.01328	6.565937
AGEY	746	4.494504	1.247487
AGEY2	746	21.75471	12.27235
FOODCRED	753	2.184525	4.916344
LNLOANTOTAL	757	0.6266557	1.082649
HHSIZEA	753	5.746348	2.206299
SEX	748	0.9625668	0.1899478

Table 5.5 Summary statistics across rounds: round 3

Variable	N	Mean	Standard deviation
LNAECAL	725	8.087952	0.3317309
CONSASSETS	757	0.402576	3.833811
HTOTLAND	757	1.34107	1.955745
LIVESTOCK	757	0.7371202	1.188952
EDUCA	730	2.580822	3.736105
FMAXEDUCA	734	5.182561	6.637109
AGEY	730	4.509726	1.251776
AGEY2	730	21.90242	12.32728
FOODCRED	734	0.2231866	1.696526
LNLOANTOTAL	757	0.5567541	1.07573
HHSIZEA	734	5.858311	2.274859
SEX	731	0.9582763	0.1992363

5.7 Econometric Framework and Methodology

The following sections explain the econometric framework that was developed for the analysis.

5.7.1 Simple Panel Data Model

The OLS regression models in the analysis are based on the following simple panel data model. The estimation model is repeated for each of the three rounds, $t \in 1, 2, 3$:

$$Y_{it} = \alpha_0 + \gamma F_i + \beta X_{it} + \theta (F_i \times X_{it}) + \varepsilon_{it} \tag{5.3}$$

where

Y_{it} is the dependent variable observed for household i at time t
F_{i} is an indicator of flood exposure for household i at time t=1 only
Y is the estimated coefficient of floods across rounds
X_{it} is a vector of explanatory variables for household i at time t
β is a vector of estimated coefficients
θ is a vector of estimated interaction term coefficients
α_0 is the constant of the equation
$\in_{\mathrm{it}}$ is the error term.

In this research, the analysis is gradually expanded by examining the following three OLS models.

5.7.2 Model 1: Effect of Flood Exposure on Calorie Consumption

To evaluate the effect of flood exposure, the following OLS regression model is estimated:

$$Y_{it} = a_0 + \gamma F_i + \varepsilon_{it} \tag{5.4}$$

It is also possible to study the effects of the flood through several different variables: *FVAR* (household level), *VFVAR* (village level) or through various food price variables. Thus, in order to identify the most significant channels for the flood effects, several variations of the model in Eq. 5.4 are used by substituting the aforementioned variables for *F*. It must be noted that whilst *F* does not vary across rounds (only when one is specifically considering the flood index variable), $\hat{\gamma}$ will vary according to the marginal effect (short, medium and long term) of the flood for all rounds.

5.7.3 Model 2: Flood Effects Controlling for Household Characteristics

It is feasible that Model 1 does not provide a realistic indication of the relationship between flood exposure and calorie consumption. Thus, other possible determinants of calorie consumption cannot be assumed to exist in the error term and remain uncorrelated with the flood exposure variable. Leaving out important variables can cause omitted variable bias. Even correlation between a single explanatory variable and the error term can generally result in all OLS estimators being biased (Wooldridge 2006).

5.7.3.1 Endogeneity of Flood Exposure

It is also possible that the flood exposure variable exhibits endogeneity in the model. By endogeneity, we mean that an explanatory variable is correlated with the error term. The existence of endogeneity creates bias in the coefficient estimates of the explanatory variables (especially the flood variables) and diminishes the ability to make inferences about the characteristics (Wooldridge 2006). One highly likely source of endogeneity arises from omitting measures of household wealth. It could well be that poorer households lived in marginal lands such as near rivers and waterways, and this would have increased their chances of being flooded.[18] For analytical purposes, the impact of floods cannot be confounded by the effects of initial endowments and characteristics. It must be noted that Del Ninno et al. (2001) did not find any strong evidence to support the hypothesis of a correlation between household flood exposure and endowments.[19]

Hence, the Model 2 specifications make direct comparisons between combinations of household characteristics (such as wealth factors) to determine if the predicted effect of flood exposure in Model 1 varies in size and significance. The addition of explanatory variables also helps identify the determinants of calorie consumption and whether they were confounding the relationship between the floods and the dependent variable. Consequently, Model 2 includes the aforementioned explanatory variables and estimates the following:

$$Y_{it} = a_0 + \gamma F_i + \beta X_{it} + \varepsilon_{it} \tag{5.5}$$

5.7.4 Model 3: Interaction Effects

Model 3 tests the assumption that some households will be better able to cope than others (with a given level of flood exposure) based on their characteristics. Also, the effects of the characteristics can be distinguished based on the level of flood exposure. For instance, it can be hypothesised that education may be more beneficial for non-exposed households than exposed ones. Hence, we wish to identify not only what the marginal effect of X is (conditional on F) but also how X affects the marginal effect of F on Y_{it}.

Thus, the following model can be estimated[20]:

$$Y_{it} = \alpha_0 + \gamma F_i + \beta X_{it} + \theta(F_i \cdot X_{it}) + \varepsilon_{it} \tag{5.6}$$

[18] On this point, it is interesting to note that there has been much discussion and research into how human-induced vulnerability escalates natural hazards into disasters (see Cannon 1994).

[19] They concluded this after running several comprehensive regression models including probit, logit, fixed and random effects models to account for various forms of possible endogeneity. On an aggregate basis, they found that even though some unions and *thanas* were exposed more than others to the floods, these do not appear to be poorer. Hence, based on our results and Del Ninno et al. (2001) conclusion, we can assume with substantial certainty that the floods were not endogenous.

[20] This approach is based on Burgess and Donaldson (2010) study of the interaction between railroads and rainfall in determining famine intensity.

5.7.4.1 Marginal Effects

Based on this model, we are interested in studying the marginal effects of the flood and the household characteristics. The following presents the assumptions for each of these marginal calculations.

a. marginal effect of flood exposure

When discussing the *VFVAR* (a continuous variable), the marginal effect of flood exposure in Eq. 5.6 can be calculated as follows:

$$\frac{\partial Y}{\partial F} = \hat{\gamma} + \hat{\theta} X_{it} \tag{5.7}$$

In the results, one would expect that $\hat{\gamma} < 0$ as the flood contributes to lower household calorie consumption. Meanwhile, the coefficient estimate, $\hat{\beta}$ presents the relationship between household characteristics and calorie consumption. Finally, taking the partial effect of the flood in Eq. 5.6 will help determine the interaction effect's size and direction, i.e. whether the household characteristics mitigate $(\hat{\theta} > 0)$ or exacerbate $(\hat{\theta} < 0)$ the flood effect.

b. marginal effect of household characteristic

In addition, the marginal effect of a household characteristic in Eq. 5.6 is:

$$\frac{\partial Y}{\partial F} = \hat{\beta} + \hat{\theta} F_i \tag{5.8}$$

This expression allows one to identify the values of $\hat{\beta}$ and $\hat{\theta}$ in order to distinguish between the effects of each characteristic depending on flood exposure. For instance, when $F = 0$, the marginal effect of a characteristic (i.e.$\partial Y/\partial X$) is $\hat{\beta}$; whereas if $F = 1$, the marginal effect is $\hat{\beta} + \hat{\theta}$. Depending on the sign restrictions on the parameters, the interpretation will vary. For instance if one assumes the following situation: $\hat{\gamma} < 0$ but $\hat{\alpha}_0 + \hat{\gamma} > 0$; then logically $\hat{\beta} > 0$ and $\hat{\theta} > 0$. The interpretation of these particular parameter restrictions imply that the flood has a negative effect, but this is mitigated by the characteristic. Also the characteristic has a positive effect regardless of flood exposure.

A negative sign on $\hat{\theta}$ does not necessarily indicate that the characteristics are not predicted to be useful for households. It simply means that it does not mitigate the effect of the floods in a direct manner. As long as $\hat{\beta} + \hat{\theta} > 0$, the cumulative effect of the characteristics is still positive. When the signs do alternate, this shows that the sign and size of the effect of the household characteristics can vary depending on the level of flood exposure. For example if $\hat{\beta} > 0$ and $\hat{\theta} < 0$ (and $\hat{\theta} > \hat{\beta}$) the characteristic has a positive relationship with calories for non-exposed households but a negative relationship for exposed households. This is an interesting result in itself as one can make more specific conclusions about the characteristics rather than grouping exposed and non-exposed households together. The distinction between marginal effects of household characteristics based on flood exposure is represented diagrammatically in Fig. 5.1.

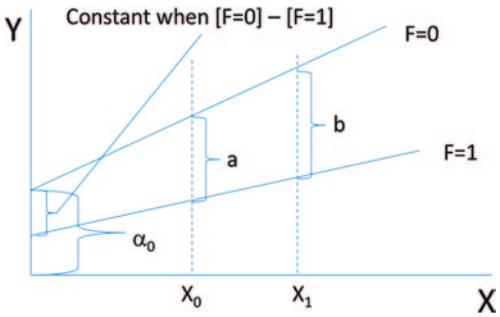

Fig. 5.1 Marginal effects of household characteristics for a given level of flood exposure

5.7.5 Econometric Issues

See Appendix 5.1 for further discussion about specific econometric and specification issues relating to the model.

5.8 Results and Discussion

5.8.1 Model 1 Results

Model 1 was used to investigate the effects of the floods on household welfare.

5.8.1.1 Household-Level Flood Exposure

The household-level flood exposure variable (*FVAR*) captures the direct effects on households through loss of either assets or crops. To identify the relationship between flood exposure and welfare, a simple linear regression (SLR) model was used. The level form of calorie consumption was used because it allows a 'comparison of means test' to be performed. After this, subsequent models utilise the logarithmic form of calorie consumption as discussed earlier. The results are presented in Table 5.6.

The constant term represents the mean calories consumed by households that were not exposed to the floods. In Round 1 there was a difference of 228.50 calories between the exposed (i.e. $[\bar{y}|F = 1] = 3230.22$) and non-exposed households (i.e. $[\bar{y}|F = 0] = 3258.72$. However, there appeared to be evidence of 'catch-up' where the gap between flood exposure categories fell to 174.41 and 141.59 calories in Round 2 and 3 respectively.

5.8.1.2 Village-Level Flood Exposure Effects

It is highly likely that even if households were not affected by the floods directly, they would be affected at the village level through indirect effects. If parts of a village are affected, the indirect effects can result from higher prices due to supply shortages,

Table 5.6 Household flood exposure effects on welfare

Variables	(1)	(2)	(3)
	R1_aecal	R2_aecal	R3_aecal
FVAR	−228.50**	−174.41*	−141.59
	(99.08)	(103.03)	(99.09)
Cons	3,258.72***	3,598.55***	3,545.11***
	(83.70)	(90.76)	(82.36)
N	743	731	712
Adj. R-sq	0.008	0.003	0.002

Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Note There are fewer observations of calorie consumption in Rounds 2 and 3. According to Mueller and Quisumbing (2010) attrition was only a possible problem when the fourth round of data was considered. Even then, only 5 % of the original households in the first round were not followed in the last survey round. Hence, the missing data in rounds subsequent to Round 1 are not likely to cause bias in the OLS coefficient estimates

Table 5.7 Results of effects of flood exposure (round 1)

Variables	(1)	(2)	(3)
FVAR	0.0085	–	−0.0091
	(0.0441)		(0.0516)
VFVAR	−0.1504**	–	−0.1090
	(0.0616)		(0.0734)
RICE	–	−0.0269*	−0.0168
		(0.0156)	(0.0156)
ATTA	–	−0.0050	−0.0038
		(0.0089)	(0.0079)
VEGETABLES	–	−0.0061***	−0.0050***
		(0.0014)	(0.0014)
Cons	8.0175***	8.5907***	8.4812***
	(0.0764)	(0.3999)	(0.3790)
N	739	612	612
Adj. R-sq	0.020	0.031	0.039

Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Note Additional regressors that were included in but not reported were *HHSIZEA* and *SEX* (all columns) and *VOILPRICE* (columns 2 and 3). Oil was included because it is a key complement in cooking. There were fewer observations in columns 2 and 3 because some villages did not report purchases of *atta*

damage to roads and bridges, and closure of markets (Del Ninno et al. 2001). Table 5.7 presents the results from an OLS regression when *LNAECAL* was regressed on *FVAR* and *VFVAR* in column 1, on key food prices in column 2 and then on all of these variables in column 3. In the following table, the analysis is restricted to Round 1 because the survey was conducted just a few months after the floods began. Round 1 was also the time when prices were highest (Del Ninno et al. 2003).

5.8.1.3 Analysis and Discussion

From the regression results above, the constant estimate represents the calorie consumption of households that were neither directly exposed to the flood nor were living in villages where at least one household was exposed to the flood. The coefficient on *VFVAR* represents the marginal effects of exposure for households that were living in flood-exposed villages. However, the actual partial effect depended on the proportion of households that were individually flood-exposed. For example, if only 50 % of households in a village were flood-exposed, the interpretation of the coefficient estimate must also be 50 %. Overall, households were predicted to consume up to 15.04 % (2 d.p.) fewer calories than households in non-exposed villages. For households that were partially flooded, the net effect was calculated by multiplying the proportion of households that were flooded in the village by the coefficient estimate. The coefficient on *FVAR* is an estimate of the difference between households within a village that were and were not individually exposed. Here, the difference in calorie consumption is relatively small (0.85 %) and is not significant. These results indicate that *VFVAR* is more significant and has a larger effect on household welfare than *FVAR*. Once one controlled for village-level flood exposure, exposure to flooding by each household did not influence their subsequent welfare.

5.8.2 Model 2 Results

Whilst flood exposure was found to be a significant determinant of calorie outcomes in Model 1 (Round 1), Model 2 was required to address omitted variable bias and concerns about possible endogeneity of the floods.

5.8.2.1 Model Specification

Due to its significance in Model 1, the aggregated *VFVAR* was used and *FVAR* was included to control for household-level direct flood exposure. Household characteristics were gradually incorporated into the models and were grouped together for ease of analysis and presentation purposes. For instance, in column 1 of the Model 2 result tables, we tested whether after controlling for various asset variables, flood exposure was still significant. Each column considered different combinations of the characteristics and gradually aggregated them to the full model (column 5 of the result tables). This specification is the most robust in testing endogeneity because it included the full set of controls.

The setup, presented in the results Tables (5.8, 5.9, 5.10) in below, is as follows:

- column 1 includes only physical capital variables to immediately address the endogeneity concern arising from wealth endowments
- column 2 includes only human capital variables

Table 5.8 Round 1 determinants of household welfare across characteristics groups

Explanatory variables	(1)	(2)	(3)	(4)	(5)
FVAR	0.0133	0.0166	0.0232	-0.0078	0.0061
	(0.0424)	(0.0452)	(0.0429)	(0.0436)	(0.0425)
VFVAR	−0.1344**	−0.1392**	−0.1246**	−0.1671***	−0.1448**
	(0.0601)	(0.0648)	(0.0626)	(0.0622)	(0.0627)
CONSASSETS	0.0016***	–	0.0011**	–	0.0012**
	(0.0005)		(0.0005)		(0.0005)
HTOTLAND	0.0146	–	0.0079	–	0.0087
	(0.0173)		(0.0178)		(0.0165)
LIVESTOCK	0.0381**	–	0.0462***	–	0.0517***
	(0.0151)		(0.0154)		(0.0146)
AGEY	–	−0.1072	−0.1155	–	−0.1764**
		(0.0717)	(0.0727)		(0.0740)
AGEY2	–	0.0140*	0.0141*	–	0.0197**
		(0.0073)	(0.0074)		(0.0076)
EDUCA	–	0.0055	0.0032	–	−0.0000
		(0.0045)	(0.0045)		(0.0044)
FMAXEDUCA	–	0.0048	0.0036	–	0.0050*
		(0.0029)	(0.0028)		(0.0026)
FOODCRED	–	–	–	0.0078***	0.0093***
				(0.0017)	(0.0016)
LNLOANTOTAL	–	–	–	0.0473***	0.0479***
				(0.0120)	(0.0130)
Cons	8.0462***	8.1914***	8.2461***	8.0255***	8.4092***
	(0.0749)	(0.1694)	(0.1729)	(0.0746)	(0.1731)
N	739	709	709	739	709
Adj. R-sq	0.053	0.039	0.070	0.065	0.125

Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Notes HHSIZE and *SEX* were included in the regression but not reported. There are more reported observations in columns 2 and 3 compared to 1 and 4 due to fewer observations of *EDUCA*

Table 5.9 Round 2 determinants of household welfare across characteristics groups

Explanatory variables	(1)	(2)	(3)	(4)	(5)
FVAR	−0.0254	−0.0270	−0.0236	−0.0337	−0.0247
	(0.0410)	(0.0384)	(0.0387)	(0.0401)	(0.0376)
VFVAR	−0.0291	−0.0317	−0.0358	−0.0221	−0.0312
	(0.0603)	(0.0601)	(0.0591)	(0.0621)	(0.0589)
CONSASSETS	0.1793**	–	0.1514**	–	0.1376*
	(0.0770)		(0.0741)		(0.0750)
HTOTLAND	0.0499***	–	0.0461***	–	0.0473***
	(0.0082)		(0.0087)		(0.0088)
LIVESTOCK	0.0150	–	0.0058	–	0.0073
	(0.0123)		(0.0118)		(0.0119)
AGEY	–	−0.0449	−0.0375	–	−0.0406
		(0.0628)	(0.0567)		(0.0570)
AGEY2	–	0.0094	0.0073	–	0.0075
		(0.0061)	(0.0055)		(0.0056)
EDUCA	–	0.0068*	0.0027	–	0.0022
		(0.0035)	(0.0034)		(0.0035)
FMAXEDUCA	–	0.0067***	0.0049**	–	0.0053**
		(0.0024)	(0.0023)		(0.0023)
FOODCRED	–	–	–	0.0067***	0.0066***
				(0.0023)	(0.0020)
LNLOANTOTAL	–	–	–	0.0017	−0.0116
				(0.0134)	(0.0130)
Cons	8.1431***	8.1131***	8.1628***	8.0844***	8.1662***
	(0.0996)	(0.1670)	(0.1557)	(0.1004)	(0.1544)
N	738	736	736	738	736
Adj. R-sq	0.088	0.055	0.116	0.005	0.123

Standard errors in parentheses
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Note HHSIZE and *SEX* were included in the regression but not reported

Table 5.10 Round 3 determinants of household welfare across characteristics groups

Explanatory variables	(1)	(2)	(3)	(4)	(5)
FVAR	0.0191	0.0244	0.0279	0.0122	0.0276
	(0.0412)	(0.0435)	(0.0402)	(0.0453)	(0.0405)
VFVAR	−0.0931*	−0.1089**	−0.0995*	−0.0967*	−0.0948*
	(0.0530)	(0.0541)	(0.0513)	(0.0568)	(0.0516)
CONSASSETS	0.0052**	–	0.0049*	–	0.0050**
	(0.0025)		(0.0025)		(0.0024)
HTOTLAND	0.0481***	–	0.0409***	–	0.0409***
	(0.0075)		(0.0077)		(0.0078)
LIVESTOCK	0.0261***	–	0.0240**	–	0.0241**
	(0.0099)		(0.0095)		(0.0095)
AGEY	–	−0.0805	−0.0798	–	−0.0882*
		(0.0608)	(0.0514)		(0.0522)
AGEY2	–	0.0122*	0.0108**	–	0.0117**
		(0.0063)	(0.0054)		(0.0055)
EDUCA	–	0.0030	−0.0006	–	−0.0012
		(0.0030)	(0.0030)		(0.0030)
FMAXEDUCA	–	0.0076***	0.0063***	–	0.0061***
		(0.0019)	(0.0018)		(0.0018)
FOODCRED	–	–	–	0.0101*	0.0090
				(0.0057)	(0.0057)
LNLOANTOTAL	–	–	–	0.0118	0.0099
				(0.0120)	(0.0117)
Cons	8.1326***	8.1992***	8.2646***	8.0765***	8.2797***
	(0.0791)	(0.1618)	(0.1498)	(0.0779)	(0.1510)
N	722	721	721	722	721
Adj. R-sq	0.095	0.055	0.117	0.006	0.117

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note HHSIZE and *SEX* were included in the regression but not reported

- column 3 includes physical and human capital variables
- column 4 includes only financial capital variables
- column 5 includes all of the variables.

5.8.2.2 Analysis and Discussion

Overall, the Model 2 analysis revealed that the floods were not endogenous in the specifications that were tested. The main flood exposure variable (*VFVAR*) remained significant and strong despite the inclusion of additional control variables such as assets and demographic variables. This was most evident in Round 1: when asset variables were controlled, the coefficient estimate of *VFVAR* was −0.1344 and was significant at the 5 % level. The result in column 1 is similar to the result when only *EDUCA*, *FMAXEDUCA* and *AGEY* were controlled in column 2 (−0.1392) and only slightly lower (whilst maintaining similar significance) than the full model in column 5 (−0.1448).This finding, which showed a very significant flood effect, was helpful for comparing the results of the explanatory variables between exposed and non-exposed households. Moreover, we are able to identify several of the characteristics that are significant in determining the calorie outcomes for households. This provides justification to proceed to Model 3 to interact the household characteristics with flood exposure.

When comparing the results across the rounds, there was some consistency in terms of the significant variables that determined household calorie consumption. The consistent significant variables across all of the rounds were consumer assets, female education and food credit purchases. Borrowing money was a temporary coping strategy that had an immediate effect only in Round 1. Age had a positive relationship with welfare in Rounds 1 and 3 but was insignificant in Round 2. Household landholding and livestock were significant in some rounds but not in others. It is unclear what caused the fluctuation but it may be that in some rounds crops were not able to be grown (e.g. *HTOTLAND*) and markets were not favourable for drawing-down assets (e.g. *LIVESTOCK*).

5.8.3 Model 3 Results

Extending further with Model 2, in this section interaction terms were included.

5.8.3.1 Model Specification

From the specification in Model 2, interaction terms were included individually across the columns for each characteristic. The full interactions model incorporating all of the characteristics is presented in the final column of each of the result tables (see the results Tables 5.11, 5.12, 5.13 for Model 3 below). It must be noted that the household characteristics were interacted with *VFVAR* only.

Table 5.11 Results for round one models

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FVAR	0.0048	0.0050	-0.0001	0.0045	0.0050	0.0055	0.0087	0.0086
	(0.0432)	(0.0434)	(0.0430)	(0.0432)	(0.0427)	(0.0428)	(0.0442)	(0.0439)
VFVAR	−0.1426**	−0.1393**	−0.1901***	−0.1393*	−0.1702**	−0.1532**	−0.2836***	−0.3184***
	(0.0647)	(0.0686)	(0.0687)	(0.0733)	(0.0672)	(0.0672)	(0.0844)	(0.0904)
CONSASSETS	0.0015**	0.0014***	0.0015***	0.0014***	0.0014***	0.0014***	0.0013**	0.0024***
	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0007)
*CONSASSETS*VFVAR*	−0.0003	–	–	–	–	–	–	−0.0013
	(0.0010)							(0.0011)
HTOTLAND	0.0001	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
*HTOTLAND*VFVAR*	–	-0.0000	–	–	–	–	–	-0.0006
		(0.0003)						(0.0004)
LIVESTOCK	0.0500***	0.0499***	0.0107	0.0503***	0.0513***	0.0502***	0.0526***	-0.0104
	(0.0149)	(0.0149)	(0.0251)	(0.0147)	(0.0149)	(0.0148)	(0.0147)	(0.0327)
*LIVESTOCK*VFVAR*	–	–	0.0548*	–	–	–	–	0.0839**
			(0.0319)					(0.0420)
EDUCA	0.0019	0.0019	0.0014	0.0031	0.0017	0.0020	0.0031	0.0070
	(0.0045)	(0.0045)	(0.0046)	(0.0075)	(0.0045)	(0.0045)	(0.0045)	(0.0091)
*EDUCA*VFVAR*	–	–	–	-0.0016	–	–	–	-0.0078
				(0.0087)				(0.0117)
FMAXEDUCA	0.0048*	0.0048*	0.0051*	0.0048*	0.0010	0.0049*	0.0048*	-0.0005
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0040)	(0.0027)	(0.0026)	(0.0050)
*FMAXEDUCA*VFVAR*	–	–	–	–	0.0056	–	–	0.0085
					(0.0047)			(0.0060)
FOODCRED	0.0091***	0.0091***	0.0092***	0.0091***	0.0093***	0.0069*	0.0090***	0.0079**
	(0.0017)	(0.0016)	(0.0017)	(0.0016)	(0.0017)	(0.0039)	(0.0016)	(0.0039)

(continued)

Table 5.11 (continued)

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FOODCRED*VFVAR*	–	–	–	–	–	0.0026	–	0.0015
						(0.0046)		(0.0047)
LNLOANTOTAL	0.0081**	0.0080**	0.0087**	0.0080**	0.0083**	0.0081**	-0.0076	-0.0064
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0061)	(0.0061)
*LNLOANTOTAL*VFVAR*	–	–	–	–	–	–	0.0227**	0.0217**
							(0.0088)	(0.0089)
Cons	8.3250***	8.3223***	8.3499***	8.3223***	8.3458***	8.3282***	8.4046***	8.4016***
	(0.1758)	(0.1827)	(0.1796)	(0.1746)	(0.1790)	(0.1745)	(0.1715)	(0.1774)
N	709	709	709	709	709	709	709	709
Adj. R-sq	0.107	0.107	0.111	0.107	0.108	0.107	0.115	0.117

Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
Note HHSIZE, AGEY, *AGEY2* and *SEX* were included in the regression but not reported
The Chow test statistic in the full model (column 8) was 2.18 with an associated p value of 0.0407

Table 5.12 Results for round two models

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FVAR	−0.0258	−0.0209	−0.0256	−0.0264	−0.0264	−0.0251	−0.0261	−0.0264
	(0.0380)	(0.0383)	(0.0382)	(0.0380)	(0.0372)	(0.0378)	(0.0382)	(0.0383)
VFVAR	−0.0279	0.0097	−0.0309	−0.0008	0.0138	−0.0199	0.0060	0.0620
	(0.0588)	(0.0652)	(0.0652)	(0.0633)	(0.0608)	(0.0625)	(0.0712)	(0.0837)
CONSASSETS	0.2639***	0.1364*	0.1389*	0.1429*	0.1446*	0.1367*	0.1408*	0.2344***
	(0.0343)	(0.0762)	(0.0766)	(0.0761)	(0.0776)	(0.0765)	(0.0767)	(0.0567)
*CONSASSETS*VFVAR*	−0.1400*	–	–	–	–	–	–	−0.1022
	(0.0985)							(0.1036)
HTOTLAND	0.0005***	0.0008***	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***	0.0010***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
*HTOTLAND*VFVAR*	–	−0.0004**	–	–	–	–	–	−0.0006**
		(0.0002)						(0.0003)
LIVESTOCK	0.0064	0.0036	0.0062	0.0061	0.0044	0.0060	0.0067	−0.0566*
	(0.0118)	(0.0119)	(0.0252)	(0.0118)	(0.0120)	(0.0119)	(0.0119)	(0.0362)
*LIVESTOCK*VFVAR*	–	–	0.0007	–	–	–	–	0.0757*
			(0.0289)					(0.0421)
EDUCA	0.0018	0.0013	0.0017	0.0097	0.0017	0.0015	0.0017	0.0003
	(0.0035)	(0.0035)	(0.0035)	(0.0087)	(0.0035)	(0.0034)	(0.0034)	(0.0090)
*EDUCA*VFVAR*	–	–	–	-0.0111	–	–	–	0.0009
				(0.0107)				(0.0112)
FMAXEDUCA	0.0053**	0.xc***	0.0053**	0.0053***	0.0121***	0.0052**	0.0052**	0.0117***
	(0.0023)	(0.0022)	(0.0023)	(0.0023)	(0.0045)	(0.0023)	(0.0023)	(0.0044)
*FMAXEDUCA*VFVAR*	–	–	–	–	−0.0093*	–	–	−0.0083*
					(0.0055)			(0.0055)
FOODCRED	0.0063***	0.0067***	0.0066***	0.0062***	0.0061***	0.0100**	0.0067***	0.0092*
	(0.0021)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0049)	(0.0020)	(0.0051)

(continued)

Table 5.12 (continued)

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*FOODCRED*VFVAR*						-0.0048		-0.0036
						(0.0060)		(0.0060)
LNLOANTOTAL	−0.0012	−0.0016	−0.0013	−0.0014	−0.0015	−0.0012	0.0046	0.0037
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0063)	(0.0065)
*LNLOANTOTAL*VFVAR*	–	–	–	–	–	–	−0.0083	−0.0076
							(0.0079)	(0.0081)
Cons	8.1714***	8.1414***	8.1791***	8.1511***	8.1416***	8.1626***	8.1584***	8.0734***
	(0.1549)	(0.1560)	(0.1549)	(0.1617)	(0.1567)	(0.1575)	(0.1555)	(0.1609)
N	736	736	736	736	736	736	736	736
Adj. R-sq	0.122	0.125	0.121	0.123	0.125	0.122	0.122	0.126

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note HHSIZE, *AGEY*, *AGEY2* and *SEX* were included in the regression but not reported

The Chow test statistic in the full model (column 8) was 1.81 with an associated p value of 0.0920

Table 5.13 Results for round three models

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FVAR	0.0303	0.0346	0.0314	0.0296	0.0298	0.0317	0.0309	0.0302
	(0.0409)	(0.0415)	(0.0410)	(0.0415)	(0.0414)	(0.0409)	(0.0412)	(0.0426)
VFVAR	−0.0980*	−0.0648*	−0.0926*	−0.0586*	−0.0573	−0.0892*	−0.0771*	−0.0235
	(0.0516)	(0.0555)	(0.0567)	(0.0552)	(0.0554)	(0.0517)	(0.0651)	(0.0719)
CONSASSETS	0.0026	0.0052**	0.0051**	0.0047*	0.0046*	0.0051**	0.0049*	0.0008
	(0.0032)	(0.0024)	(0.0025)	(0.0025)	(0.0025)	(0.0024)	(0.0025)	(0.0030)
*CONSASSETS*VFVAR*	0.0046*	–	–	–	–	–	–	0.0068*
	(0.0042)							(0.0042)
HTOTLAND	0.0004***	0.0006***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0007***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
*HTOTLAND*VFVAR*	–	−0.0003*	–	–	–	–	–	−0.0003*
		(0.0002)						(0.0002)
LIVESTOCK	0.0238***	0.0235***	0.0274*	0.0247***	0.0236***	0.0240***	0.0240***	−0.0037
	(0.0097)	(0.0094)	(0.0189)	(0.0095)	(0.0096)	(0.0096)	(0.0095)	(0.0212)
*LIVESTOCK*VFVAR*	–	–	−0.0037	–	–	–	–	0.0323*
			(0.0223)					(0.0261)
EDUCA	−0.0009	−0.0012	−0.0009	0.0091*	−0.0009	−0.0008	−0.0010	0.0034
	(0.0030)	(0.0030)	(0.0030)	(0.0051)	(0.0030)	(0.0030)	(0.0030)	(0.0073)
*EDUCA*VFVAR*	–	–	–	−0.0138**	–	–	–	−0.0066
				(0.0065)				(0.0090)
FMAXEDUCA	0.0064***	0.0065***	0.0064***	0.0065***	0.0121***	0.0062***	0.0064***	0.0107***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0032)	(0.0018)	(0.0018)	(0.0038)
*FMAXEDUCA*VFVAR*	–	–	–	–	−0.0078**	–	–	−0.0055*
					(0.0036)			(0.0046)
FOODCRED	0.0086*	0.0090*	0.0087*	0.0079*	0.0081*	0.0165***	0.0086*	0.0149***

(continued)

Table 5.13 (continued)

Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.0056)	(0.0054)	(0.0056)	(0.0053)	(0.0055)	(0.0039)	(0.0056)	(0.0036)
*FOODCRED*VFVAR*	–	–	–	–	–	−0.0218***	–	−0.0195***
						(0.0052)		(0.0050)
LNLOANTOTAL	−0.0016	−0.0018	−0.0018	−0.0021	−0.0018	-0.0017	0.0015	0.0013
	(0.0031)	(0.0031)	(0.0031)	(0.0032)	(0.0031)	(0.0031)	(0.0063)	(0.0066)
*LNLOANTOTAL*VFVAR*	–	–	–	–	–	–	−0.0045	−0.0042
							(0.0077)	(0.0080)
Cons	8.2711***	8.2434***	8.2677***	8.2386***	8.2409***	8.2617***	8.2553***	8.2005***
	(0.1513)	(0.1540)	(0.1510)	(0.1506)	(0.1515)	(0.1510)	(0.1489)	(0.1525)
N	721	721	721	721	721	721	721	721
Adj. R-sq	0.116	0.118	0.115	0.118	0.118	0.118	0.116	0.117

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note HHSIZE, *AGEY*, *AGEY2* and *SEX* were included in the regression but not reported

The Chow test statistic in the full model (column 8) was 3.44 with an associated p value of 0.00

This is because, based on the Model 2 results, when compared to *FVAR*, *VFVAR* was more significant and was a stronger determinant of the effect of the floods on household welfare. *HHSIZE* and *SEX*, *AGEY* and *AGEY2* are included as controls without being interacted. Interacting age variables tended to distort the significance of *VFVAR* and further were not significant even at the generous 10 % level.

5.8.3.2 Analytical Methods

To determine which characteristics mitigate the effects of the flood, either individually or collectively, *t* and *F* tests were used. In addition, the *Chow* test was used to test the slopes across the exposed and non-exposed categories.[21] To further assist in interpreting the effects of the interactions (of certain explanatory variables) on calorie consumption, we derived an elasticity equation. The elasticity helps measure how much the percentage of calories consumed changes when there is a small change in one of the household characteristic variables (holding the flood variable constant). However, to focus on a specific level of the explanatory variable, we are interested in calculating the elasticity at the *mean* value of the dependent variable (holding flooding constant).

Using the point-elasticity formula, the (units-free) elasticity at the mean value of any given variable is given by[22]:

$$\eta M(\bar{X}) = \hat{\theta} \cdot \left(\frac{\bar{X}}{\hat{Y} + \hat{\theta} \cdot \bar{X}} \right) \tag{5.9}$$

5.8.3.3 Analysis and Discussion

After introducing interaction effects in Model 3, the characteristics that mainly influenced the effect of the floods across rounds were livestock assets, consumer assets, total landholding, female education and food credit purchases. Particularly in Round 1, livestock assets were found to directly mitigate the effects of the floods in all rounds. When we considered the partial effect of the flood alone (dY/dF), an additional unit of livestock raised consumption by up to 8.39 % (5 % significance level). This meant that livestock assets mitigated approximately one quarter of the effect of flood exposure (if $F = 1$). The elasticity for livestock at the mean of 0.6069 was calculated as:

$$\eta M(0.6069) = 0.0839 \left(\frac{0.6069}{-0.3184 + 0.0839 \times 0.6069} \right) = -0.1904.$$

[21] This is a statistical and econometric test of whether the coefficients in two linear regressions (exposed and non-exposed households) are equal.

[22] The derivation of the elasticity at the mean value $\left(\eta M(\bar{X}) = \hat{\theta} \cdot \left(\frac{\bar{X}}{\hat{Y} + \hat{\theta} \cdot \bar{X}} \right) \right)$ is illustrated in Appendix 5.2.

Thus, holding all other factors constant, another 1 % of livestock (at the within sample mean level [0.6069]) was expected to reduce the (adverse) effects of the flood by 19.04 %. This was quite a large effect when compared to the actual size of the effect of the floods in the same regression model results (−0.3184).

Another significant factor which proved to be beneficial for households across Rounds 2 and 3 was total female education (*FMAXEDUCA*). Particularly for non-exposed households in Round 3, the effects were most significant where an additional year of total female education was estimated to raise calorie consumption by 1.07 % (1 % significance level). These results perhaps suggest more long-term effects of education taking into account the delays in a slowly-recovering labour market. However, the beneficial effect for exposed households was almost half of the effect for non-exposed households ($1.07 - 0.55 = 0.52$ %, 10 % significance level). It is not clear what the cause for the disparity was, but one could perhaps expect that skilled workers were cut off from their usual occupations due to the floods compared to low skilled, rural workers.

Meanwhile, borrowing loans or purchasing food on credit were temporary measures, and their associated benefits were limited to Round 1 only (there was a positive and significant effect across most of the columns in the Round 1 results). When distinguishing between categories of households, the results of the coefficient estimates of consumer assets, landholding and female education showed that these benefitted both exposed and non-exposed households. However, the coefficient estimates also indicated that the net beneficial effect of these characteristics on exposed households were lower than for non-exposed households. With respect to food credit, the coefficient estimate of the interaction term in Round 3 was negative and highly significant. As a result, food credit appeared to benefit non-exposed households (0.0149 with 1 % significance level) but actually exacerbated the effects of the floods for exposed households ($0.01490.0195 = 0.0046$, 1 % significance level) because they incurred far greater long-term costs on their well-being.

This research has been able to identify certain important household characteristics that influence a household's ability to mitigate the effects of flooding on welfare. However, the precise policy implications of the characteristics are difficult to identify based on this research. For instance, access to credit may be an important short-term coping strategy but could also delay household misery by creating a debt trap. Also, without further research, we are unable to readily explain the significant differences in outcomes between exposed and non-exposed households. Nonetheless, the results suggest that merely identifying the determinants of household welfare masked the differences between exposure categories. For instance, as a whole, a certain characteristic may show a positive or negative effect on welfare but the experiences of exposed and non-exposed households could vary starkly. Policy-makers should consider this as an important distinction when designing appropriate response strategies in the aftermath of natural shocks.

5.9 Conclusion

Large parts of the developing world lie in areas that are substantially at risk of being impacted by natural disasters such as floods, droughts, storm surges and cyclones. Under even modest projections of climate change, more intense and frequent natural disasters are predicted globally. The associated adverse impacts of these extreme weather events are predicted to increase disproportionally more in developing countries (IPCC 2007a). Furthermore, the people living in under-developed areas have limited capacity to cope with natural shocks. Consequently, extreme weather events can have persistent effects on their welfare. This research undertook a case study of Bangladesh, which is one of the countries most vulnerable to global climate change and associated extreme weather events. Bangladesh's geography, topography and poverty make it particularly prone to regular flooding and cyclone-induced storm surges. With very little overall contribution to greenhouse gas emissions, Bangladesh's only protective response is through adaptation—though it is currently lacking in adaptive capacity. Specifically, the 1998 floods were studied because it was one of the most severe natural disasters in Bangladesh's history. Whilst the 1998 floods had significant effects on income, consumption, nutrition, employment and wages, households also employed various coping strategies to maintain well-being. These included borrowing, skipping meals and selling assets.

This chapter presented a simple empirical framework to study how a diverse set of household characteristics can influence welfare in the context of an environmental shock. Preliminary results indicated that the floods had significant effects on household welfare. When household and village-level flood effects were compared, only the village-level effects had a significant and strong adverse effect on household welfare. In terms of mitigation, household calorie intake was positively influenced by a number of factors including livestock assets, female education, food credit purchases and loans. Moreover, there was a significant difference in the effects of several household characteristics between exposed and non-exposed households.

The research in this chapter proceeded on the premise that a better understanding of household characteristics (which encompasses endowments and coping responses) can assist policymakers and researchers. Using the findings, practitioners may be able to develop suitable strategies to help vulnerable nations to adapt to extreme weather events associated with global climate change.

5.10 Further Testing and Research

From the basic model presented here, there is ample scope for further research using other sophisticated econometric methods. Concrete panel and instrument variables models could be constructed which can deal with time-invariant omitted variables and fixed effects concerns. Additionally, alternative forms of endogeneity testing could help comprehensively settle the issue regarding the endogeneity of flood effects. Econometric models can also assist in testing other interesting variables such as health outcomes and migration. The framework in this chapter could perhaps be utilised in further research using a more suitable dataset. Nonetheless, this chapter has illustrated how an econometric framework can assist in determining the relationships between mitigation of flood effects on household welfare through various household characteristics.

Appendixes

Appendix 5.1: Discussion of Econometric and Specification Issues

In attempting to develop robust econometric modelling and interpretation techniques, several econometric issues that were peculiar to the dataset were considered.

Heteroskedasticity Testing and Standard Errors

To justify the use of heteroskedasticity-robust methods, the *BREUSCH-PAGAN* test was used to test for possible heteroskedasticity in the variance error term. The test was applied to the Model 2 specification because it contained the full set of explanatory variables. The *BREUSCH-PAGAN* test revealed a Chi square value of 2.92 and an associated p-value of 0.0876. The hypothesis that there was constant variance in the error term was rejected at the 9 % significance level. Hence, heteroskedastic robust methods were preferred.

In the presence of heteroskedasticity (non-constant variance of the error term), inferences cannot be made because the OLS standard errors are no longer valid for constructing confidence intervals and t statistics (Wooldridge 2006). Hence, robust standard errors were used in all of the models to account for heteroskedasticity of unknown form (Wooldridge 2006).

Clustering

The use of sampling clusters in the IFPRI-FMRSP dataset required an additional adjustment of the standard errors. It is assumed that that there are 'clustered errors' in the IFPRI-FMRSP dataset due to the cluster-sampling technique that was used. This means that observations within in each group are correlated in some way. In the presence of cluster errors, OLS estimates are still unbiased but standard errors may be wrong, leading to incorrect inferences (Wooldridge 2006). In this chapter, the village-level cluster size is used because it is a sufficiently high cluster-level. A higher cluster level is preferred because it aggregates the correlated standard errors. Kézdi (2003) showed that 50 clusters (with roughly equal cluster sizes) are often sufficient for purposes of forming accurate inferences. This requirement is satisfied in this dataset because there are roughly 117 equal village clusters.

Specifications Testing

To justify the use of logarithmic form for the dependent variable (*AECAL*) specification testing was conducted using the *RAMSEY-RESET* test. Again the test was applied to only the full Model 2 specification. The *RAMSEY-RESET* statistic for the level form was 2.42 and had an associated p-value of 0.0648. Thus we do not reject this specification at the 7 % significance level. The *RAMSEY-RESET* statistic for the logarithmic form was 2.21 and had an associated p-value of 0.0857. In this case, we do not reject this specification at the 9 % significance level. With a higher significance level, the logarithmic specification was preferred.

Appendix 5.2: Deriving an Elasticity Measure of Interactive Effects

It is possible to develop an elasticity-based interpretation using our parameters, $\hat{\gamma}_{\text{it}}, \hat{\beta}_{\text{it}}$ and $\hat{\theta}_{it}$, with two values of any household characteristic (X_1 and X_2). For instance, one may choose to note the percentage change in the effect of the flood on $ln(c_{it})$ when education is 5 years (completion of primary school) compared to 10 years (completion of Matriculation level in Bangladesh). The following diagram illustrates the difference in marginal effects of the flood for two arbitrary values of the *X* characteristic. This diagram compares the outcomes between exposed and non-exposed households. Here, the most ideal situation is assumed: where $\hat{\gamma} < 0$ but $\hat{\alpha}_0 + \hat{\gamma} > 0$, $\hat{\beta} > 0$ and $\hat{\theta} > 0$ (Fig. 5.2).

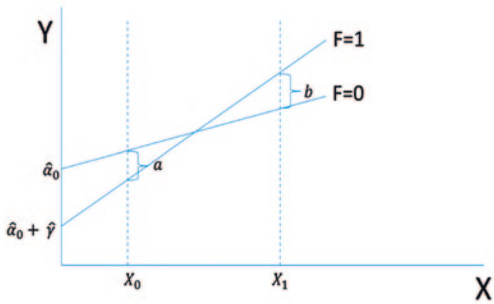

Fig. 5.2 Variance in marginal effects of household characteristics for varying flood exposure

Based on the diagram above, the predicted percentage change in calorie consumption based on the X can be calculated as follows:

$$\%\Delta = \frac{b-a}{a} \times \frac{100}{1} \tag{5.10}$$

However, for ease of comparison, a units-free elasticity measure can be developed. First, it can be noted that Eq. 5.1 can be draw as a line curve (assuming that $\hat{\theta} > 0$) (Fig. 5.3).

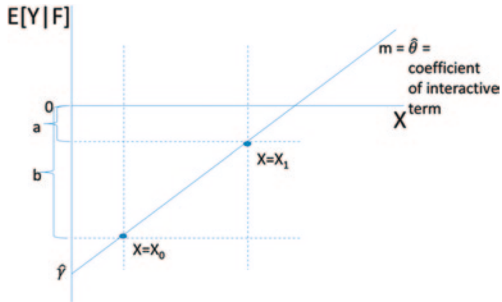

Fig. 5.3 Line curve of the coefficient of interactive terms

The equation of the line simply reveals that *X* influences the marginal effects of the flood. The y-intercept, $\hat{\gamma}$, is the constant term of the marginal function. Also, the slope of this curve is the coefficient estimate, $\hat{\theta}$, because $\partial Y/\partial F$ is allowed to vary with changes in X.

It is hypothesised that if $\hat{\gamma} < 0$ and $\hat{\theta} > 0$, then as X increases, the (adverse) effect of the flood diminishes.

However, from the figure above, the change in the marginal effects of the flood—between any two values of X– will result in different measures of responsiveness. To simplify interpretation, the elasticity at the mean $(\bar{X})$ can be used. It is also possible to calculate the elasticity at corresponding quintile levels to distinguish the effects based on household expenditure.

Calculating Units-Free Elasticity Measures

Starting with Eq. 5.1, $M(X) = \hat{\gamma} + \hat{\theta}.X$, the mean value of the X, the point elasticity measure of the responsiveness of the marginal effect of the X characteristic is:

$$\eta M(\bar{X}) = \hat{\theta} \cdot \left(\frac{\bar{X}}{\hat{\gamma} + \hat{\theta} \cdot \bar{X}}\right) \tag{5.11}$$

This units-free measure enumerates the effect of a 1% change in X (at the mean) on the percentage change in the effect of the floods on $ln(c_{it})$.

Functional Forms and Types of x-Characteristics

When calculating elasticities and to better enable interpretation of the various characteristics, alternative approaches need to be undertaken depending on the functional form of the characteristic. The following describes how different functional forms may be analysed:

- *discrete variables*: directly apply the formula above
- *logarithmic variables*: the coefficient estimates already reveal an elasticity measure but a similar calculation can still be made.
- *dummy variables*: calculate the difference in outcomes between the two groups

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