The Micro-Economic Implications of Natural Disaster Risk for Developing Countries: Evidence from Nicaragua

Ph.D. Thesis

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Chapter 1

Introduction

I. Motivation

Natural disaster risk is a global concern and one that is particularly acute for members of the developing world. Unlike developed nations, developing countries often lack the resources to mitigate and recover from the economic damages caused by natural disasters. Governments, particularly of poorer nations, are unable to invest much in disaster mitigation due to the pressing needs of other immediate development priorities. When a disaster strikes these nations are often ill-prepared to meet the humanitarian or economic costs.

At the micro-level, the economies of these countries have not developed to the point of offering affordable, or often any type of formal insurance (World Bank 2006), which is often the primary line of defense against disaster damages in the developed world. These economies are often also characterized by incomplete credit markets and as a result households must rely on informal mechanisms to meet the needs that arise in the post-disaster environment or must take their chances with receiving sufficient amount of domestic or international aid. At the household level, the dependence on aid is problematic because it relies on aid to be both available and effectively allocated. In many cases, less publicized disasters do not receive aid proportionate to their impact. Disasters often also strike rural areas, which make the delivery of aid difficult. Micro-level arrangements which households use to safeguard their welfare such as informal insurance networks or storing assets can also be rendered ineffective by disasters.

In relative terms, poor households in developing nations suffer the most acute losses when disasters strike. As the adage goes, the poor have less to lose, but when they lose that they lose everything. In the developing world, disaster-prone areas are populated not by the rich, but by the poor because they cannot afford to live in lower-risk areas. Unlike aggregate economic shocks, disasters can physically destroy assets held by the poor be they livestock, crops, tools or even their home not to mention kill household members. Frequently disaster damage strikes the poor doubly hard: first, with the direct losses due to the disaster, and secondly, by potentially disrupting loan-financed development programs (Freeman et al., 2003: 37). In the wake of disaster a household may find its assets destroyed and lives of family members lost. All this makes for a recovery process that may be difficult at best.

For the poor in the developing world who do not hold financial assets, the destruction of physical assets and loss of work opportunity can be particularly crippling. As Sen (1982) has argued, the ability to avoid starvation and destitution hinges on ownership and exchange entitlement.[1] As he and subsequently Ravallion (1987) demonstrated it is possible to reduce welfare either by a decline in ownership or loss in exchange ability. Natural disasters may simultaneously reduce a household's ownership assets and its exchange possibilities. These, in turn, hold implications for a household's non-durable consumption, which includes food. This is not a study about subsistence and hunger, however, they are particularly salient concerns given the deleterious effects of hunger and starvation (Dreze and Sen 1989). Events such as natural disasters, which may severely disrupt household consumption and threaten household welfare, merit consideration. Only by better understanding the degree and nature of disaster impact at the household level will more effective preventive and response measures become possible.

From an economic perspective the incidence of natural disasters provides a unique research opportunity to investigate several important themes in development economics such as risk and informal insurance, the usage of non-market risk coping mechanisms and the benefits and efficacy of aid targeting. This dissertation argues that the incidence of large-scale natural disasters places extreme stress on informal coping mechanisms and generates exogenous, one-off flows of "windfall" aid transfers. The confluence of these factors offers fertile ground for research into how these mechanisms perform in the wake of a large, unanticipated exogenous shock.

The unpredictability of disaster occurrences makes compiling panel or even cross-sectional data around the pre and post disaster period difficult since the disaster must fall between scheduled surveys. Fortunately a series of surveys conducted as part of the World Bank's Living Standards and Measurement Surveys captures valuable data on household behavior before and after Hurricane Mitch in Nicaragua in 1998. The impact of disasters on informal coping mechanisms and the role of aid in sustaining welfare is the focus of this dissertation. To engage this research question I seize research opportunities which arise in the post-disaster period to analyze the behavior of informal insurance mechanisms in response to damages caused by Hurricane Mitch. The remainder of this section will orient the reader to themes in development economics which are relevant to the topics of risk coping and the role of post-disaster aid that are touchstones of this dissertation.

II. Introduction

In many of the world's poorest countries the population is rural and relies on agriculture for a living. The poorest households may often be close to subsistence level poverty and in the poorest countries welfare is not measured in currency units but by caloric intake. Even those agricultural households which are not characterized by extreme poverty remain vulnerable to disruptions of their income and consumption. They are beset by numerous risks such as illness or personal injury and more general risks such as a downturn in crop prices, insect infestation or drought.

[1] "The set of all the alternative bundles of commodities that he can acquire for what he owns may be called the 'exchange entitlement' of what he owns" (Sen 1982: 4).

Unlike households in the developed world these households must endeavor to safeguard their income and consumption levels without many of the market mechanisms that are taken for granted in the developed nations. Access to complete credit and insurance markets is often severely curtailed in developing countries. In addition legal institutions which exist to enforce contracts are not found or ineffective due to reasons such as illiteracy or corruption. Despite these obstacles economists have found that households in developing nations manage to develop informal, "nonmarket" institutions which mimic formal credit and insurance markets. Households are able to use informal institutions to mitigate risk and guard against drops in income and consumption levels. In agricultural societies weather risk is a prevalent concern. It is here we begin our discussion as there are several parallels which emerge between weather risk and natural disaster risk.

III. Weather Risk and Natural Disaster Risk

III. A. Weather Risk

Earlier work on weather risk vulnerability chiefly focuses on agricultural households, which are vulnerable to adverse shocks affecting both crop price and yield. These studies typically examine the seasonal aspect of weather (usually rainfall or lack of) or the impact of weather on investment decisions. As for weather risk, some studies present weather risk as covariate, while others caution that it may be less covariate than anticipated. Obviously, the scope for local and informal insurance will decrease as weather risk becomes increasingly covariate.

III. A. 1. Weather Risk and Investment Decisions

Rosenzweig and Binswanger (1993) investigate the relationship between wealth, weather risk and the composition and profitability of agricultural investments. They use panel data from India (ICRISAT survey) to "(i) measure the riskiness of farmers' investment portfolios in terms of their sensitivity to weather variation, (ii) test the existence of a positive association between average returns to individual production assets and their sensitivity to weather variability, and (iii) estimate how the influence of exogenous weather risk on portfolio riskiness and on farm profitability varies with total wealth." The authors argue that an emphasis on weather-related risk is useful due to the availability of weather data and that:

> although weather is not the only factor exogenously affecting the variability in farm output and profits, it is the factor contributing to income variability that is most likely to influence welfare. *This is because weather risk is spatially covariant. Unlike for idiosyncratic risk, it is difficult for farmers to undertake arrangements that insure against risk factors such as rainfall that affect everyone in their local environment similarly. Only to the extent that risk is not insurable will risk be reflected in ex ante production decisions, and weather risk appears to be uninsured in most low-income settings* (italics mine) (Rosenzweig and Binswanger 1993: 57).

The authors find that farmers living in riskier environments choose asset portfolios that are less sensitive to rainfall variation and that uninsured weather risk exacerbates income inequality. They also find that common weather shocks to income have greater consequences for consumption than idiosyncratic risk. Thus, weather related profit variability may be less insurable than idiosyncratic profit variability. As an example they describe how credit becomes difficult to obtain following a late monsoon and how the timing of a monsoon has a significant effect on total farm profitability. But, given that not all households are affected equally by the shocks there appear to be gains from weather insurance. Yet, the authors suggest that since a portion of profit risk remains idiosyncratic and since weather variations adversely impact the poor, the wealthy are unlikely to wish to participate in such an insurance program.

III.A. 2. Weather Risk and the Permanent Income Hypothesis (PIH)

Intertemporal mechanisms allow households with different time preferences to consume now or trade current for future consumption. Friedman's permanent income hypothesis (PIH) often serves as a foundation for intertemporal analysis (e.g. Wolpin, 1982; Paxson, 1992). The PIH decomposes income into permanent income and transitory income. With respect to the consumption smoothing, the PIH indicates that consumption is smooth because it responds to changes in permanent income.[2] Households will save (dissave) out of positive (negative) shocks, with the marginal propensity to save theoretically equaling the portion of income devoted to saving (consumption).

Paxson (1992) uses Thai data and demonstrates that the marginal propensity to save out of transitory income (due to transitory rainfall) is not one, but is relatively high. Paxson (1993) investigates Thai consumption and income seasonality. She finds that seasonal variations in consumption are the result of seasonal preferences or prices and not a failure to use savings as a means of smoothing consumption. Saving behavior does not follow that exactly predicted by the PIH, but it may come close. An earlier study by Wolpin (1982) tests the impact of weather on the income and consumption of rural households vis-à-vis the PIH. The idea is that income is determined by a portion related to "normal" weather events and a component related to random weather shocks. Wolpin finds, using district-level rainfall data from India, households observe and respond to weather when formulating consumption decisions. He demonstrates that the permanent income elasticity falls between 0.91 and 1.02 and shows that this value is sensitive to consumption.

III. A. 3. Weather Risk and Natural Disaster Risk: Idiosyncratic?

In most cases weather risk is considered to be covariate, however work by Townsend in India shows that households at disparate points in villages receive varying amounts of rainfall. Townsend argues that:

> the development literature typically portrays risk as covariate, imagining that most people are doing the same thing and experiencing the same weather, for example . . . evidence on

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[2] Campbell and Deaton (1989) challenge this view and argue that consumption tracks lagged income changes.

> actual households from a number of developing countries suggests that the incomes of households in a village or region move together much less than expected (1995: 84).

To support this view, Townsend cites data from India, Thailand and Cote d'Ivoire, which suggests a significant amount of household-specific, idiosyncratic risk (and thus the possibility for insurance). In India, ICRISAT data in three villages that shows that "incomes do not commove across households in each of the villages because households earn their income in different ways, subject to different risks and do not diversify much." Townsend mentions that, for example, Lim (1992) finds that 25 percent of income-variance is household specific. Wolpin (1982) offers a concrete example: irrigation. Clearly farms without irrigation are vulnerable to an additional risk. Not only are they concerned with how much rain falls, but when it falls as well. As such assuming that low rainfall levels will affect all households equally is not necessarily true.

Thai survey data shows, despite common fixed effects for certain regions, the presence of sizeable idiosyncratic shocks even across counties in the same region. Townsend also draws on Angus Deaton's work in the Côte d'Ivoire to demonstrate idiosyncratic income variability. Idiosyncratic income variability may yield fertile ground for risk pooling, although as mentioned idiosyncratic income variability need not lead to risk pooling (for reasons discussed later). On the whole, Townsend (1994) indicates that:

> if the risks are largely idiosyncratic, as the empirical evidence argues, then risk-averse households should group together to share risks. These risks will include the weather, that is, rainfall, temperature, humidity, and the like; shocks associated with incidence of crop disease and human illness; shocks associated with changes in prices outside the group or the local economy; and random factors helping to determine births, deaths, migration, division of extended families and other endogenous demographic states.

Following Townsend, although not explicitly enumerated, natural disasters may qualify recognizing certain caveats. The characterization of natural disaster risk as idiosyncratic must be qualified. Risk posed by extreme weather events such as low-frequency, high-impact natural disasters may be idiosyncratic depending upon the type and severity of the disaster and the size of the risk pool relative to the total population. The degree to which informal mechanisms extend beyond the at-risk (or affected) area will impact the effectiveness of these mechanisms at smoothing consumption. That is to say informal mechanisms, which do not pool risks across distinct covariant groups, are unlikely to be effective against natural disaster risk. It is likely that the reduction of consumption variability will still require that risk be spread someplace other than the local community. In this respect, informal networks that include inter-regional or international transfers are more likely to be able to effective depending upon monitoring capabilities and information asymmetries.[3] One means of coping with risk is risk pooling.

[3] Rashid (1990) found that risk pooling deteriorated with distance in Pakistan, however Townsend (1995) does not find conclusive results to support this in Thailand.

III. B. Risk Pooling

III. B. 1. Why Pool Risk?

In much of the developing world, rural populations are vulnerable to erratic and unpredictable swings in income and consumption. Such swings may be the result of changes in agriculture prices, weather, changes in the general price level, and other exogenous shocks. Given that households are assumed to be risk averse such swings are undesirable. Risk averse households will prefer steady income and consumption. In order to achieve these aims households can use income smoothing and consumption smoothing strategies.

III. B. 1.1 Income Smoothing and Consumption Smoothing

Income smoothing minimizes income variance, but in doing so often reduce future expected future income streams. An example of income smoothing would be to plant low-risk, low-profitability crops or to work at a fixed wage rate to guarantee income security. These measures sacrifice higher income (and in turn higher consumption) for income stability. Income smoothing may be considered a second-best option (Morduch 1994), although income and consumption smoothing are not mutually exclusive options. While income smoothing is a viable means of managing income risk, the emphasis in this dissertation is on consumption smoothing vis-à-vis risk pooling.

Consumption smoothing is preferable to income smoothing because it allows consumption to be maintained even in the face of income fluctuations. Consumption can be smoothed across states of nature (e.g. insurance) or across time (e.g. saving). Risk pooling allows consumption to be smoothed by sharing risk across households in a given state of nature. Risk pooling may take a number of forms including state-contingent transfers (e.g. remittances or reciprocal gift giving) in addition to "disguised" insurance mechanisms such as share tenancy, credit contracts with state-contingent repayments, and long-term labor contracts (Alderman and Paxson, 1994: 49).

III. B. 2. Managing Risk without Insurance

In addition to intertemporal smoothing in accordance with the PIH, credit markets offer another consumption smoothing alternative. Udry (1994) details informal, rural credit markets in northern Nigeria, which function as insurance. The loans are state-contingent and the parties often do not agree on the interest rate or repayment date prior to disbursing loans. An option for credit constrained households is to buy and sell assets to smooth consumption. Selling unproductive assets may not have adverse economic consequences for future periods, but the sale of productive assets will lower expected future income. This is an imperfect solution for another reason since assets are often not divisible (e.g. a cow). The seller may then have to part when the whole asset, when the amount she requires is less than the sale price. Furthermore, asset prices may become depressed due to a simultaneous sell off following a covariate shock.

Multi-period consumption models can be used to model this behavior. They assume the individual will adjust current and future consumption levels to maximize utility given her rate of time preference. Rosenzweig and Wolpin (1993) construct a finite horizon model using longitudinal data to track asset sales and purchases relative to income shocks. Their model captures income uncertainty in each period, constraints on borrowing and renting productive assets (bullocks), returns to experience, and the use of assets to generate income and smooth consumption. At the end of each period, the farmer determines asset allocation for the next period so as to maximize profit, but also requiring a minimum amount of consumption in each period. In this fashion, their model allows them to solve for the profit-maximizing number of productive assets (bullocks). Comparing the optimal to the actual quantity guides further study towards explaining the discrepancy as well as assessing the impact of policies targeted to improve farmer welfare. It should be noted that, in practice, intertemporal and risk pooling strategies may be enacted contemporaneously.

III. B. 3. Characteristics of Risk Pooling

Given the desire of households to smooth consumption and the option to smooth across states of nature, we may expect some risk pooling to occur in the absence of formal insurance markets. The absence of complete credit markets is also assumed for risk pooling to take place. If households had complete access to credit they could simply borrow and save to adjust to transitory shocks and smooth consumption over time (Morduch 1995).

There are several distinguishing factors which characterize risk pooling networks. First, households forming a risk pooling network will have a relatively unimpeded flow of information on other households in the network. This reduces the moral hazard problem of households making claims on the network due to negligence rather than ill fortune. Second, there must be a credible enforcement mechanism to punish households if they renege on their obligations (Coate and Ravallion 1993). This could be a pecuniary measure or social exclusion or reputation effects. Third, households must be sufficiently forward looking (discount factor). If households are insufficiently worried about future income flows they will renege on their obligations. Fourth, risk pooling networks must weigh the costs and benefits of geographic proximity of the member households. A village of agricultural households, for example, will benefit from lower information costs since all households are fairly close together and easier to observe (e.g. similar crops, soil types, etc.). The same village also suffers from the disadvantage of highly covariate income streams.

Tests of risk pooling began to increase in frequency in the economic literature in the early 1990s and continue to the present. Irac and Minoiu (2005) offer a useful review of risk pooling studies which is summarized here. The theoretical foundations for risk pooling are rooted in work done by Cochrane (1991), Mace (1991) and Townsend (1994). The theoretical and econometric contributions of these pieces are amplified in Chapter 3. On the whole, studies by scholars using data from across the developing world find that full insurance is not achieved, but household consumption is reasonably smooth despite the expected variation in income associated with income risk. In many studies (Deaton 1992; Townsend 1994) risk pooling is studied at the village level although others have found risk pooling to take place through cast ties (Morduch 1990 and 2003), ethnic groups (Grimmard 1997) and friends and relatives (Fafchamps and Lund 2003). Most studies of risk pooling use data from rural, agricultural villages where poverty, income risk and the lack of formalized market mechanisms is particularly pervasive.

Although tests of risk pooling are frequently confined to rural villages there is no reason why urban households can not engage in risk pooling. Studies of risk-sharing typically focus on agricultural households at the village level for several reasons. In rural areas credit markets are less likely to be established and functioning. Monitoring and information costs are lower as all households share common information about farming. As a result they have more intimate knowledge of occupational hazards which can reduce moral hazard problem. In addition, analyses of risk sharing in rural areas contain a game theoretic component of repeated interactions. In a rural environment it is realistic to expect that households will have repeated interactions across generations. In urban areas where the households and individuals may move frequently repeated interactions and the threat of sanctions may become less credible if information flows poorly and legal mechanisms operate slowly. Households in urban environments also differ in several other respects. There is substantial diversification of income streams in the urban environment. This could decrease risk sharing since it raises moral hazard concerns. A plumber can not know if a baker has taken steps to minimize his own ill fortune. On the other hand, the reduced income covariance in the urban environment is a desirable trait for partners in the risk-sharing network (Cox and Jimenez 1998).

Cox and Jimenez study urban households in Cartagena, Colombia. The authors find evidence of insurance motivated risk sharing in the urban environment. The probability of receiving transfers is sensitive to network quality. Those households with large networks mostly comprised of better-off members have a higher probability of receiving transfers. They also find strong evidence that transfers are targeted to female-headed households. When all other characteristics are equal having a female headship raises the probability of transfer receipt by 33 percent.

Much of the work on informal insurance typically assumes that the risk pooling network is formed by households often at the village level or across the family. In these cases the risk pooling network is exogenously determined based upon geography or family ties. Work by De Weerdt (2006) shows the formation of risk pooling networks in Tanzania is complex and dependent upon several factors including kinship, geographical proximity, common friends, clan membership, religious affiliation and wealth. The wealth factor is particularly interesting since it clearly shows that not all links are equal. Total household links are correlated with its livestock and land holdings (wealth). Simply put, the rich have denser networks than the poor do. Rich households are more desirable as network partners and select other rich households to be in their network. Poor households are less desirable network partners. Thus although many households may be linked in a risk pooling network, the strength of each individual household's ties may exhibit variation. For this reason the impact of a covariate shock will vary with the strength of the networks. Unfortunately, the LSMS data does not contain information on household networks. As a result this has not been a focal area of this dissertation. Nevertheless the role of networks will be useful in interpreting the results in later sections. We now review a method for evaluating the degree of risk pooling.

III. B. 4. Testing for Risk Pooling: Theory of Full Insurance: Advantages and Limitations[4]

A common test for the degree of risk pooling uses the theory of full insurance. Empirical work has its foundations in models specified by Debreu (1959) and Arrow (1964). When risk is fully pooled, household consumption depends only upon average village consumption. Since households are perfectly insured, household income shocks should not affect household consumption. Thus, if there is full insurance, in equation 1 β_1 will equal 1 and β_2 will equal 0. Although we know β_1 will likely never equal 1, we use this as a benchmark with which to compare the actual level of risk pooling. The exact equation may vary across studies, but the basic idea is:

(1) $c_{ivt} = \beta_0^{\,i} + \beta_1 \bar{c}_{vt} + \beta_2 Y_{ivt} + e_{ivt},$

where c_{ivt} = consumption in house i, in village v, in time t; $\bar{c}$ = average consumption in village v in time t; Y = income of household i; and e = error term to allow for idiosyncratic shocks (Alderman and Paxson, 1994: 65). A number of studies use this premise to test the full insurance theory, although the equation may undergo slight modifications. The consumption equation is highly flexible and adaptable. Additional independent variables can be added as appropriate and the model allows for comparison of sub-unit to unit (e.g. household to village; village to county; etc., Townsend, 1995).

While the consumption equation can be a useful approach, there are several caveats that must be heeded. From an econometric perspective, it is necessary to show that:

(i) comovement in consumption is due to risk pooling;
(ii) measurement error is minimized; and
(iii) correlation between income and the error term is addressed.

Results yielded by the consumption equation must be critically examined since any situation where household consumption and average village consumption comove for reason unrelated to risk pooling will indicate an artificially high level of risk sharing. For example, household and village consumption may co-move due to the nature of village-level and idiosyncratic shocks, not because people pool risk.[5] Ravallion and Chaudhuri draw on Deaton (1990) to note that in a manner consistent with the PIH, if all households

[4] A fuller treatment of econometric tests for full insurance is given in Chapter 3.
[5] E.g. village-level income shocks, a change in prices for example, are permanent because the village all faces the same prices and idiosyncratic income shocks are transitory (Alderman and Paxson, 1994: 68). Under such a scenario, consumption would co-move as households simultaneously recalculate the expected value of their income stream. Over time the expected value of transitory income shocks should average to zero.

received simultaneous information about future income shifts, this could lead to co-movement in consumption, which is unrelated to risk pooling.[6]

IV. Post-Disaster Behavior: The Impact of Aid

Since risk pooling entails the distribution of positive as well as negative shocks it is important to consider the role of post-disaster aid. Donations of aid following a large disaster can be sizeable and it is important to consider the impact of these transfers on consumption. Differences in the patterns of aid distribution may emerge among official and unofficial, inter-household transfers. Before proceeding to a discussion of aid and consumption we briefly review economic explanations for charitable behavior after a disaster.

IV. A. Post-Disaster Charitable Behavior

In the post-disaster environment, simple economic theory would predict that as goods become scarce and demand increases prices will rise. Nevertheless, economists have repeatedly observed an increase in charity giving and cooperation following a disaster. There are two dominant theories which explain the rise in charity after disasters: shifting utility and the alliance hypothesis. The conclusions in this dissertation are insensitive to the underlying motivations for why aid transfers occur. The focus is on whether they do occur, in what magnitude and through what mechanisms. Nevertheless it is useful to consider the prevailing theories on post-disaster behavior to put the research in this dissertation into a broader context.

Dacy and Kunreuther (1969) and Douty (1972) argue that the rise in charity and relative price stability is attributed to a shift in utility functions which increases preferences for charity. Charity is preferred because of an interdependence of utility functions in which the giver values the welfare of the recipient. When the recipient's utility crashes, the donor receives a proportionally greater increase in her own utility with each donation. This is the principal argument although a corollary is that a disaster causes a shift in relative prices and the price of charity falls (lower search and information costs to identify the needy). As charity becomes cheaper the supply increases.

De Alessi (1975) and Hirshleifer (1967) argue it is possible to explain this behavior without any adjustment in utility functions. De Alessi draws from the collective action literature to elaborate upon an "alliance hypothesis" proposed by Hirshleifer. The alliance hypothesis states that the continued functioning of a society in a well ordered manner is a collective good. When the stability is jeopardized even the most selfish will engage in altruism to support the society's continued stable functioning. In short,

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[6] Ravallion and Chaudhuri observe that while Townsend (1994) finds a high comovement of consumption in Indian villages, this is not due to risk pooling and may indeed indicate a lack of consumption insurance. (p. 183). To demonstrate this they argue that "if comovement in consumption is being driven by risk-sharing, and if the correlation between individual consumption changes is due to endogeneity of labor-leisure choices, then individual household consumption changes ought to be correlated as well with aggregate income changes since risk-sharing implies the pooling of incomes", however their results do not support this assertion.

disasters increase the marginal effectiveness of individual efforts to preserve society. As the fruits of individual efforts increase, the collective action problem begins to dissolve since there are clear returns to individual behavior. However a tipping point exists beyond which individuals will prioritize their own wealth preservation and antisocial behavior will begin to dominate. The recent example of New Orleans post-Katrina suggests a situation in which antisocial behavior temporarily dominated.

IV. B. Aid Transfers

IV. B. 1. Official Aid

The role of aid in sustaining consumption emerges as a strong theme in Chapter 3 and throughout the dissertation. Empirical work on the benefits of aid transfers is large and typically shows that aid is effective at raising consumption. There are of course questions of targeting, but poorly targeted aid can still provide positive benefits for consumption. Using data from Ethiopia Dercon and Krishnan (2002) find that despite food aid being poorly targeted, it contributed to improved consumption which is largely attributed to intra-village risk sharing. Since a third of all aid received by sampled Nicaraguan households was food aid it is useful to quickly review the work of Dercon and Krishnan and the relationship between food aid and intra-village risk sharing.

Food aid (and aid in general) is subject to targeting problems: errors of inclusion and exclusion. In practice errors of inclusion dominate as people and households are unnecessarily included due to cultural or political pressures. As a result a finite amount of food aid becomes thinly stretched across too many recipients and its impact is minimized (Sharp 1997). An alternative to food aid distribution is work-for-food programs which require self-screening by the recipients. Dercon and Krishnan find that participation is highly sensitive to idiosyncratic crop shocks (statistically significant at 1 percent) in Ethiopia. The authors also find that having a male headed household is statistically shown to increase receiving aid (at 5 percent, although food aid declines as the number of household adult males increases).

Food aid may have a deleterious effect on risk pooling networks if food aid crowds out informal mechanisms (Albarran and Attanasio 2002; Cox et al. 1998; Cutler and Gruber 1996). This is manifested by a change in relative values of participating in the informal network. If formal aid makes foregoing participation in informal risk-sharing arrangements an optimal decision there will be less informal insurance, which can make some households worse off. Furthermore, risk-sharing dictates that the impact of both positive and negative shocks is shared. Even with imperfect risk-sharing food aid should still be shared. In a network with complete risk-sharing the distribution of food aid does not matter. The positive shock will simply be distributed by the recipients. However, no studies have found full risk sharing, which makes such a scenario unlikely. Thus the distribution of aid will hold implications for exclusion and coverage of needy households. The combinations of risk sharing and targeting are succinctly summarized by Dercon and Krishnan (reproduced in Table 1.1 below). Based upon earlier studies which show an absence of full risk pooling and assuming aid is imperfectly targeted this produces the outcome in the middle grid. When risk is imperfectly shared some risks will be imperfectly insured and some state-specific outcomes will be excluded. Similarly when aid is imperfectly targeted errors of inclusion will dominate giving excess aid coverage.

Table: 1.1 Targeting and Informal Risk-Sharing

	Perfect Targeting	Imperfect Targeting	No Targeting
Full Risk-Sharing	No exclusion; Full excess coverage	No exclusion; Full excess coverage	No exclusion; full excess coverage
Imperfect Risk-Sharing	Possible exclusion; Possible excess coverage	Possible Exclusion; Possible excess coverage	Possible exclusion; excess coverage
No Risk-Sharing	No exclusion; No excess coverage	Some exclusion; some excess coverage	No exclusion; Full excess coverage

Source: Dercon and Krishnan 2003
Note: Exclusion refers to poor households who did not benefit from the transfer (in terms of higher living standards); excess coverage refers to non-poor households who benefited from the transfer scheme.

After empirical tests Dercon and Krishnan find that food aid is shared albeit to a limited extent. They also find that evidence that food aid crowds out informal risk-sharing mechanisms. The results from Ethiopia are interesting compared to post-Mitch Nicaragua since food aid in the surveyed villages is formalized and distributed on a regular basis. By contrast the aid which arrived after Mitch for Nicaraguan households was unanticipated. This may not lessen the problem of excess coverage, but could hold implications for a household's decision to maintain participation in risk-sharing networks. If a household expects that formal aid distribution will occur in perpetuity this must be weighed against the costs of participating in the informal network. By contrast unanticipated aid disbursement which is clearly state-contingent is unlikely to be similarly priced into a household's decision making function.

IV. B. 2. Private Aid Transfers

Private transfers also play a role in sustaining post-disaster household welfare and are motivated by two reasons: altruism and exchange (Cox et al. 1998). The altruism model (Becker 1974) presumes an interdependence of utility functions and argues that donors derive utility from the welfare of the recipients. The exchange model states that one party gives because it expects reciprocal behavior in the future. Reciprocal giving could include cash or non-monetary assets such as labor. A key implication of these theories is the relationship between transfer motivation and public sector insurance programs. Under the altruism model donors give to raise the welfare of the recipients and to satisfy altruistic motivations. Thus if public sector transfers increase we can expect private transfers to reduce by an equivalent amount (Becker 1974; Barro 1974). The implications are different for the exchange model, which need not lead to a crowding out of private transfers. Using data from Peru Cox et al. (1998) find that transfer behavior can not be explained purely by altruism. Instead results suggest exchange motives since there is a positive relationship between transfer amounts and recipient income.

Private transfers can be either inter-household transfers or remittances from family members living outside the home areas (urban migrants) or migrants abroad. Since the Nicaraguan data set does not disaggregate the two types the role of remittances is not a focal point of the dissertation. Nevertheless it is useful to acknowledge the motivations for remittances and their potential role as an insurance mechanism. Using data from Botswana Lucas and Stark (1985) show that the two prevailing theories for remittance motivation, altruism and self-interest, are incomplete. Instead remittances are better explained by a model of "tempered altruism" or "enlightened self-interest" which considers both theories when modeling remittances. It is important to note that remittances may occur for reasons other than risk pooling. For example, remittances may be part of a life-cycle process in which children abroad are repaying parents for money invested in their education earlier in life. Alternatively, remittances may also occur to fund investment, maintenance or upkeep of property or assets at home for which the remitter anticipates inheriting or may already own. In these cases remittance flows would not occur for reasons of risk pooling. In other situations sending household members abroad (or even from rural to urban environments) offers risk diversification by virtue of diverse income streams in heterogeneity of risk. In response to a widespread shock Lucas and Stark show that during a drought in Botswana the remittances are not targeted to maintain recipient welfare, but instead to protect those families with more cattle.

V. Non-Market Coping Mechanisms

In addition to financial arrangements households may also use non-market mechanisms to cope with risk. Lacking access to savings, credit or informal market risk coping mechanisms, one method of coping with risk is to alter household size. Early work on the economic formation of the household (Samuelson 1956, Becker 1981) states that households may benefit from forming to take advantage of economies of scale and from sharing public goods. Similarly, adjusting household size can be an effective mechanism to improve household per capita consumption. There is some evidence from the developing world to suggest that larger households are poorer on a per capita basis (Lanjouw and Ravallion 1995) although results are not consistent across the countries surveyed. In theory, adjusting household size can impact household per capita consumption depending on how the household is restructured (Atkinson 1992). One example of how household composition impacts per capita welfare is with the amount of children in a household. Since adults and children have different nutritional and welfare requirements adding or removing can impact welfare vis-à-vis food costs.

VI. Gender and Risk Coping

Across the developing world women frequently encounter inequalities which leave them economically disadvantaged and often marginalized (UN 2006, World Bank 2002). Lacking equal economic opportunity female headed households may potentially be constrained as they seek to execute the same risk coping strategies as male headed households. Evidence from the development economics literature tends to suggest that female headed households are favorably targeted by inter-household transfers (Cox and Jimenez 1998; Cox et al. 1998, Cox et al. 2004). Female headed households are often targeted as recipients of inter-households since the donors are frequently migrant husbands who are working abroad. Since female headed households have comparatively fewer economic opportunities they have a higher income risk (Cox and Jimenez 1998). Private transfers may contain a risk coping component. As mentioned earlier the post-disaster period is accompanied by exogenous aid flows, which are distributed through organized, formal channels. Although explicitly designed to help cope with risk, gender inequalities in the allocation decision making process may diminish the effectiveness of post-disaster aid for female headed households (Bradshaw 2004).

VII. Analytical Focus

The dissertation builds on risk-sharing themes and the research is focused in three areas: household response to covariate risk, adjusting household size as a non-market coping mechanism and coping behavior of female headed households after Mitch.

VII. A. Household Response to Covariate Risk

Nicaraguan household panel data surrounding Hurricane Mitch presents an opportunity to examine the impact of covariate shocks on household consumption and the role of aid in maintaining household consumption. Chapter 3 analyzes the performance of informal insurance when the risk pooling mechanisms designed to handle idiosyncratic risk are confronted with widespread damages across the risk pooling group. This chapter also explores post-disaster aid targeting. Results indicate that aid played a critical role in sustaining Nicaraguan household consumption. Official aid was targeted around harvest losses, but inter-household transfers were not targeted based upon hurricane damages and were insufficient to act as adequate means of insurance. Results suggest that household consumption was sensitive to harvest losses and damage to income-generating assets, but relatively insensitive to other hurricane damage types.

VII. B. The Impact of Hurricane Mitch on Household Size

Deprived of the ability to turn to well functioning market mechanisms households may utilize other non-market mechanisms to cope with Mitch damages. Chapter 4 studies the decisions of households to adjust household size as a non-market coping mechanism. The actual process by which a household adjusts size could take many forms. To reduce household size parents may send a child to live with grandparents or other relatives. Alternatively elderly parents may move to reside with another child. In other cases adult members may separate and form their own household. Young adults (or other members) may migrate to urban areas in search of employment. To increase household size the household could absorb relatives from other households.

The analysis in this chapter is rooted in economic work on the relationship between household size and welfare (as measured by household per capita consumption). Starting from the simple premise that more affected households may decrease size in order to increase household per capita consumption, we explore this hypothesis and also identify the probability of altering household size based upon Mitch damages and demographic characteristics.

Using panel data from the LSMS surveys it is possible to analyze patterns of household change during two periods. The first period (1998 – 1999) begins several months prior to Mitch and ends the next year. The second period (1999 – 2001) offers an additional period for comparative and analytical purposes. This chapter tests for (i) factors which significantly affected the probability that a household would alter size after Mitch and (ii) that households adjusted size as a coping mechanism to increase per capita consumption after Mitch. Results suggest that the incidence, but not the size, of agricultural losses significantly increased the probability of reducing household size after Mitch. Demographic factors such as the gender of the household head and household size strongly influenced the probability of changing household size. We also find evidence to suggest that households with agricultural losses adjusted size as a post-Mitch coping mechanism.

VII. C. Aid Distribution to and Behavior of Female Headed Households

In the development literature it is widely reported that female headed households are economically disadvantaged. They tend to be poorer and are often socially or politically marginalized. Research from disaster anthropologists suggests that female headed households also have less access to post-disaster relief. Chapter 3 demonstrates that female headed households received less official aid than male headed households. Chapter 4 shows that female headed households were more likely to increase household size after Mitch. These conclusions raise two questions about the female headed households which are the focus of Chapter 5: (i) Were female headed households disadvantaged in receiving official aid because of their gender? (ii) Why were some female headed households more likely to increase household size after Mitch?

Analysis of survey data shows a mixed pattern of aid distribution to female headed households. On the whole, female headed households received less aid, but having a female household head is not a statistically significant determinant of aid received. However, when focusing on agricultural households we find evidence of a gender bias in official aid distribution. After Mitch households with female heads were likely to temporarily add members. A closer look at the welfare and Mitch damage indicators for female headed households offered no clear evidence as to why some female headed households added members, while others did not. Tests to identify why certain female headed households increased household size are inconclusive.

VII. D. LSMS Data

Before proceeding it is useful to quickly review the applications of this data set for its suitability for use in this dissertation. The World Bank LSMS data from Nicaragua has been used in a number of research papers. A listing of these papers is maintained on the

World Bank's web site.[7] The LSMS data has been used for departmental research papers, papers published in peer-reviewed journals as well as Master's and Ph.D. Theses. The themes of these papers are diverse. Topics include labor choice, ethnic wage differences, unemployment and education. At the time this dissertation was submitted none of the papers using the Nicaragua LSMS data focused on the impact of Hurricane Mitch. After submission, an additional internal World Bank study was listed on the World Bank website entitled "Hurricane Mitch: A Study of Vulnerability in Nicaragua" (Cha 2006).[8] A review of these papers revealed no data insufficiencies which would preclude the use of the LSMS as the data source for this dissertation. Based upon the list of peer-reviewed papers and Ph.D. theses which use the Nicaraguan LSMS and discussion with my advisors the data was deemed suitable and reliable to investigate the research questions posed in this dissertation.

The dissertation refers frequently to household consumption, harvest losses and long-term losses and other damage metrics caused by Mitch. Before proceeding we briefly review how these variables are constructed. Household consumption as reported by the LSMS is aggregate household consumption divided by the number of household members to yield per capita household consumption. Consumption includes durables and excludes large purchases of "one off", big ticket non-durable items. Consumption is weighted to account for regional price differences. Consumption is constructed consistently across surveys before and after Mitch. Price levels were fairly consistent between the 1998 and 1999 survey periods and the implicit price deflator actually declined by 2%.[9] Harvest losses are reported by the household and estimate the total value of crops destroyed by Hurricane Mitch. Long-term losses are also reported by the household and estimate the total value of agricultural assets destroyed by Mitch. These assets may include, but are not limited to, irrigation networks, farm tools, livestock, barns, seeds and fertilizers.

It is important to address how the construction of these variables may impact the results before advancing. The construction of the LSMS consumption variable ensures that consumption can be compared consistently across regions and survey periods having consistently addressed the composition of consumption and the impact of price changes. Since the dissertation deals in great detail with agricultural households and in particular harvest losses as well as consumption it is important to ensure that the survey construction does not impact the analysis.

A key issue is whether the timing of harvest sales impacts consumption. Our principal concern is whether 1999 consumption is financed out of the 1998 harvest receipts and thus any impact on consumption in the post-hurricane period would be minimized. If 1999 consumption is heavily dependent upon 1998 harvest receipts we would expect 1999 consumption to be relatively unaffected by Mitch losses. The impact of harvest

[7] http://www.worldbank.org/LSMS/research/country4.html/#nicaragua

[8] The author attempted to locate a copy of this paper (unavailable online or in print), but was unable to prior to the revision submission deadline.

[9] United Nations National Accounts Main Aggregates Database http://unstats.un.org/unsd/snaama/Introduction.asp

losses due to Mitch would then be evident in 2000 consumption. This scenario assumes that consumption patterns are largely derived from earned harvest income. In theory and practice it is possible that consumption decisions are based both on past income and expected future income. Nevertheless, this scenario represents a valid concern. Fortunately there are several checks that enable us to know that this possible scenario will not adversely affect the analysis.

The 1998 and 1999 surveys measure consumption at the time of their respective surveys. The resources to finance household consumption are constantly accumulated over the course of the year whether the source be crop sales or other sources (e.g. labor income, or remittances). The principal harvested crops include corn, beans, wheat, sorghum, coffee and rice. Other crops such as various fruits and vegetables are grown to a lesser degree. Obviously the harvest season will vary according to the crop(s) each household grows. Particularly, as households grow a diverse range of crops for sale and self consumption there is no singular fixed sale date. There are no receipts if the food is for own consumption and harvest receipts may be received on a rolling basis. Thus, there is no uniform harvest date that can be applied to all agricultural households as the date is sensitive to the type of crop grown as well as if the crop can be stored. In addition households which grow crops for their own consumption can not store these (e.g. fruits and vegetables) and they can not be financed out of past receipts since they would have also been grown and consumed in the previous period.

Clearly, it is difficult to argue that consumption is not financed to some degree out of past earnings. At issue is whether the degree is such that the impact on next period consumption is minimal because of a heavy reliance on pre-Mitch harvest earnings to finance post-Mitch consumption. In this case the rolling nature of harvests implies that crop income is a stream rather than an annual or seasonal event. Secondly, consumption is both forward looking as well as backward looking meaning decisions are not made entirely based upon past harvest receipts (as elaborated upon in the discussion of the permanent income hypothesis in Chapter 1). Finally, households which grow their own food obviously do not receive revenue for this food, but losses to these households still has a fiscal value which can impact post-Mitch consumption decisions. Considering these factors the structure and design of the LSMS survey is deemed not to adversely impair the author's ability to answer the research questions posed here.

VII. E. Outline

The dissertation proceeds as follows. Chapter 2 provides background information on disasters and development, Nicaragua and Hurricane Mitch. Chapter 3 focuses on the performance of informal insurance networks in the face of Mitch and the targeting efficiency of post-Mitch aid allocation. Chapter 4 explores the decision of many households to adjust household size after Mitch as a possible post-Mitch, non-market coping mechanism. Chapter 5 examines the role of gender in receiving post-Mitch aid and focuses on the behavior of female headed households following the hurricane. Chapter 6 concludes.

Finally, all financial losses in the dissertation are quoted in Nicaraguan cordóbas unless otherwise indicated. At the time of Hurricane Mitch, the official exchange rate was approximately 10.8 cordóbas per USD. The currency depreciated to 11.5 per USD in April 1999 (the outset of the second survey round).

Chapter 2

Disasters, Development and Mitch

I. Disasters and Development

I. A. Global Economic Loss Trends from Natural Disasters

In recent years, there has been a common perception that disaster losses have been increasing at a rapid rate. Recently some organizations have published figures to illustrate the rapid increase in disasters losses, particularly in the last 30-50 years (e.g. Swiss Re 2005). Figures from the United Nations, for example, indicate that global economic losses attributed to natural disasters have increased from US $75.5 billion in the 1960s to $659.9 billion in the 1990s (UNDP, 2004). More recent events such as Hurricane Katrina in 2005 have reinforced the perception of an increasing loss trend associated with natural disasters.

However, such a perception may be inaccurate. Recent work questions the accuracy of a rapidly increasing trend in losses (Pielke 2005, Van der Vink et al. 1998). Earlier work on loss trends likely overstates losses because they only control for changes in inflation over time. Rising loss trends are also driven by two other important dynamic components: changes in population and changes in wealth. It is only natural that as societies become larger and wealthier over time that there will be more assets and people in vulnerable areas. New work on normalizing loss trends by controlling for changes in inflation, wealth and population over time and finds minimal evidence of an upward trend for US hurricane (Pielke and Landsea 1998, Collins and Lowe 2001, NOAA 2005) and flood losses (Pielke et al. 2002). A subsequent global survey of weather-related losses[10] over time that adjusts for all three factors finds evidence of an upward global trend of approximately 2% per annum (Miller et al. 2007, Figure 2.1 below) – which while notable is lower than rates previously implied (Swiss Re 2005).

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[10] Weather related losses exclude losses from geophysical phenomena such as earthquakes, volcanoes and tsunamis.

Figure 2.1

Source: Miller et al (forthcoming 2006)

These trend results are encouraging in that they no longer imply an exponential increase in global disaster losses. However, the losses in Figure 2.1 are in nominal USD and do not capture the relative impact of losses. The weight of a large loss event can be almost negligible in a large economy such as the US or Japan. By contrast losses in developing regions may be felt more severely in relative terms.

I. B. Disasters and Development

The impact of disasters varies based upon the level of economic development. The least developed countries are the most vulnerable and have the highest losses relative to the country's wealth. Lower-middle and middle income countries can also be increasingly vulnerable in different ways. As the economy develops, the breakup of family support networks and traditional coping mechanisms can leave the poorest groups even worse off. Wealthy countries typically experience high financial costs with disasters, but in relative terms the impact is often negligible on growth when compared to poorer countries (ODI 2005).

The economic impact of natural disasters can be broken down into three types: primary, secondary and indirect effects. The primary impact of disasters can be summarized by the cost of physical assets or capital stock destroyed. Examples may include housing, roads, utility distribution networks, factories and crops. Secondary effects refer to include the costs of disruption to normal economic activity as well as. Indirect effects include an increase in public sector borrowing, inflation, changes in housing prices and any change to pre-planned development projects (Benson and Clay 2000).

There are differing methodologies to evaluate the impact of disasters on development. One means is to use a post-event approach and analyze the movement of macro-economic indicators in the periods before and after the event. Albala-Bertrand (1993) analyzes the movement of key macro-economic variables in 28 disaster situations for 26 countries (24 developing and two developed) over the twenty year period from 1960 to

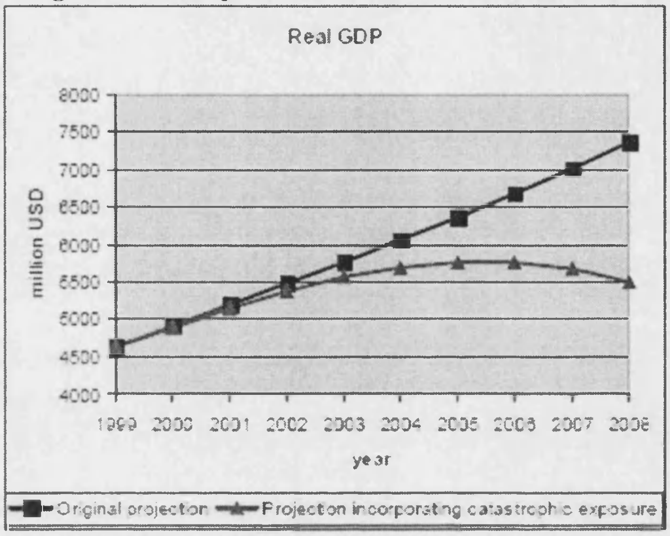
1979. In general, there is neither a fall in GDP due to disasters nor a decrease in the growth rate of GDP. The impact of disasters on these variables is usually positive if anything. The positive relationship between disaster losses and GDP is one which is frequently observed. Since GDP is a measure of economic activity it is natural that GDP will increase following a disaster (particularly due to reconstruction activity). However, focusing only on GDP ignores the value of destroyed assets that must be replaced as well as disrupted economic activity that would have otherwise occurred (Cobb et al. 1995).

In Albala-Bertrand's study he used post-event analysis to show that most other indicators such gross fixed capital formation, the public deficit and the performance of the manufacturing and agricultural sectors either improve in the year of the disaster or remain neutral and improve in the following year. The trade deficit tends to increase in the year of the disaster, but this increase moves towards pre-disaster levels in the years following the event. Overall, "there is no dramatic loss of current GDP due to natural disasters even if there are some people, groups or sectors which bear important income losses on these occasions."

An alternative to a post-event analysis is to use simulated probabilistic models to project the impact of large disasters and chronic vulnerability on macroeconomic performance. Since the most destructive disasters strike only once every 100 or 500 years a probabilistic model can capture hypothetical impacts that can not be captured solely by using historical data. Furthermore, focusing only on one event ignores the cumulative impact of disaster vulnerability and losses. Work by the International Institute of Applied Systems Analysis (IIASA), the World Bank and the Swiss Reinsurance Company models the impact of chronic disaster incidence on the Honduran economy.[11] Researchers considered the expected frequency and severity of disasters, vulnerability and the expected macroeconomic conditions when the disaster occurs. Using Monte Carlo simulations the researchers find that the incidence of infrequent (occurring between every 100 or 500 years) but possible disasters could destroy between 12 and 31 percent of Honduran capital stock. More regular, smaller-scale events indicate that Honduras requires an annual average of USD $170 million to meet disaster costs. If these financing needs are not met growth is projected to follow the triangled line in Figure 2.2. Whether and how financing needs are met is a separate avenue for discussion, which falls outside the scope of this thesis. We will however touch briefly upon this in a discussion of multi-lateral institutions in the next section.

[11] This work is summarized in Freeman 2000.

Figure 2.2: Projected Honduran GDP 1999 - 2008



Source: Freeman 2000

Overall, the macroeconomic impact of disasters can be limited if large amounts of productive capital stock are not destroyed and external financing is available if needed. While aggregate macroeconomic performance may be only mildly disturbed by a disaster, the people and groups which are most strongly affected are the poor. Albala-Bertrand summarizes: "the people and activities most affected by natural disasters are bound to be those belonging to the poorest and most powerless social sectors of less developed countries." The struggles of low-income citizens of New Orleans after Katrina are a recent reminder that this relationship holds even in the world's largest economy. We now review the impact of disasters on international financial institutions.

I. C. Impact of Disaster Losses on International Financial Institutions: Evidence from the Inter-American Development Bank

Even with a more muted trend in global disaster losses, the economic and social impact of disasters in the developing world remains a real concern. Disaster losses continue to impact the development efforts of multi-lateral institutions such as the World Bank (WB), Asia Development Bank (ADB) and Inter-American Development Bank (IDB). The costs associated with natural disaster damages present several problems for international development lending institutions. The IDB has explicitly enumerated economic damages from disasters as a threat to its mission (IDB 2004.

Disasters threaten the development process advanced by international institutions in several ways. One example is the destruction of loan-financed projects. For example, in 2000 over 500 schools were damaged or destroyed by flooding in Mozambique. Many were financed by World Bank loans (World Bank 2006). A second concern is that the funds are often diverted from approved development loans to meet reconstruction needs. Loan reallocation is a useful mechanism due to its flexibility which allows post-disaster needs to be met, but by definition entails a diversion of funds from a scheduled development project to address disaster costs. Disasters can also have adverse consequences for local development initiatives such as microfinance programs (Pantoja 2002) which slows the advancement of development programs.

Using data from the IDB we can examine the economic impact of disasters from the perspective of an International Financial Institution (IFI). In Latin America and the Caribbean estimated regional losses from disasters occurring between 1975 and 2002 approximated US$92 billion, or an annual average of around US$3.4 billion (IDB 2004. Economic losses in the region are attributed to the interaction of several factors, including: (i) the location of geophysical phenomena in Latin America and the Caribbean; (ii) increased population growth and human activity in disaster-prone areas; (iii) a low use of mitigation and preventive measures; (iv) regional underdevelopment, which limits government resources available to meet disaster costs; and (v) environmental degradation and unsustainable land use policies (Miller and Keipi 2005).

To address the impact of disasters, the IDB allocated nearly US$4 billion to prevention and mitigation and disaster-related response loans between 1975 and 2002 (Table 2.1). On an annualized basis IDB disaster-related loan activities since 1995 were roughly US$475 million per year and amounted to only a fraction of the annual regional losses (IDB 2004. While the amount spent on response and reconstruction provided vital aid to safeguard economic and social programs, the need might have been reduced if additional mitigation spending and risk transfer instruments had been implemented. Of the $3.8 billion in loans the share directed to emergency response and reconstruction outnumbers prevention and mitigation by roughly three to two (59 versus 41 percent, IDB 2003a). Since the annual costs of disasters in the region far exceeds the funds available from the IDB minimizing losses through prevention and mitigation is an important task (Miller and Keipi 2005).

Table 2.1 Total Losses Due to Natural Disasters in Latin America and the Caribbean (1975 – 2002, in nominal amounts)

	Total Loss (US$ bn)	Total Loss per capita in 2001	Highest Annual Loss (US$ bn)	Average Annual Loss (US$ bn)
Caribbean	7.07	322	2.54 (1998)	0.47
Central America*	15.43	268	3.30 (1998)	0.77
Mexico	15.69	158	6.67 (1985)	0.92
South America	533.84	65	8.56 (1983)	1.92
Total	92.03	-	-	-

*Includes Panama

Source: EM-DAT (2003), OFDA/CRED (2002), LaRed (2003) (As it appears in IDB 2004).

Some nations may be able to manage their disaster losses with domestic resources, but that ability diminishes as the severity of disasters increases which creates a resource gap. Cardona (2005) estimates the potential resource gap for 12 countries in Latin America and the Caribbean using the probable maximum loss in the event of an extremely severe (once a century) disaster. Half of the countries are projected to have resource gaps. These gaps would be even larger if expected aid from the IDB and World Bank would not materialize.

The IDB and the international community will continue to offer post-disaster aid. Yet, the IDB and other IFIs are not disaster relief organizations and, as such, narrowing the resource gap with increased IDB (and other external) assistance is not a sustainable long-term strategy. The emphasis must be on reducing losses. This is a task that the IDB continues to embrace. If losses in Latin America and the Caribbean continue to rise, the IDB's direct and indirect exposure will also increase. For this reason the IDB continues to push more forward thinking initiatives to reduce disaster damages. Focal points in this strategy are (i) contributing to the improvement of country risk management strategies and programs, (ii) strengthening its internal capacities and organization to facilitate risk management, and (iii) evaluating existing financing instruments and possibly introducing new IDB instruments (Miller and Keipi 2005). If successfully implemented, a balanced risk management approach can reduce the threat that disasters pose to the Bank's mission as well as to the economic and social development of Latin America and the Caribbean.

II. Nicaragua and Hurricane Mitch

II. A. Nicaragua: Socio-Economic Background

Nicaragua is located on the Central American isthmus and is bordered by Honduras to the north and Costa Rica to the south. The country is divided into 15 departments and two autonomous administrative regions. In 2005 the population was estimated at approximately 5.5 million (UN Population Database). Nicaragua is one of the poorest countries in the Western Hemisphere with a GNI per capita of US$ 710 and a total GDP of US$ 4 billion (World Development Indicators 2004). Agriculture makes up roughly a fifth of GDP. In 2001 49.1% of the country survived on less then $1 a day. Approximately 75% of households live in poverty. Nicaragua ranks 121st out of 175 countries in the Human Development Index (HDI) and 98th out of 144 countries in the UNDP Gender related Development Index (GDI, UNDP 2003). A sizeable cash transfer program, Red de Protección Social, exists in Nicaragua. This program did not begin until 2000 so household behavior after Mitch is unaffected by these transfers.

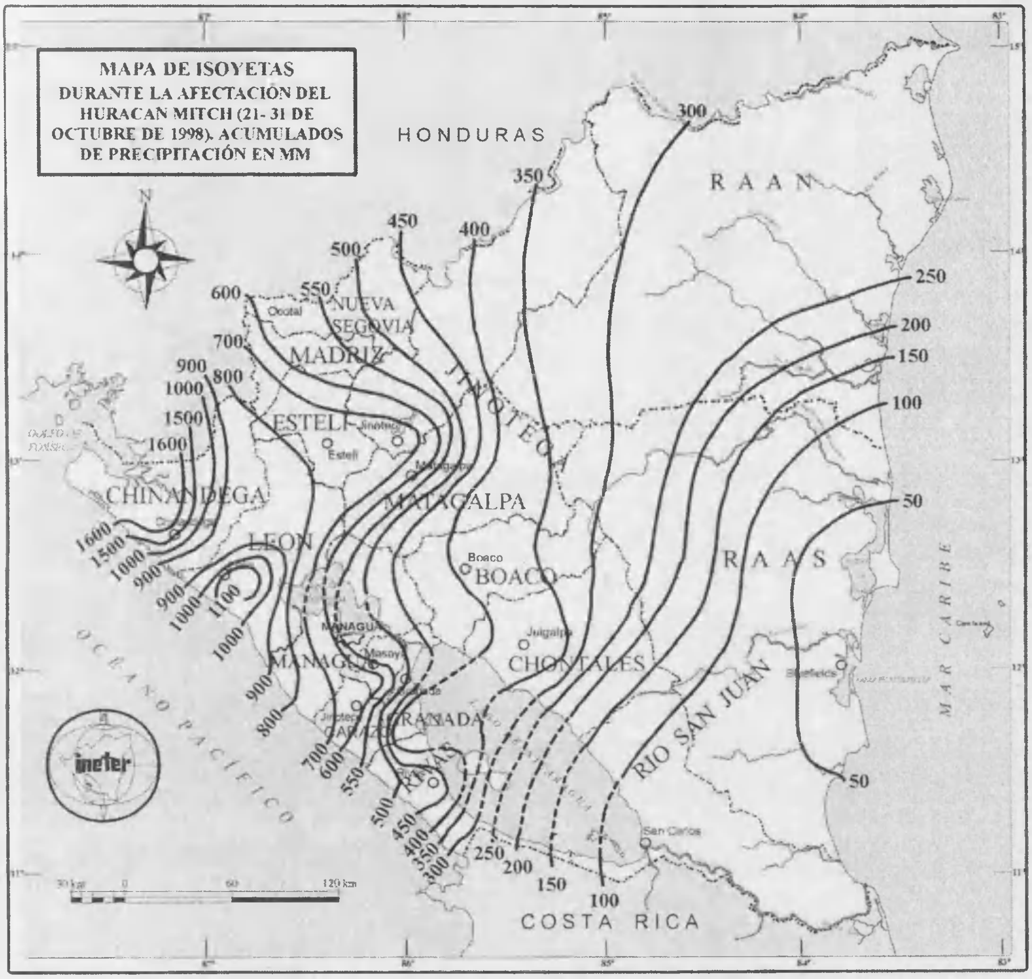
In addition to its poverty, Nicaragua is extremely vulnerable to a myriad of natural disasters including volcanic eruptions, hurricanes, floods and landslides. Since 1970 Nicaragua has been the hardest hit country by disasters in Central America. It has the highest ratio of fatalities per capita and the ratio of cumulative losses to GDP over this time is 338.4% (Charvériat 2000). Historical evidence suggests that Nicaragua's hazard vulnerability contributed to the eventual construction of the Panama Canal in Panama rather than in Nicaragua (McCullough 1978). Several large disasters have impacted

Nicaragua in the past century. In 1931 an earthquake (6.5 magnitude) struck Managua and killed an estimated 2,000 people. Although the quake was not exceptionally strong the epicenter was below Managua and much of the city was destroyed by the quake and ensuing fires. In 1972 an earthquake (6.2 magnitude) struck Managua on December 23rd. Significant aftershocks followed and the death toll approached 6,000. Much of the building stock was destroyed and service to communications and utilities was disrupted. In 1998 Hurricane Joan struck Nicaragua along the Caribbean coastline and affected approximately 300,000 people and caused an estimated US$ 400 million in damages. A series of lesser hurricanes and tropical storms have also struck Nicaragua in recent history but their impact was negligible compared to Hurricane Mitch in 1998.

II. B. Hurricane Mitch

Mitch was identified as a tropical depression on October 22, 1998. The storm slowly built strength and by October 26 it was classified as a Category 5 hurricane with winds in excess of 180 miles per hour. Mitch moved in from the Caribbean coast and made landfall on October 29th. It passed over Nicaragua and Honduras and slowly weakened until it diminished on November 1st. Mitch easily classifies as one of the most intense Caribbean hurricanes in the past 200 years. Its effects were felt in five countries across Central America. Mitch brought with it extremely high winds and tremendous rainfall (Figure 2.3). Between the 25th and 31st of October parts of Honduras received three feet of rainfall. Approximately 19,000 people in Central America were classified as dead or disappeared following the storm, with the bulk of these concentrated in Honduras and Nicaragua (IDB 1999).

Figure 2.3 Precipitation Caused by Mitch in Nicaragua (in mm)



Source: Instituto Nicaraguense de Estudios Territoriales (INETER) Dirección General de Meteorología.

The overall economic damage caused by Mitch in Nicaragua is estimated at approximately US$ 1 billion (EM-DAT). Lost production was estimated at US$ 100.6 million (approximately 5% of annual GDP). The macroeconomic impact of Mitch is visible across several indicators. GDP growth slowed from an estimated 6% prior to Mitch to 4% for 1998. Inflation increased from 13% to 18.5% for 1998. Unemployment increased from 12.2% to 13.3% after Mitch. This increase is largely attributable to the displaced agricultural workers. The value of exports decreased by US$ 54 million although this may be partly attributable to the effects of the Asian Crisis, which made Nicaraguan exports less competitive. The decline in exports combined with an increase in imports after Mitch led the balance of payments deficit to increase to 41% of GDP. Public sector finances decreased as tax revenue slowed after Mitch due to lower levels of business activity. Public sector finances were further strained by the need to provide post-disaster assistance.

Agriculture was the most affected sector and its forecasted share of GDP fell from 14.8% to 6% in 1998. Official sources estimate the agricultural losses translate into 27.3% of lands ready for harvest (or 67.8 thousand hectares) having their crops lost to Mitch. Production of key crops for domestic consumption and for export such as rice, beans, sorghum, corn and soy beans were heavily affected. In addition to crop loss some farmlands were rendered unusable due to heavy accumulation of mud, sediment and rocks on the fields caused by the intense rain and flooding.

The impact on Nicaraguan infrastructure was severe as 114 municipalities (78% of the total) were affected by Mitch (CCER 1999). Of these 72 were strongly affected. These areas also experienced substantial damage to water distribution networks, which exposed the population to diseases associated with unclean drinking water. In many municipalities schools and community centers were also destroyed which had a perverse impact on the education of children in those areas. Damage to infrastructure was widespread and included the loss of 1,500km of paved roads, 6,500km of unpaved roads, 3,800 bridges, and 31,737 destroyed homes. The education and health sectors lost 1,600 classrooms and 90 health centers and 416 more rural *puestos de salud* as well as the medical equipment these facilities contained. Damage also extended to fire stations, potable water systems, latrines, hydroelectric power generation facilities and electricity distribution networks (CCER 1999).

After Mitch the provision of food, shelter and health care were pressing concerns. From January to March 1999 the Coordinara Civil para la Emergencia y la Reconstrucción (CCER) carried out a survey on the distribution of aid and welfare of people after Mitch. This survey found the following notable responses at the time of the survey:

- 50% of households said no household member had a "stable" household income;
- 46% of households indicated the harvest was their most important loss;
- For every 10 families suffering losses three did not receive aid;
- Food aid was the most useful type of aid;
- NGOs were identified by 41% as giving the most community support (as perceived by the population) followed by local governments (21%), Catholic Church (16%), Red Cross (16%), Other Churches (4%) and the National Government (2%);
- 46% found the distribution of aid to orderly compared to disorderly (36%).

Analyzing the impact of Mitch several patterns are evident. Poverty in Nicaragua is widespread and as most household are rural, poverty is concentrated in rural areas. Agriculture is an important means of income for Nicaraguan households. We can expect that households heavily engaged in agriculture will be most strongly affected by Mitch. After the hurricane households relied on outside aid since income stability was a concern, inflation pushed prices up and the provision of public services was curtailed. Of the factors affecting Nicaraguan households after Mitch two are emphasized throughout this dissertation: agricultural losses and post-disaster aid. With these antecedents in mind, the focus of this dissertation moves to a household level focus.

Chapter 3

Household Response to Covariate Risk: Nicaragua and Hurricane Mitch

I. Introduction

Households in developing nations must manage risk without many of the formal mechanisms established in the developed world. Since many of the world's poor rely on agriculture for a living, they are subject to weather risk as well as an array of idiosyncratic risks that may affect household production, investment decisions, income and consumption. Households are often, but not always, able to use informal insurance and second-best coping mechanisms to mitigate idiosyncratic income risk and smooth consumption fluctuations. Studies of risk pooling have found evidence to suggest high, but less than perfect, levels of risk pooling (Deaton 1990, Townsend 1994, 1995) across the developing world. Despite a failure to achieve Pareto efficiency, risk pooling can still achieve a high degree of effectiveness in smoothing household consumption from idiosyncratic household income risk.

In cases where risk pooling is ineffective due to covariate risk or impossible due to social or organizational reasons, households must rely on second best coping strategies. Evidence from the developing world shows that households are able to utilize risk pooling and coping mechanisms to mitigate the impact of idiosyncratic risk. Household coping strategies may include saving (dissaving) during transitory positive (negative) shocks (Paxson 1992), the accumulation of buffer stocks (Fafchamps et al. 1996), asset sales, as well as altering the composition of agricultural investments (Rosenzweig and Binswanger 1993). In India, for example, Rosenzweig and Wolpin (1993) found that credit constrained households smooth consumption by accumulating livestock as a buffer stock. While contributions in the literature have provided excellent insights as to how households respond to idiosyncratic risk, comparatively less is known about a household's ability to smooth consumption against covariate risk. This question is particularly relevant since covariate shocks can not only overwhelm informal insurance arrangements, but may weaken or remove second best coping options as well. This scenario plays out regularly in the developing world when a destructive natural disaster strikes.

If informal insurance mechanisms are sufficiently broad households may be able to mitigate severe drops in consumption. In this case it would be essential for the risk pooling network to extend beyond the afflicted area. Given that risk pooling is likely to dissipate with distance this is unlikely (Rashid 1990). Indeed, the basic premise of insurance dictates that risk pooling is ineffective at mitigating highly covariate risk. At the extreme, when all households are affected mutual insurance arrangements are ineffective as all households simultaneously require insurance payments in excess of the pool's ability to pay. When a large-scale natural disaster strikes insurance arrangements in the developing world (and often the developed world) are overwhelmed by the magnitude of losses.

The ineffectiveness of informal insurance arrangements may not be problematic for consumption smoothing if households have access to other effective coping mechanisms. But, large scale disasters are both disruptive and destructive. They frequently wash away crops, flood homes and farm land, destroy stores of grain and income-generating assets, damage homes and kill livestock. Coping strategies founded upon these assets can have their effectiveness radically reduced. A third line of defense is the influx of post-disaster transfers in the form of disaster relief aid provided by governments, NGOs, international organizations and inter-household transfers (both domestic and from abroad). These mechanisms are likely to be less efficient than risk pooling networks given increased asymmetric information and monitoring challenges that confront donors and remitting households. Despite these imperfections, these mechanisms may assume paramount importance after large-scale natural disasters, particularly when assets are destroyed. The occurrence of Hurricane Mitch in Nicaragua in 1998 combined with panel survey data provides an opportunity to investigate the ability of households to mitigate consumption against covariate risk.

With these antecedents in mind this chapter has three objectives. The first is to test the ability of households to effectively insure against specific types of quantitative and qualitative hurricane damage (enumerated in the next section). The second goal is to evaluate the relationship between aid transfers and shocks. Although transfers are by definition part of an informal insurance strategy, the incidence of windfall aid transfers from government, relief organizations, etc. does not typically occur in response to idiosyncratic or even other types of covariate risk and merits attention. Whether donors were able to effectively target these transfers is an important question. Well targeted transfers could play a crucial role in moderating the impact on household consumption, while poorly targeted transfers may be at best inefficient and at worst, do nothing to ameliorate the impact of Mitch, especially for the neediest households. The final objective is to investigate alternative coping mechanisms.

The chapter is organized as follows. Section II reviews the data set and background information. Section III presents the impact of Mitch-specific shocks on consumption. Section IV discusses the relationship between shocks, transfers and coping strategies. Section V concludes.

II. Data and Background

II. A. Data

In the past, the evaluation of the household impact of natural hazard shocks has been complicated by the lack of *ex-ante* and *ex-post* panel data closely surrounding the hazard date. Fortunately, the LSMS in Nicaragua offers an opportunity to test the impact of covariate disaster shocks. A few months prior to Mitch INEC executed a scheduled national household survey as part of the World Bank's LSMS. Following the hurricane INEC revisited 595 households in 1999, which, among other goals, assessed the impact of Mitch on panel households in affected regions.

In the 1999 survey, survey selection was weighted to give a higher probability of selection for households in areas affected by the hurricane. The sample was drawn using a two-stage stratification process, with the population stratified geographically.[12] Of the 595 households approximately 10% (55) could either not be located or had incomplete interviews, with the majority not located. An additional 48 were "split" households from 1998. Split households were substituted back in depending on where the head resided. Of the 48, 23 were substituted and 25 removed. The direction of a possible bias this elimination may introduce will be discussed further in Section V. This yields 528 total households for analysis here. Some regressions (presented in the next section) which use agricultural losses as the dependent variable use 321 households since not all households were engaged in agricultural activity.

II. B. Background

In October of 1998, Hurricane Mitch caused numerous deaths and large-scale economic losses to Nicaragua and much of Central America. Mitch caused a wide range of damages to household assets, homes, and household infrastructure. To capture the range of possible idiosyncratic damages five damage metrics are considered: (i) damage to current harvest; (ii) damage to long-term (income-generating) assets[13]; (iii) days homeless due to Mitch; (iv) housing damage; and (v) damage to the household water source. Together these shocks account for the bulk of household-specific damage a household could have received from Mitch, with the exception of injuries and fatalities. Summary statistics are presented in Table 3.1.

[12] The 1998 survey was administered between April and August, while the 1999 survey was administered between May and June. Although the dates are not identical, the driving concern is whether variation in the survey periods is correlated with consumption. Since both periods fall largely within the third quarter, seasonal issues, which might correlate with consumption, should be minimal.

[13] Long-term assets include all agricultural damages other than harvest losses. Examples include damages to irrigation infrastructure, tools, machinery and work animals.

Table 3.1: Survey Summary Statistics

Households:	
Total	528
Engaged in Agriculture	321
By Poverty Line:	
Extreme Poverty	127
Poverty	197
Not Poor	204
Female Headed	103
With Composition Change Between Surveys	266
Mean Per Capita Household Consumption (in cordóbas):	
1998	4746
1999	4756
Mean Shock Values:	
Lost Harvest (in cordóbas)	3865
Long-term Losses (in cordóbas)	1369
Days Homeless	4.8
Aggregate Shock Values:	
Households with Wall Damage	120
Households with Water Infrastructure Damage	92
Mean Aid Values (in cordóbas):	
Official Aid	611
Unofficial Aid	143
Total Aid	754

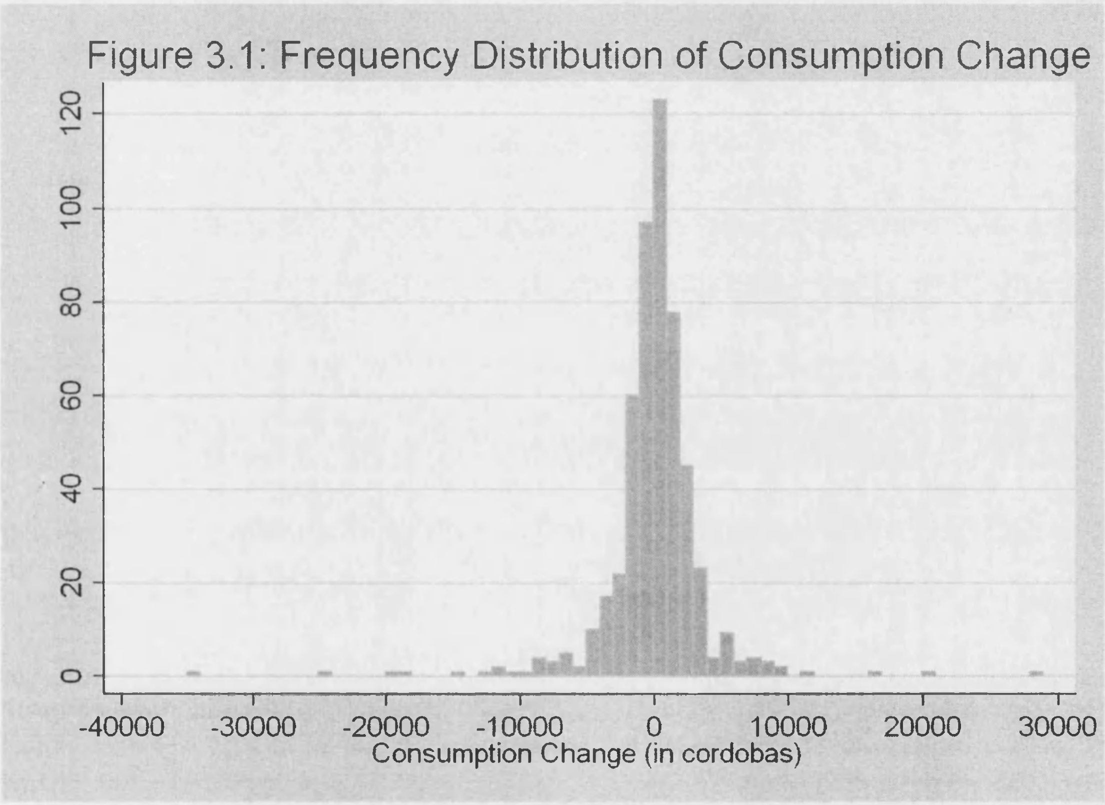
Source: Author's calculations

From the data in the table we can observe that many of the surveyed households were relatively poor. It is interesting to note that despite the distribution of Mitch damages and in particular the high mean harvest loss, mean household consumption marginally increased. The increase appears somewhat counterintuitive, but may be explained by mean aid which accounted for roughly 16% of mean household consumption. We investigate this possibility later. Descriptive statistics provide a useful starting point, but a more rigorous analysis is required in order to more fully understand the impact of Mitch damages on consumption and the relative role of aid in the recovery process. The models presented in parts III and IV explore the relationship between hurricane damages and consumption, and aid and damages, respectively.

III. Effect of Mitch Shocks on Consumption

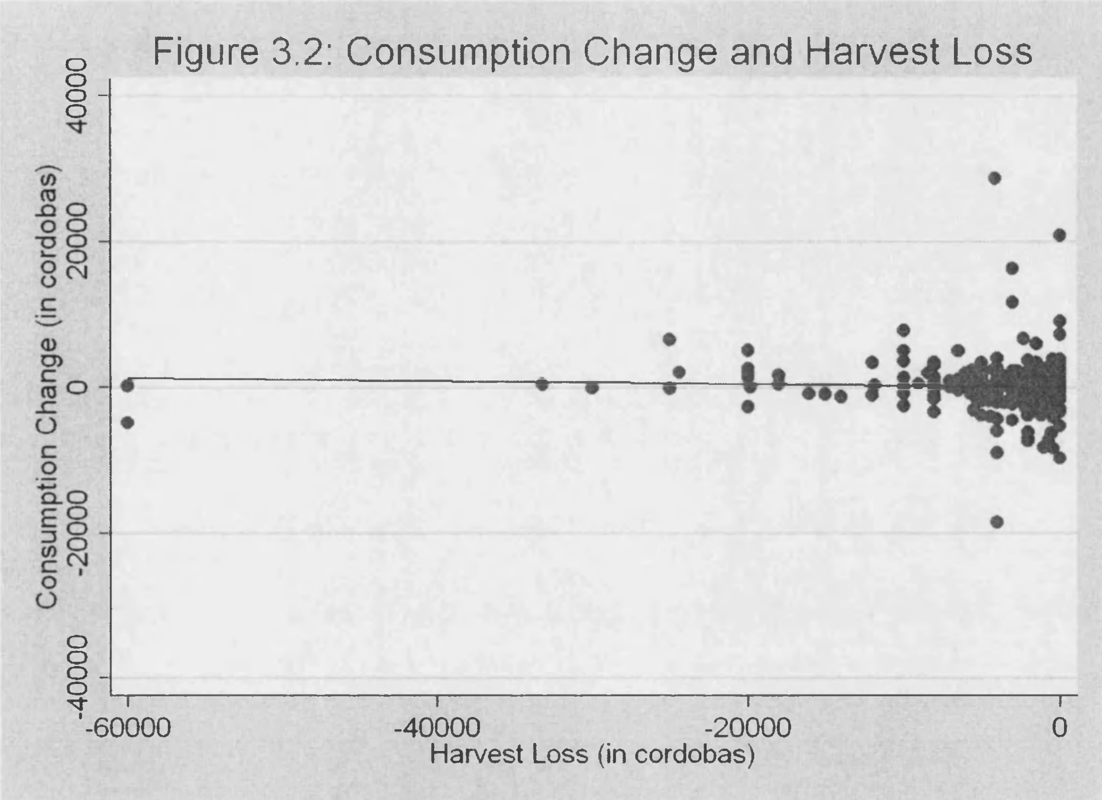
III. A. Data Diagnostics

Before proceeding to a discussion of regression results we present plots of consumption change for the survey as a whole and for specific shocks. Figure 3.1 presents a frequency distribution of consumption change. The distribution shows that the consumption change for most households was relatively mild in nominal terms, although any drop could have serious consequences for poorer households.



Source: Author's calculations

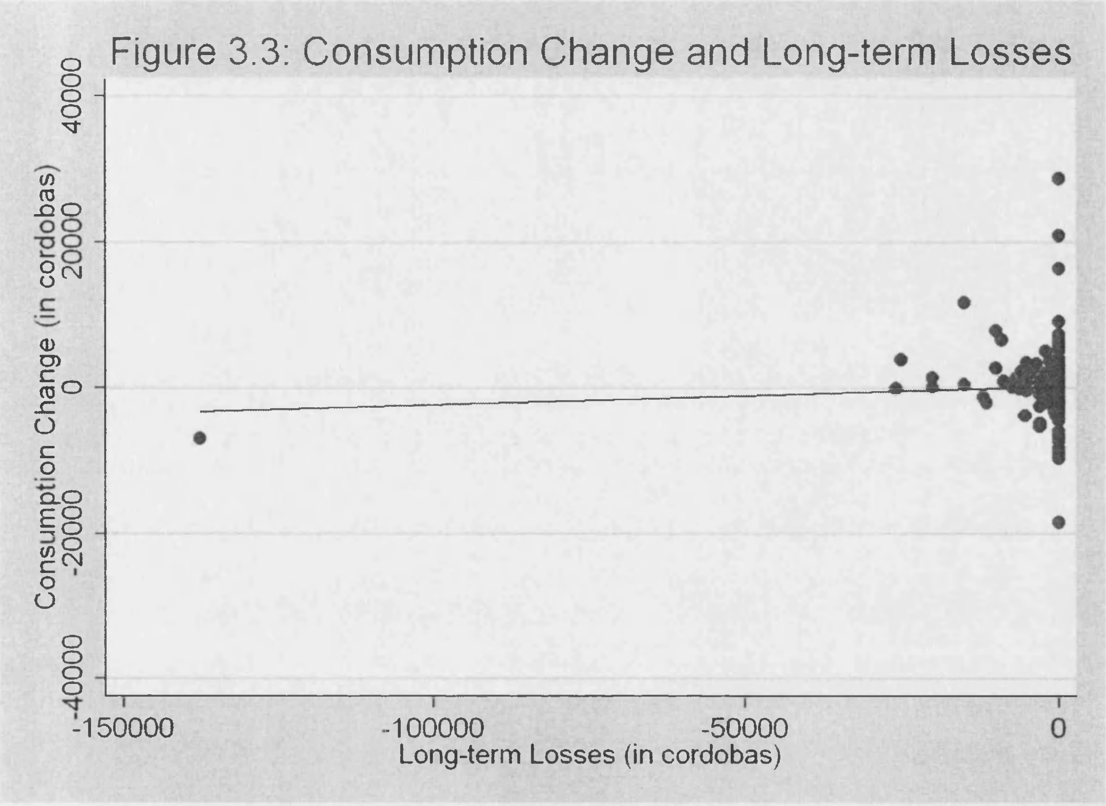
Figure 3.2 considers the relationship between our first shock, harvest losses, against consumption change (both measured in córdobas). Since a harvest loss is by definition a negative value the x-axis terminates at zero on the right-hand side. The data is fairly clumped with the impact of several outliers quite apparent. The mean harvest loss is -3,865 cordóbas with a standard deviation of -6,708. There are two outliers which are 8.5 standard deviations above the mean with a reported harvest loss of -60,000 cordóbas. Of these two households, one household changed composition and the other did not. There are an additional five observations which lie between 3 and 4.5 standard deviations above the mean with reported losses between -24,400 and -33,200 cordóbas. Excluding the two extreme outliers alters the mean loss size by approximately 350 cordóbas to -3,513.



Source: Author's calculations

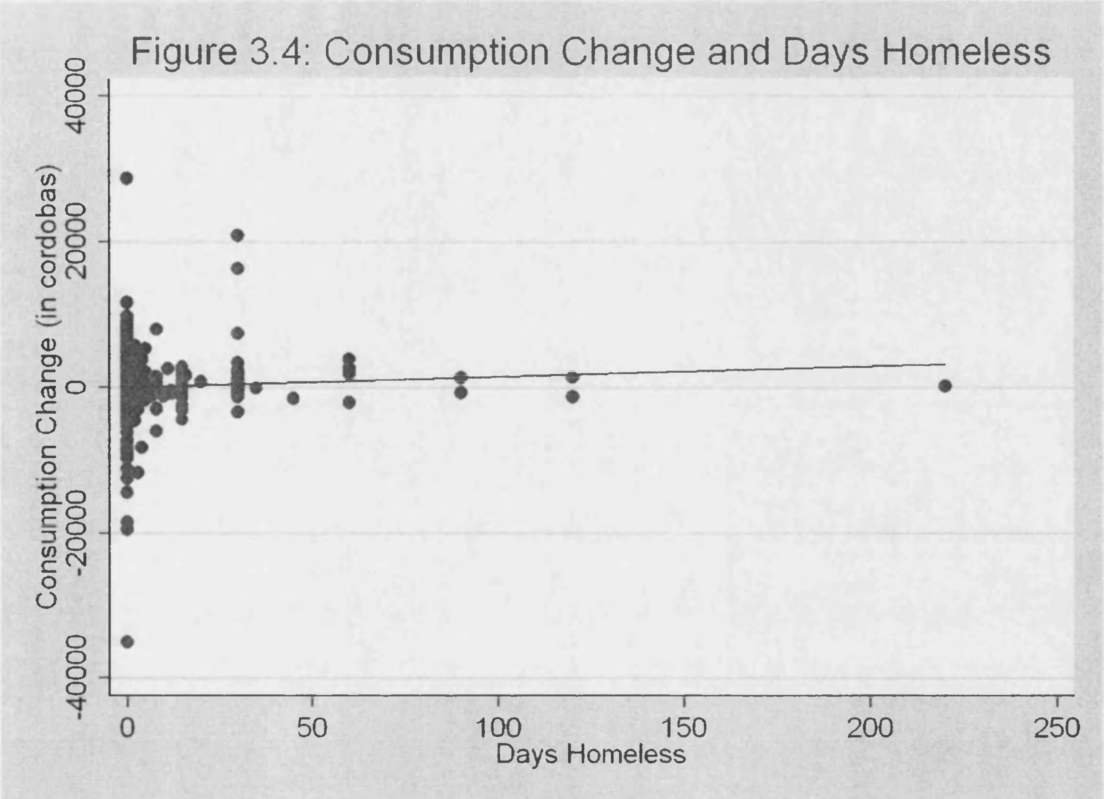
From the slope of the best fit line we would anticipate a small, negative coefficient due to the relatively flat slope of the line. The flatness of the slope is a function of a large number of households with a positive consumption change.

Figure 3.3 plots the distribution of long-term losses against consumption change. The mean long-term loss is -1,369 cordóbas with a standard deviation of -8,293. The mean value is influenced by an outlier with a loss value of 137,625 which is 16.5 standard deviations from the mean. With this observation excluded the mean long-term loss drops by over a third to -943 cordóbas. Figure 3.3 suggests a "best fit" regression line being relatively flat with a slightly positive coefficient.



Source: Author's calculations

The scatter plot of days homeless and consumption change is given below in Figure 3.4. The mean time homeless is 4.8 days and mean consumption change for all surveyed households is 89 cordóbas. The positive slope in Figure 3.4 supports these statistics. However, when we distinguish between households with non-zero days homeless mean consumption change for households whose time homeless is non-zero is 691 cordóbas while the mean consumption change for households with a reported time of zero days homeless is surprisingly -168. Also, several observations for time homeless seem quite high, however days homeless refers to time displaced from the primary residence and should not literally be interpreted as a household sleeping without shelter.



Source: Author's calculations

Table 3.2 summarizes mean consumption change for the final two shocks. In the case of wall damage and damage to the household water supply we can observe that affected households experienced an increase in consumption while unaffected households underwent a modest drop.

Table 3.2: Mean Consumption Change (in Cordóbas) for Categorical Shocks

Shock	Mean Consumption Change (Whole Sample)	Mean Consumption Change (Affected)	Mean Consumption Change (Unaffected)
Wall Damage	58	251	-14
Water Supply Damage	58	450	-45

Source: Author's calculations

In reviewing all five shocks, a general trend emerges which suggests that the impact of shocks may be relatively mild and the coefficient may actually be positive in some cases. This trend also appears to hold for the binary outcome variables which report an overall increase in mean consumption change for the whole sample. This is somewhat counterintuitive, as we may be inclined to speculate that a stronger negative relationship would hold between shocks and consumption change.

Before implementing statistical analysis, we can consider what explanations be driving this result. One possible explanation could be that so far we consider only shocks in isolation. For example, a household may have been unaffected by one shock type, but experienced another shock which caused a drop in consumption. This is a rather unconvincing explanation since the mild relationships appear to hold for all shocks.

A more plausible explanation could be that affected households received more aid than unaffected households which facilitated higher consumption growth. When total aid is subtracted from each household's 1999 consumption, the mean consumption change drops from 126 cordóbas to –803 cordóbas. To address this scenario in more detail Table 3.3 presents descriptive statistics on consumption change for affected and unaffected groups with and without total aid received. For continuous variables unaffected households are defined as those reporting a loss of zero.

Table 3.3: Impact of Aid on Mean Consumption Change

Shock	Affected Households			Unaffected Households		
	Mean Consumption Change	Mean Consumption Change with Aid Removed	**Difference (Absolute Terms)**	Mean Consumption Change	Mean Consumption Change with Aid Removed	**Difference (Absolute Terms)**
Lost Harvest	46	-915	**961**	781	110	**671**
Long-term Losses	319	-776	**1095**	63	-812	**875**
Days Homeless	691	-234	**925**	-168	-789	**621**
Wall Damage	251	-955	**1206**	-15	-528	**513**
Water Supply Damage	450	-572	**1022**	-45	-661	**616**

Source: Author's calculations

With aid removed the swing from mean consumption change with aid to mean consumption change without aid is always greater for affected households. For example, mean consumption change falls for both affected and unaffected groups in the case of harvest loss. But, the drop is much larger (961) in absolute terms for the affected households than for the unaffected (671). This result is consistent for all shock types and suggests that mean consumption growth for affected households was heavily buoyed by aid.

Despite the difference highlighted in Table 3.3 it is interesting to note that even with aid factored out slightly more than half of the households vulnerable to harvest losses (116 of 321) had positive consumption growth. Table 3.4 summarizes consumption change statistics for those households with harvest losses.

Table 3.4: Harvest Loss Diagnostics

Mean Harvest Loss (in cordóbas)	3,865
Households with Consumption Increase (Aid Included)	168
Mean Consumption Change (Aid Included)	125
Households with Consumption Increase (Aid Excluded)	116
Mean Consumption Change (Aid Excluded)	-803
N =	328

Source: Author's calculations

The diagnostics presented in this section suggest that the impact of aid on consumption may be pronounced, however we have also provided evidence to suggest that, in the case of harvest losses, more households had positive consumption growth than negative even with aid removed. In order provide more concrete conclusions we model the relationship between shocks and consumption.

III. B. Theoretical Background

In theory we would expect hurricane damages to affect household consumption to the extent that income is disrupted. When income is disrupted, insurance and coping mechanisms should be utilized to smooth consumption. The theory of full insurance offers a useful starting point to assess household response to idiosyncratic risk. The theory states that when risk is fully pooled, household consumption depends only upon average village consumption. In other words, since households are perfectly insured, an income shock to a single household should not affect its consumption. This is because its consumption is effectively pooled with all other village households. The exact equation may vary across studies, but the basic idea is:

(1) $c_{ivt} = \beta_0^{\,i} + \beta_1 \bar{c}_{vt} + \beta_2 Y_{ivt} + e_{ivt},$

where c_{ivt} = consumption in house i, in village v, in time t; $\bar{c}$ = average consumption in village v in time t; Y = income of household i; and e = error term to allow for idiosyncratic shocks (Alderman and Paxson, 1994). If there is full insurance, β_1 will equal 1 and β_2 will equal 0. Although we know β_1 will likely never equal 1, we use this as a benchmark with which to compare the actual level of risk pooling.

This approach has been widely used, perhaps most notably by Townsend in his study of risk pooling in India (1994). Townsend found evidence to suggest that the full insurance hypothesis holds up reasonably well and that household income exerted a minimal influence on household consumption. Townsend specified the change in the difference between household consumption growth and mean consumption growth on the left-hand side. The change in income and the error term are on the right-hand side.

Townsend starts from the premise that the utility function of individual (k) in time (t) can be expressed by components of consumption (c), leisure (l) and their age and sex (A). He assumes that the utility function is separable. This is evident with c and l separated in equation 1 below. He then assumes that each household is equally risk averse and that the utility function expressed indicates that total household consumption is arranged so that the marginal utility of consumption is equal across individual household members.

(1) $$W^k[c_t^k, l_t^k, A_t^k] = U^k(c_t^k, A_t^k) + V^k(l_t^k, A_t^k)$$

Given the supposition that total consumption is shared and allocated to equalize marginal utility of consumption Townsend addresses Pareto-optimal allocation of consumption under conditions of shocks and random weather-related variables. The expected utility of an individual over a fixed time period (a lifespan for example) can be shown as the summation of probability of an event and the associated consumption and leisure for such an event. He assumes that the objective is to maximize the sum of utilities according to combinations of consumption and leisure as well as resource constraints. The sum of the expenditures on consumption and leisure in the village economy must equal full income. The next step is to consider the consumption of a given household j. Solving for consumption in household j maps to the reduced form equation shown below which is used to test for full insurance (Townsend 1994, pp. 553 – 561). In the reduced form equation consumption (c) of household j in time t is determined by the average village consumption per adult equivalent (cbar), the demographic term and an X is used to represent any other variable(s) of interest related to income. Under full insurance ß will approach one and ? will approach zero.

$$c_t^{*j} = \alpha^j + \beta^j \bar{c}_t + \delta^j \tilde{A}_t^j + \zeta^j X_t^j + u_t^j$$

However, Ravallion and Chaudhuri (1997) question this approach.[14] They revisit the specification used by Mace (1991) and Deaton (1990, 1992) and in which the dependent variable is only the change in consumption for household *i* in time *t*. A dummy variable, D, is introduced on the right-hand side, which is set equal to 1 if the household is located in the village of interest. The introduction of the village fixed effect allows for the separation of aggregate village risk from idiosyncratic household risk. Ravallion and Chaudhuri demonstrate that excluding the village dummy from the model will cause the income coefficient to be biased downwards if there is a common element to income changes across households. The specification used by Deaton (1990, 1992) and Ravallion and Chaudhuri (1997) is:

(2) $? C_{it} = ?_k a_k D^k_{it} + ß? Y_{it} + ? u_{it}$,[15]

[14] Townsend's paper has generated subsequent analysis using the ICRISAT data. For example, Morduch (2002) has also analyzed the ICRISAT data and found that households can reduce total income risk by as much as 90%, but risk-sharing remains imperfect and functions with limited effectiveness as a substitute for formal credit markets.

[15] The supporting work for this reduced form equation is detailed in Mace 1991.

where ? C is the change in consumption of household i in year t, D^k_{it} is a dummy as described above and Y is the change in income for household i in year t, and u is the error term. After retesting the village India data Ravallion and Chaudhuri find that this results in an increase in the income coefficient which is less indicative of risk pooling.
The authors are also concerned that Townsend's specification fails to account for measurement error which will bias the conclusion towards full insurance. Their discussion focuses on the method for estimating consumption since the ICRISAT data set does not measure consumption directly. Since the LSMS measures consumption directly we move on to address three concerns raised by Cochrane (1991).

Cochrane carries out tests for full insurance against specific household shocks in the U.S. As before the dependent variable is the change in household consumption. However, he makes three observations. First among these is exclusion of income on the right-hand side. He excludes income on three grounds: (i) most income is labor income, which will likely be related to preference shifts; (ii) reported income also includes consumption insurance related payments; and (iii) the high correlation between income and consumption measurement error. Economic theory tells us that when full insurance prevails consumption growth should be cross-sectionally independent of exogenous shocks caused by Mitch (Cochrane 1991). This foundation, along with the exclusion of income, yields the model in equation 3 below.

(3) $\log(c^j_{t+1} / c^j_t) = a + ßS_{ijt+1} + e^j_{t+1}$;

Including the shock variable (S) as the only explanatory variable is based upon the proposition that with full consumption insurance, consumption growth should be cross-sectionally independent of idiosyncratic variables. In other words, if household consumption is independent of household shocks the shock coefficient should be zero.

The second observation is the impact of demographic changes on the estimates. Including households with composition changes could introduce bias by virtue of their shifted utility function (Cochrane 1991). In the case of Hurricane Mitch, a household decision to adjust composition is a plausible response to hurricane damages. Households that add or drop members may likely exhibit altered total household consumption. The change in household composition may impact household preferences, which could translate into changes in income and consumption levels. This may be particularly acute for households which add or lose multiple members. Failure to account for this possibility could potentially bias estimates of consumption growth due to correlation between explanatory variables and the possible preference shifts will introduce bias in measuring the change in consumption. However, if shocks are not correlated with the preference shifts, the inclusion of those households is not only acceptable, but beneficial due to the increased sample size. The role of changing household size as a coping mechanism is the focus of Chapter 4.

The third observation Cochrane makes concerns the nature of analysis using cross-sectional versus panel data. He cautions that when using panel data the right-hand variables must be uncorrelated with variations in preference shocks and measurement error. Variables such as individual income generally do not satisfy these criteria. One remedy is to include aggregate consumption growth on the right-hand side, but this may be inadequate for similar reasons. Although taking aggregate consumption reduces the impact of household preferences on individual household's consumption, this does not eliminate the possibility that homogenous preference shifts will impact aggregate consumption. By definition the individual household's consumption would also be affected by a preference shift.

III. C. Specification

Given these antecedents we can construct an appropriate model specification. Deaton (1990, 1997) also uses panel data and his approach offers a useful starting point. However, since our aim is to test household insurance against specific shocks instead of general levels of insurance some modifications are required. The inclusion of income is problematic for the reasons given above. In addition, many households received aid payments which could be used for consumption but may not be recorded as income. We retain the village fixed effect since it allows a distinction between aggregate and idiosyncratic risk components. This gives the model in equation 4 below:

(4) $? C_{it} = ?_{k} a_k D^k_{it} + ßX_{it} + u_{it},$

where ? C is the change in household consumption, D is the village dummy fixed effect, and X is the impact of a given shock on household *i*. This approach tests for the impact of a given shock on household consumption while controlling for village level effects. We are first concerned with whether the shock is significant for consumption. If this is the case we turn our attention to the coefficient. A shock coefficient that is significant for consumption, but not significantly different from zero would support the notion that household consumption is unaffected by Mitch shocks. In contrast a shock that is significant for consumption, but closer to 1 is indicative of a strong relationship between consumption and the shock. In order to separate idiosyncratic household risk from aggregate village risk a village fixed effect was used.

As a final concern, we address the issue changes in household composition. Of the 528 households, 262 had no change in composition. The remaining 266 had a change in composition with a median loss of one member. Table 3.5 provides descriptive statistics on mean consumption change by household composition change.

Table 3.5: Percentage Change in Household Consumption 1998 - 1999

	No Change in Household Composition (n = 262)	Change in Household Composition (n = 266)	Sample (n = 528)
Mean consumption growth (%)	19.72	22.63	21.19
Standard deviation	.7511	.8424	.7978

Source: Author's calculations

The difference of nearly 3 percent indicates houses with modified composition having a higher mean consumption growth. Regressions were run on both the full sample to benefit from the reduced standard error and on the static group to allow for the impact of preference shifts on consumption.

III. D. Results

Discussion of regression results in this section is consistent with the model outlined earlier which incorporates village fixed effects. Regression results without fixed effects are also provided in the bottom half of all tables for completeness and comparative purposes. The model results without fixed effects do not capture the difference between aggregate village risk and idiosyncratic household risk (see discussion above). Also the aim of the regressions is to test hypotheses of risk sharing and shock impacts (emphasis on t-stat and significance levels) and not to "explain" changes in consumption. For this reason the discussion of the results does not focus overly on the R^2 values. Nevertheless it is worth noting that the fixed effects models all yield much higher R^2 values than when the fixed effects are excluded.

III. D. 1. Harvest Losses

We first consider the relationship between harvest losses and consumption since harvest losses represent the largest nominal losses attributable to Mitch. Table 3.6 presents the regression results. The results suggest several interesting conclusions. The first is that over the entire sample harvest losses are not significant for consumption at any loss threshold. However, harvest losses are significant for static households for all loss thresholds above 1,000 cordóbas. In other words, loss size matters. Losses become significant above a threshold of 1,000 cordóbas at 10% and at 5% above 2,000. Significance levels then fall back to 10% when the loss threshold increases to 3,000 cordóbas. At higher thresholds results are not significant and the sample size becomes prohibitively small to draw meaningful conclusions.

We also note the difference between households which change composition and those that do not. Harvest losses are never significant for households that change composition. This may be indicative of composition changes as a possible coping mechanism. If this were the case we could expect harvest losses to be a significant determinant of the decision to adjust household composition. We will address this possibility in the next section.

The results in Table 3.6 also show low harvest loss coefficients all less than 0.05. At face value this would indicate that households are highly effective at pooling risk and that consumption is independent of harvest losses. While it is reasonable to expect that households can overcome small scale losses using a range of informal mechanisms, the contention that they were able to almost perfectly insure against widespread crop damages caused by one of the most destructive hurricanes in recent memory is more difficult to support. In order to support a risk pooling conclusion we must be able to rule out econometric reasons which could falsely indicate high levels or risk pooling.

As discussed earlier in this section there are several factors which could bias the shock coefficient towards zero and give a false indication of risk pooling. Among these is the co-movement of consumption. Any factor that causes consumption to co-move across households will generate a false impression of risk pooling. Such factors could include shifts in the price level, changes in factor endowments, technology or other events that impact all households across the risk pooling network. The impact of natural disasters and of Mitch in particular certainly fits this criterion. Given the widespread impact of Mitch not only across Nicaragua, but Honduras as well the co-movement in household consumption is not surprising and can account for the low value of the shock coefficient. It is entirely plausible that the widespread damages of Mitch were significant for consumption *and* caused consumption to co-move among the surveyed households. This is a more convincing explanation which does not rely on the ability of hyper-efficient Nicaraguan households to approximate perfect risk pooling.

Table 3.7 presents the regression results with the exclusion of the two outliers (households with losses equal to 60,000 cordóbas). As we discussed in the Data Diagnostics section there are two high loss households (losses of 60,000 cordóbas). To illustrate the impact of these outliers on the overall results we rerun the regression with these households excluded. When compared to the results in Table 3.6, we can observe three effects of the outliers. The first is to depress the significance of harvest losses across the whole sample for households with losses above 1,000 cordóbas. Regression results in Table 3.6 were never significant for the whole sample at any loss threshold. Removing the outliers shows that harvest losses are significant for consumption for all households at 1% or 5% depending upon the loss threshold. A second difference is that harvest losses are no longer significant for consumption for the static grouping. This grouping was the only one in Table 3.6 to show statistical significance. Finally, at the 1,000 and 2,000 loss thresholds harvest losses are now significant for consumption for those households with a change in composition. Previously results were not significant for households with a change in composition. The results in Table 3.7 are not intended to replace those in Table 7 nor somehow imply that the results in Table 3.7 are unrepresentative, but rather illustrate the impact of these two large losses on the overall results and provide some information on what the results would have been in their absence.

Table 3.6: OLS Regression of Consumption Change on Harvest Losses with Village Fixed Effects
Dependent Variable: Household Per Capita Consumption Change 1998 – 1999 (in cordóbas)

Harvest Loss Size (in cordóbas)	< 0			< -1,000			< -2,000			< -3,000		
Harvest Losses	-0.02 (0.035)	-0.016 (0.049)	-0.028 (0.037)	-0.04* (0.021)	-0.011 (0.048)	-0.026 (0.038)	-0.043** (0.021)	-0.006 (0.052)	-0.027 (0.032)	-0.044* (0.025)	-0.01 (0.06)	-0.03 (0.03)
Constant	138.75 (274.82)	-27.13 (284.5)	16.99 (201.96)	105.78 (155.36)	190.84 (400.73)	136.95 (250.76)	114.25 (194.61)	593.24 (519.01)	337.26 (290.62)	141.96 (291.88)	229.15 (762.11)	162.6 (414.8)
Household Composition Type	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2												
Harvest Losses	-0.01 (0.05)	-0.03 (0.03)	-0.02 (0.03)	3.34** (1.32)	-0.69 (0.79)	1.36* (0.8)	0.77 (0.56)	0.34 (0.40)	0.55 (0.34)	0.13 (0.31)	-0.49 (0.41)	-0.18 (0.26)
Constant	223.88 (348.86)	-134.49 (283.91)	46.56 (224.64)	1502.3* (759.99)	-622.22 (428.13)	422.21 (448.21)	677.25 (573.17)	-240.67 (428.92)	223.68 (359.36)	276.3 (613.58)	-740.3* (430.05)	-215.14 (384.21)
Household Composition Type	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.03	0.01
N =	161	160	321	62	57	119	91	83	174	115	105	220

Robust standard error in parenthesis. * Significant at 10% ** Significant at 5% *** Significant at 1%.

Table 3.7: OLS Regression of Consumption Change on Harvest Losses with Village Fixed Effects (Outliers Removed)
Dependent Variable: Household Per Capita Consumption Change 1998 – 1999 (in cordóbas)

Harvest Loss Size (cordóbas)	< 0			< -1,000			< -2,000			< -3,000		
Harvest Losses	-0.02 (0.035)	-0.016 (0.049)	-0.03 (0.04)	-0.05 (0.04)	-0.095* (0.053)	-0.10*** (0.036)	-0.064 (0.044)	-0.10* (0.059)	-.10*** (0.038)	-0.08 (0.06)	-0.096 (0.076)	-.10** (0.047)
Constant	138.75 (274.82)	-27.13 (284.5)	16.99 (201.96)	70.37 (212.53)	-240.82 (401.3)	-242.43 (231.1)	24.64 (293.25)	-12.91 (530.59)	-101.62 (299.98)	-64.08 (535.05)	-497.89 (810.74)	-406.21 (465.24)
Household Composition Type	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.40	0.40	0.32	0.89	0.51	0.49	0.93	0.52	0.69	0.95	0.64	0.78
N =	160	159	319	106	110	216	87	75	162	59	62	121
Harvest Losses	-0.01 (0.04)	-0.1** (0.04)	-0.07** (0.03)	-0.03 (0.04)	-0.1** (0.04)	-0.07*** (0.03)	0.01 (0.05)	-0.11** (0.05)	-0.07* (0.04)	0.01 (0.08)	-0.07 (0.06)	-0.05 (0.05)
Constant	169.45 (359.62)	-335.61 (282.22)	-108.28 (227.87)	52.31 (433.69)	-229.97 (429.05)	-126.2 (307.02)	464.05 (717.17)	-387.67 (587.68)	-67.45 (453.98)	513.52 (1058.88)	182.01 (831.16)	251.5 (654.47)
Household Composition Type	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.01	0.04	0.03	0.01	0.03	0.01	0.01	0.04	0.01	0.01	0.02	0.01
N =	160	159	319	106	110	216	87	75	162	59	62	121

Robust standard error in parenthesis. * Significant at 10% ** Significant at 5% *** Significant at 1%.

III. D. 2. Long-term Losses

Results for long-term losses are presented below in Table 3.8. Long-term losses are measured in cordóbas and exhibit similar results to harvest losses. Among the static households long-term losses are significant at 5%, but not significant for any other groupings. We do not present the results by loss threshold because the sample size becomes prohibitively small. As with harvest losses the coefficient suggests an extremely high level of risk pooling, which is again likely to be more attributable to the covariate scope of the hurricane damage rather than a highly attuned level of risk pooling.

Table 3.8: OLS Regression of Consumption Change on Long-term Losses with Village Fixed Effects
Dependent Variable: Household Consumption Change Per Capita 1998 – 1999 (in cordóbas)

	Household Composition Type					
	Static	Change	Both	Static	Change	Both
Long-term Losses	-0.11** (0.05)	0.03 (0.02)	0.02 (0.02)	-0.05 (0.04)	0.03 (0.02)	0.02 (0.03)
Constant	125 (271.99)	101.99 (225.1)	155.39 (174.58)	168.9 (322.62)	99.89 (243.9)	160.07 (196.47)
Fixed Effects Included	Yes	Yes	Yes	No	No	No
R^2	0.40	0.38	0.30	0.01	0.01	0.01
N =	160	161	321	160	161	321

Robust standard error in parenthesis. * Significant at 10% ** Significant at 5% *** Significant at 1%.

III. D. 3. Days Homeless, Water Supply Damage and Household Damage

Regression results for days homeless and qualitative shocks are presented in Table 3.9. Days homeless is measured as a continuous variable. Home damage and water damage are dummy variables. Overall, these shocks appear relatively benign towards consumption. Days homeless and damage to the household water supply are both significant at 10% for the whole sample. However, none of the shocks are significant for consumption for either sub-sample. For all three shocks the coefficients are larger than one, which is attributable to the coarseness of the variable measurement units.

In contrast to harvest losses and long-term losses, which are relatively precise quantitative indicators of hurricane damage, days homeless and the qualitative variables in particular offer comparatively lower resolution. Wall damage and damage to the water supply are qualitative in nature. They allow for breadth in the degree of damage. One household may be only mildly damaged while another may be uninhabitable. Yet both would register as damaged. Days homeless, while a quantitative indicator does not quantify the relative impact (fiscal or otherwise) on a household. Unfortunately, these variables are the best the LSMS has to offer on non-agricultural Mitch damages.

The relative lack of statistical significance for these shocks is not to imply that the ensuing damage is completely benign. For example, damage to water infrastructure could easily have tangible effects that do not show up in short term consumption such as increased labor to acquire clean water or negative health effects due to prolonged exposure to impure drinking water. Additional labor to retrieve water reduces labor hours available for domestic tasks or external employment. Illness and disease not only reduce income-earning ability, but may require the allocation of household income to purchase medical care. Nevertheless, these[48] are long-term impacts and the focus here is on short-term risk pooling.

III. E. Review

The principal goal of this section was to test the relationship between shocks and consumption in order to evaluate the effectiveness of risk-pooling against Mitch-related shocks. We first plotted survey data and reviewed theoretical foundations in order to develop a model to test the impact of shocks on consumption. Results showed that harvest losses and long-term losses represented the most significant disruption to consumption, while days homeless, wall damage and water supply damage tended to be not significant, or significant only at 10%.

Results also showed that harvest losses and long-term losses demonstrated a significant impact on consumption, but only for households that did not change size. The tendency of the shock coefficient to approach zero is surprising as this would imply highly perfect levels of risk pooling. However, this is unlikely and such a conclusion was rejected based upon alternate theoretical explanations which could induce co-movement in consumption and be mistaken for risk pooling.

As a word of caution we acknowledge the possibility that results have been biased by households that left the survey group. An argument could be made that poor households left the survey area since their assets were destroyed, which would bias the results upwards. An equally compelling argument could be made that the wealthy possessed the resources to leave and the results are biased downwards. However, neither scenario meshes well with the disaster anthropology literature, which has traditionally found survivors reluctant to leave their home in the post-disaster period (Doughty 1999).

Analysis in this section also yielded interesting results concerning the possibility of aid-financed consumption mitigating the impact of shocks. When aid-financed consumption was excluded we found that the impact of shocks on static households appears to have been greater. Static households also have a smaller shock coefficient than their counterparts. These results call for an analysis of the determinants of aid and an examination of the possibility that either household reformation may have been a coping strategy or aid was targeted towards households that changed composition. These questions are examined in the next section.

Table 3.9: OLS Regression of Household Consumption on Shocks with Village Fixed Effects
Dependent Variable: Household Consumption Change Per Capita 1998 – 1999 (in córdobas)

	Shock								
	Days Homeless			Home Damage			Water Supply Damage		
Shock Coefficient	9.241 (10.238)	24.35 (15.72)	14.855* (8.569)	92.01 (428.741)	-231.04 (614.57)	182.995 (318.219)	-177.561 (472.195)	1094.44 (752.62)	675.855* (389.962)
Constant	321.117 (249.931)	-312.6 (295.23)	17.763 (184.464)	304.132 (305.082)	-175.64 (320.96)	8.243 (221.202)	369.821 (288.129)	-445.14 (338.5)	-82.138 (222.608)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.17	0.17	0.13	0.01	0.01	0.01	0.18	0.17	0.13
Shock Coefficient	8.83 (10.61)	23.21 (13.72)	14.29 (9.18)	257.17 (420.91)	200.47 (496.17)	264.29 (321.13)	-196.75 (418.6)	1248.94** (588.02)	494.15 (352.8)
Constant	323.16 (260.13)	-307.38* (286.78)	20.45 (193.1)	255.81 (340.29)	-281.52 (344.75)	-13.68 (242.13)	374.01 (312.13)	-475.18 (316.38)	-44.57 (222.85)
Fixed Effects Included	No	No	No	No	No	No	No	No	No
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Household Composition Type	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	227	218	445	227	218	445	227	218	445

IV. Relationship between Aid and Shocks

Attention to the relationship between shocks and transfers is of interest for at least two reasons. In the first instance, the resiliency of consumption to hurricane shocks may be strengthened by aid-financed consumption. Focusing on the relationship between aid and shocks allows us to analyze the counterfactual of the potential shock impact on consumption without aid. Secondly, identifying significant determinants of transfers allows us to evaluate the effectiveness of transfer targeting. In theory if transfers are well targeted based on shocks (as opposed to other objectives), we would expect that the shocks that are significant for consumption should also be significant determinants of aid. In practice such a relationship may not hold for a variety of reasons. For example, the effectiveness of official aid transfers may be limited due to monitoring costs, imperfect information and transaction costs which reduce the donor's ability to effectively target transfers. These factors may be less limiting for family (inter-household) donors since they would presumably benefit from more complete information and a more detailed knowledge of the recipient's needs. However, family transfers may also be affected by existing network arrangements and the strength of an affected household's ties to potential donor households. Finally, it is possible that aid flows were not allocated based upon Mitch damages, but upon some other criteria such as poverty level.

IV. A. Background

After Mitch, affected households received large amounts of official aid from a variety of sources including the Nicaraguan government, foreign governments, religious organizations and NGOs. A program by the Red Cross donated cash and farm equipment to agricultural households in Nicaragua and Guatemala. The agricultural components included seed, fertilizer, grain and spray pumps. The cash (US$ 30) was given to the wife or adult female and was intended to be used to buy other agricultural necessities or food. The agricultural equipment was given to the males. These disbursements were made to approximately 17,000 households in both countries (Peppiatt et al. 2001). Unfortunately there is no way of identifying overlap between Red Cross recipient households and LSMS households. We must assume these donations (and others) are captured in the LSMS questions on official aid received. In addition to official aid donations, households also received unofficial aid in the form of remittances from abroad and inter-household transfers from friends and relatives living in Nicaragua. Table 3.10 provides descriptive statistics on the type of mean aid received.

Table 3.10: Household Mean Aid Received by Type (in cordóbas)

Official:	**611**
Food	202
Home	194
Clothing	87
Other	128
Unofficial	**143**
Total	**754**

Source: Author's calculations

As far as the distribution of aid is concerned, the disaster literature indicates that aid may be distributed around a number of parameters. These may include disaster damages, poverty level, or some combination of both. In their study on post-Mitch aid in Honduras, Morris and Wodon (2002) model a two-stage allocation process in which donors first decide whether or not to administer household aid and then decide how much to allocate per household. In the allocation process (first stage), aid may be targeted according to different relief objectives. The authors found the probability of receiving aid was positively correlated to asset losses and negatively correlated to wealth, however when controlling for home damage both relationships disappeared. Disaster anthropologists have also noted the relative disadvantage of women in receiving post-disaster aid (Blaikie 1994, Shaw 1992). In disaster stricken communities women may be unfavorably positioned due to existing gender relations, networks or resources constraints which limit their ability to obtain equivalent aid of their male counterparts. We briefly consider these issues before moving to a discussion of the regression framework.

Table 3.11 provides a summary of official aid transfers by poverty level. The LSMS groups households into one of three categories: extremely poor, poor and not poor. These groupings are defined by the household's 30 day per capita expenditures.[16] The data presents a picture of official aid as sensitive to poverty level. Family transfers were inversely related to poverty level. Households classified as "extremely poor" received nearly 70% more official aid than non-poor households and poor households received 20% more than non-poor households. In the case of remittances and family transfers, the inverse relationship between poverty level and aid received does not hold. Extremely poor and poor households received only 42 and 82 percent, respectively of inter-household transfers received by non-poor households. One explanation for the low level of transfers received by poor households may simply be that they are more likely to have less extensive networks or networks comprised of poor relatives who are less able to make transfers (De Weerdt 2006).

Table 3.11: Mean Aid by Poverty Level (in cordóbas)

Group	Mean Official Aid	Mean Family Transfers	Mean Total Aid
Extremely Poor	833	75	909
Poor	588	148	736
Not Poor	495	180	674

Source: Author's calculations

[16] The extreme poverty line is a mean per capita 30 day expenditure amount of 101.32 cordoóbas. Households below this line are classified as extremely poor. The poor poverty line is 214.47 cordóbas. Households below this line, but above the extremely poor line are classified as poor and those households above the line are classified at not poor.

From the data in Table 3.11 it appears at first glance that official donors may have used poverty level as a guide in distributing aid since poorer groups are recipients of higher aid amounts. We will subsequently explore whether this relationship holds when considering hurricane damages. If official aid was tied to poverty rather than hurricane damages we would expect a household's poverty level to be a significant determinant of official aid. Table 3.11 also suggests that the family transfers decline as the poverty level decreases (discussed further in this section).

Based upon the Morris and Wodon findings it is also prudent to review the distribution of aid for households with home damage. Table 3.12 presents mean aid amounts for those households with and without wall damage. Whereas family transfers slightly favored households with no reported wall damage, official aid favored damaged households by nearly a three to one margin.

Table 3.12: Mean Aid by Home Damage (in córdobas)

Group	Mean Official Aid	Mean Family Transfers	Mean Total Aid
Walls Undamaged	340	175	514
Walls Damaged	1095	110	1205

Source: Author's calculations

Table 3.13 provides data on aid by gender of the household head. In the survey group approximately 25% of the households had female heads in 1998.[17] Mean aid for female and male headed households is equal, but this total conceals asymmetries between official and family transfers. Female headed households received only 71% of the official aid received by male headed households, but received nearly three times as much in family transfers.

Table 3.13: Mean Aid by Gender of Household Head (in córdobas)

Gender of Household Head	Mean Official Aid	Mean Family Transfers	Mean Total Aid
Male	648	106	753
Female	459	295	754

Source: Author's calculations

Overall, the descriptive statistics suggest that poorer, male headed households with wall damage tended to be greater recipients of official aid while the reverse is true for receipts

[17] Data is unavailable on the gender of the household head in 1999, but drawing the head of household data from the pre-hurricane survey has the advantage of avoiding endogeneity problems, which may lead households to form in response to benefits (Edmonds et al. 2005, Duflo 2003).

of family transfers. However, from this data it is unclear if these characteristics are statistically significant determinants of transfers.

IV. B. Role of Aid in Sustaining Consumption

Before proceeding to an analysis of aid distribution, it is important to note that the consumption figures do not exclude transfer financed consumption. As the data in Table 3.1 demonstrates, official transfer payments alone averaged over 700 cordóbas per household. This amount could account for a substantial component of consumption growth and also give a potentially misleading level of risk pooling, which may more appropriately be attributed to one-off post-Mitch aid transfers.

In order to consider the counterfactual, the impact of shocks on consumption without aid-financed consumption, we repeat the regressions from the previous section with aid excluded from consumption. Table 3.17 summarizes the impact of removing aid on the regression results. The regression results are listed in detail in Tables 3.14 – 3.16. Table 3.14 presents regression results for harvest losses using consumption change less total aid as the dependent variable. Once aid is removed harvest losses are still significant for consumption with some minor changes. As in the previous section harvest losses are not significant if we do not differentiate by loss size. Once we begin to introduce loss thresholds losses become significant for static households at thresholds of 1,000 córdobas and 2,000 córdobas at 5% and above 3,000 cordóbas at 10%. The increase in significance from 10% to 5% for static households suggests were more reliant on aid to finance consumption vis-à-vis harvest losses. The removal of aid does not lead any households with altered composition to become significant.

Table 3.15 presents the regression results for the impact of long-term losses on consumption with total aid excluded from consumption. Results showed that long-term losses were significant at 5% for static households. When aid is removed from the consumption total long-term losses are no longer significant (they fall just outside the 10% threshold). This is somewhat counterintuitive as we would expect that the removal of aid-financed consumption should make damages more significant for consumption – not less.

Table 3.16 presents results for the remaining three shocks with aid removed from consumption. These results can be contrasted against those in Table 3.9 which included aid-financed consumption in Table 3.16. The days homeless coefficients are negative for the static and full samples although the coefficient is relatively unchanged for the change sample. All coefficients for wall damage are negative and smaller which suggests a large role for aid-financed consumption in mitigating the impact of wall damage. In the case of damage to the water supply the coefficient remains negative and becomes much smaller for the static sample. The coefficient remains relatively similar for the change sample and remains positive for the full sample, but is much smaller.

The hypothetical impact of the removal of aid on sustaining consumption for affected households is summarized in Table 3.17. Overall, the results of our exercise suggest shocks which increased in significance had their impact most strongly mitigated by post-disaster aid flows. In the absence of aid these shocks would have exerted a stronger impact on household consumption after Mitch. One such example is the case of households with a loss threshold of 1,000 cordóbas. When aid is removed from consumption, significance increases from 10% to 5%. By contrast it would appear that other shocks were minimally reliant on aid to buttress consumption. Table 3.17 also suggests that the impact of aid-financed consumption does not move systematically across all shock types. Indeed, only for agricultural losses at the 1,000 cordóba threshold do we see an increase. In other cases the statistical significance was either unchanged or decreased when removing aid-financed consumption. This exercise suggests that poor agricultural households were most benefited by aid transfers.

Table 3.14: OLS Regression of Consumption Change Less Total Aid on Harvest Losses with Village Fixed Effects
Dependent Variable: Household Consumption Change Per Capita 1998 – 1999 (in cordóbas)

Harvest Loss Size (cordóbas)	< 0			< -1,000			< -2,000			< -3,000		
Harvest Losses	-0.036 (0.04)	-0.019 (0.047)	-0.03 (0.035)	-0.06** (0.03)	-0.01 (0.049)	-0.02 (0.036)	-0.072** (0.033)	0.002 (0.051)	-0.018 (0.031)	-0.058* (0.033)	0.001 (0.06)	-0.018 (0.033)
Constant	-971.58*** (400.63)	-841.11*** (298.3)	-917.66*** (246.81)	-1097.23*** (194.23)	-533.68 (399.89)	-733.68*** (280.54)	-1010.04*** (254.66)	-120.2 (513.37)	-443.84 (280.84)	-917.99** (341.34)	-639.93 (744.29)	-708.66* (408.72)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.24	0.36	0.22	0.64	0.50	0.40	0.88	0.50	0.60	0.91	0.61	0.69
Harvest Losses	-0.03 (0.03)	-0.02 (0.04)	-0.02 (0.03)	-0.04 (0.03)	0.005 (0.039)	-0.02 (0.03)	-0.01 (0.02)	0.004 (0.04)	-0.003 (0.03)	0.03 (0.04)	-0.02 (0.03)	0.008 (0.03)
Constant	-953.05** (437.5)	-841.94*** (310.57)	-897.17 (270.03)	-1026.69** (508.74)	-439.89 (426.35)	-730.75** (336.29)	-536.97 (485.56)	-454.68 (564.99)	-489.39 (379.74)	120.28 (764.34)	-659.55 (648.11)	-269.74 (508.03)
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Hhold Comp Type	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	160	161	321	107	111	218	76	88	164	63	60	123

Robust standard error in parenthesis. * Significant at 10% ** Significant at 5% *** Significant at 1%.

Table 3.15: OLS Regression of Consumption Change Less Total Aid on Consumption Change Less Total Aid with Village Fixed Effects

Dependent Variable: Household Consumption Change Per Capita 1998 – 1999 (in cordóbas)

	Household Composition Type		
	Static	Change	Both
Long-term Losses	-.16 (0.1)	0.02 (0.016)	0.018 (0.022)
Constant	-974.18** (394.44)	-722.12*** (242.1)	-778.61*** (215.05)
Fixed Effects Included	Yes	Yes	Yes
R^2	0.24	0.37	0.22
Long-term Losses	-0.05 (0.04)	0.03 (0.02)	0.02 (0.03)
Constant	168.9 (322.62)	99.9 (243.9)	160.07 (196.47)
Fixed Effects Included	No	No	No
R^2	0.01	0.01	0.01
N =	160	161	321

* Significant at 10% ** Significant at 5% *** Significant at 1%.

Table 3.16: OLS Regression of Household Consumption Less Total Aid on Shocks with Village Fixed Effects
Dependent Variable: Household Consumption Change Per Capita 1998 – 1999 (in cordóbas)

	Days Homeless			Home Damage			Water Supply Damage		
Shock Coefficient	-40.14 (28.01)	24.71 (16.03)	-19.23 (24.94)	-1159.9 (857.39)	-401.33 (618.11)	-542.04 (498.48)	-1021.2 (988.87)	1178.83 (760.8)	193.02 (607.3)
Constant	-281.71 (313.26)	-884.54 (296.25)	-531.41 (217.05)	-169.73 (318.63)	-686.57** (323.54)	496.87** (220.25)	-286.12 (308.78)	-1014.26*** (336.33)	-682.94*** (224.33)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.14	0.13	0.12	0.14	0.19	0.12	0.14	0.12	0.11
Shock Coefficient	-45.25 (29.6)	20.51 (13.22)	-21.08 (27.64)	-866.59 (723.95)	55.70 (493.97)	-426.73 (459.82)	-953.95 (820.01)	1272.87** (602.81)	89.27 (528.71)
Constant	-256.3 (306.61)	-865.28*** (290.04)	-522.56** (224.6)	-255.55 (311.44)	-798.71** (352.15)	-527.96** (235.09)	-300.81 (306.87)	-1032.54*** (320.88)	-661.49*** (222.23)
Fixed Effects Included	No	No	No	No	No	No	No	No	No
R^2	0.04	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01
Household Composition Type	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	227	218	445	227	218	445	227	218	445

Table 3.17: Effect of Removing Aid-Financed Consumption on Shock Significance (When Including Village Fixed Effects)

Shock	Effect	Impact
Harvest Losses (by Loss Threshold):	-	-
0	Unchanged	Not Significant.
1,000	Changed	Increased from 10% to 5% for static households.
2,000	Unchanged	Significant at 5% for static households.
3,000	Unchanged	Significant at 10% for static households.
Long-Term Losses	Changed	Decreased from significant at 10% to Not Significant.
Days Homeless	Changed	Decreased from significant at 10% to not significant for full sample. Coefficients for all samples switched sign from positive to negative.
Wall Damage	Unchanged	Shock not significant. Coefficients negative.
Water Supply Damage	Changed	Significance decreased from 10% for full sample to not significant.

Having reviewed the role of aid in sustaining consumption we now move to this section's primary objective: to model aid allocation and view the distribution of aid relative to the impact of shocks on consumption.

IV. C. Model

Equation 5 evaluates the relationship between shocks and aid received, while considering the role of gender and poverty level as determinants of aid. The relationship is modeled as:

(5) $T_j = a + ß_1 SHOCK_{ij} + ß_2 FEMALE_j + ß_3 EPOOR_j + ß_4 POOR_j + e_j$;

where T is the transfer received (in córdobas) by household *j* after Mitch. On the right hand side the SHOCK variable is impact of shock i on household j. The FEMALE dummy variable is included to test the hypothesis that female-headed households are disadvantaged in receiving aid. If female headed households were significantly disadvantaged in receiving aid, we would expect the coefficient on the gender dummy to be both negative and significant for aid. Dummy variables are used to capture a household's status as extremely poor (EPOOR), poor (POOR) or non-poor.

The regression in equation 5 is repeated three times to allow for variation in the definition of the dependent variable: official aid, inter-household aid and total aid.[18] Inter-household aid is used as an explanatory variable to test the responsiveness of unofficial aid to shocks. LSMS reports family assistance received by households after Mitch,

[18] Official aid is the sum of all types of aid (housing, clothing, food, etc.). There were insufficient observations to run separate regressions using each aid category.

which includes both domestic inter-household transfers as well as international remittances. It is not possible to disaggregate these using the data.[19]

IV. D. Results

The regression results from equation 3 are presented below in Tables 3.18 – 3.23. Tables 3.18, 3.19, and 3.20 focus on harvest losses. The dependent variables in these tables are official aid, unofficial (family) aid, and total aid received, respectively. The structure in these tables parallels that of the significance tests in the earlier section and facilitates a comparison of sensitivity between harvest losses for consumption and harvest losses for aid. Results for the remaining shock types are presented in Tables 3.21 – 3.23.

Table 3.18 presents results for the regression of official aid on harvest losses. In general there are strong parallels between these results and those in Tables 3.6 and 3.7. In particular, harvest losses are significant in both tables at the same levels across identical thresholds and household composition types. This suggests that aid was well targeted. Such a finding is encouraging as there are many problems that could potentially diminish the efficacy of official aid donations. While problems, such as monitoring costs, imperfect information and transaction costs were undoubtedly present, they apparently did not present too great an impediment to efficient aid targeting. Moreover, examining the results by household composition shows that harvest losses were significant for static households only. These results are encouraging since the results for static households are unencumbered by the issue of preference shifts associated with composition change.

By contrast harvest losses were not significant determinants of family aid at any loss threshold. This is somewhat surprising for the reverse of the logic cited in explaining official aid targeting. We would expect family aid to benefit from better information about the recipient household than donor aid. However it is unclear if family aid donors had this information and simply chose to use other criteria in distributing aid, or if information on losses was not as well transmitted as we would have anticipated. Since official aid constitutes the lion's share of total aid it is unsurprising that harvest losses were also a significant determinant of total aid (significant at 5% at 1,000 and 2,000 thresholds). The somewhat surprising conclusion from Tables 3.18 – 3.20 is that official aid was sensitive to harvest losses while family transfers were not.

Tables 3.21 – 3.23 explore aid targeting for the remaining four shocks. Days homeless and wall damage were significant determinants of official aid at 10%. While days homeless was significant only for the static group, wall damage was significant for both the static group and full sample. It is somewhat surprising that none of the shocks was a significant determinant of family aid and it is unclear what criterion was used to allocate inter-household aid, particularly since the income group and female dummy variables were also not significant. Additional tests which modeled the number of children in recipient households also failed to show significance. Finally, as expected the results for

[19] In Honduras, Morris and Wodon (2003) found that remittances declined for less than 2% of the surveyed households after Mitch.

total aid mirror those for official aid, with days homeless and wall damage again being significant at 10%.

Although the income groups and gender of household head are not significant there are some observations we can make based on the regression results. Having a female headed household was not a significant determinant of any aid type (discussed further in Chapter 5). However, the regression results provide further support to the descriptive statistics on aid to female headed households (Table 3.13). While not statistically significant, the coefficient for the female dummy variable is always negative for official aid and always positive for family aid. This is a strange dichotomy, but since the coefficients are not significant we can not make any stronger claims. We can only point out the observations in the gender literature which describes official donors as more generous to male-headed households or that male-headed households were more skilled at acquiring official aid. The latter is more likely as female-headed households may not be inherently more vulnerable to disaster impact than male-headed ones but tend to have a reduced ability to recover from disaster impacts (Bradshaw 2004). Based on the regression results, however we can not find a statistical basis to support the claim. Neither poverty characterization (poor, extremely poor) is a significant determinant of any aid type. In addition to a lack of statistical significance there is no systematic distribution of coefficients across shock, household type or aid type. This result suggests that aid was not distributed based upon an anti-poverty criterion. If this had been the case we would have expected the poverty group to be significant, or at the very least for the extremely poor coefficient to be consistently larger than the poor coefficient.

Table 3.18: OLS Regression of Official Aid Received on Harvest Losses (in thousands) with Village Fixed Effects
Dependent Variable: Official Aid Received (in cordóbas)

Harvest Loss Size	< 0			< -1,000			< -2,000			< -3,000		
Harvest Losses	30.06* (17.03)	15.3 (14.24)	17.94* (9.77)	26.95** (11.64)	0.09 (11.42)	8.97 (7.31)	33.31** (14.25)	-3.6 (13.29)	4.06 (7.01)	23.67 (17.46)	-5.96 (26.43)	-0.13 (9.7)
Female	-670.59 (661.7)	-182.33 (199.22)	-364.15 (275.93)	-360.4 (274.39)	-326.45 (305.47)	-908.6 (644.01)	-363.07 (328.6)	-499.07 (461.8)	-399.62* (235.93)	-546.11 (509.78)	-1029.7 (1044.3)	-632.73 (406.48)
Poor	-159.72 (522.21)	-58.8 (290.46)	-215.82 (346.09)	-474.55 (319.4)	2.56 (295.38)	-580.75 (478.18)	-497.66 .(411.32)	7.03 (420.76)	-134.58 (208.03)	-612.53 (656.06)	-51.6 (779.15)	-269.76 (296.27)
EPoor	313.81 (596.12)	-163.3 (289.25)	-214.86 (339.58)	24.02 (276.9)	84.11 (352.56)	-208.45 (319.29)	106.59 (405.51)	35.18 (458.57)	-52.71 (240.61)	-238.6 (613.97)	216.02 (829.8)	-246.15 (355.83)
Constant	1077.8** (462.33)	775.6*** (235.23)	1035.44 (321.77)	1247.06*** (235.07)	590.81*** (213.15)	1193.01*** (400.87)	1139.96*** (361.97)	566.5 (293.84)	764.15*** (170.12)	1276.09** (518.6)	644.43 (555.9)	887.44 (250.59)
R^2	0.15	0.28	0.11	0.97	0.34	0.34	0.61	0.36	0.38	0.63	0.40	0.38
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Harvest Losses	28.11 (17.92)	4.27 (10.89)	15.91 (10.67)	32.15 (28.43)	-0.66 (10.59)	16.75 (15.23)	18.05** (7.16)	-2.30 (10.57)	6.57 (6.68)	19.25* (11.14)	2.72 (10.6)	9.64 (7.47)
Female	-543.89 (367.22)	-194.34 (153.23)	-372.55* (197.77)	-548.58 (378.15)	-152.89 (190.62)	-393.94* (225.9)	-404.47* (208.07)	-225.53 (208.67)	-312.08** (140.63)	-521.19** (236.73)	-185.3 (319.16)	-337.97** (172.12)
Poor	-119.2 (668.49)	68.41 (245.01)	-59.89 (362.35)	-1206.04 (1144.30)	170.84 (244.9)	-451.5 (528.92)	-220.95 (328.99)	171.60 (269.39)	10.75 (193.44)	-419.59 (411.54)	243.26 (363.34)	-42.07 (257.05)
EPoor	284.05 (708.12)	26.94 (248.73)	150.04 (394.2)	-781.42 (1146.41)	131.51 (293.88)	-219.42 (510.98)	208.78 (379.87)	97.20 (367.4)	220.64 (237.15)	-189.39 (490.26)	233.4 (513.88)	73.43 (325.26)
Constant	1050.3* (615.26)	626.16*** (215.01)	867.15** (354.77)	1858.97 (1319.22)	479.35*** (168.70)	1117.65* (607.63)	893.08** (359.44)	466.22** (192.2)	635.4*** (175.8)	1133.91** (476.39)	523.83** (251)	766.26*** (239.12)
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.01	0.01	0.01	0.03	0.01	0.01	0.08	0.01	0.02	0.09	0.01	0.02
Hhold Type	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	160	161	321	98	104	202	69	78	147	46	55	101

* Significant at 10% ** Significant at 5% *** Significant at 1%.

Table 3.19: OLS Regression of Unofficial (Family) Aid Received on Harvest Losses (in thousands) with Village Fixed Effects
Dependent Variable: Unofficial (Family) Aid Received (in cordóbas)

Harvest Loss Size	< 0			< -1,000			< -2,000			< -3,000		
Harvest Losses	-13.35 (11.75)	-12 (13.58)	-16.87 (11.97)	1.82 (2.31)	-3.55 (6.31)	-12.41 (11.23)	2.1 (2.68)	-3.55 (6.31)	-12.22 (11.05)	-3.96 (11.10)	-4.92 (13.84)	-8.36 (9.73)
Female	763.95 (570.9)	248.67 (291.36)	456.23 (308.34)	4.89 (44.19)	434.4 (395.28)	214.53 (244.63)	7.22 (46.62)	434.4 (395.28)	261.79 (324.35)	362.28 (246.13)	1825.59 (1394.26)	702.49 (652.63)
Poor	390.47 (344.29)	-83.51 (142.9)	211.37 (190.49)	-7.67 (15.24)	-68.36 (162.84)	36.41 (76.74)	-7.1 (17.57)	-68.36 (162.84)	56.03 (98.92)	-18.51 (214.33)	78.39 (216.8)	12.8 (150.86)
EPoor	198.96 (185.98)	-151.26 (196.66)	91.83 (124.83)	12.88 (21.29)	-397.42 (349.5)	-50.88 (107.53)	27.29 (36.29)	-397.42 (349.5)	-80.01 (180.44)	345.3 (266.48)	-1063.55 (897.58)	-267.8 (329.9)
Constant	-208.41 (236.21)	174.22 (153.1)	-79.22 (139.29)	192.5 (40.36)	221.69 (139.29)	84.59 (83.71)	249.1*** (60.18)	221.69 (139.29)	107.72 (96.91)	298.91 (201.14)	294.89 (247.3)	197.43 (153.56)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.33	0.35	0.23	0.96	0.51	0.67	0.96	0.64	0.72	0.66	0.71	0.78
Harvest Losses	-2.49 (3.29)	-16.37 (19.89)	-11.77 (11.69)	1.99 (3.99)	-21.32 (21.94)	-11.81 (12.23)	3.08 (4.98)	-19.69 (21.57)	-10.17 (12.64)	-11.99 (18.29)	3.93 (6.79)	-6.38 (12.58)
Female	623.74 (570.15)	264.56 (318.78)	427.91 (309.16)	754.49 (744.99)	510.73 (507.69)	644.74 (460.04)	853.38 (864.11)	761.18 (767.82)	831.09 (598.55)	1342.7 (1262.09)	1236.47 (1265.53)	1289.83 (918.07)
Poor	152.10 (210.11)	-200.4 (153.42)	-34.06 (122.6)	192.64 (294.18)	-112.08 (173.47)	14.89 (186.12)	294.17 (403.62)	-181.07 (259.23)	15.94 (244.08)	-364.82 (404.54)	280.7 (507.6)	-102.28 (319.94)
EPoor	-120.20** (60.87)	-248.29 (172.91)	-188.16** (94.12)	-197.62* (113.51)	-302.8 (244.47)	-260.05* (141.66)	-155.89 (166.35)	-410.11 (351.43)	-322.51 (197.99)	-736.59 (564.52)	-202.53 (260.27)	-531.71* (311.15)
Constant	24.52 (85.34)	229.61 (128.71)	118.8* (72.08)	92.14 (118.53)	94.7 (139.07)	95.86 (94.89)	50.19 (212.66)	140.59 (167.38)	122.69 (122.42)	367.61 (275.91)	54.71 (285.57)	249.78 (175.51)
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.06	0.06	0.05	0.08	0.09	0.07	0.08	0.11	0.08	0.11	0.15	0.12
Hhold Comp	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	160	161	321	98	104	202	69	78	147	46	55	101

* Significant at 10% ** Significant at 5% *** Significant at 1%.

Table 3.20: OLS Regression of Total Aid Received on Harvest Losses (in thousands) with Village Fixed Effects
Dependent Variable: Total Aid Received (in cordóbas)

Harvest Loss Size	< 0			< -1,000			< -2,000			< -3,000		
Harvest Losses	16.71 (19.13)	3.3 (19.86)	1.07 (15.31)	28.77** (12.39)	-3.46 (12.99)	-3.44 (14.28)	35.41** (15.15)	-7.62 (15.7)	-8.17 (13.34)	23.67 (17.46)	-10.88 (28.05)	-8.49 (14.39)
Female	93.37 (902.48)	66.34 (360.36)	92.07 (427.87)	-355.52 (292.83)	107.95 (511.51)	-694.07 (701.9)	-355.84 (347.15)	363.78 (917.21)	-137.83 (414.98)	-546.11 (509.78)	795.86 (2012.69)	69.76 (785.15)
Poor	230.76 (644.76)	-142.31 (328.28)	-4.44 (400.24)	-482.22 (323.79)	-65.8 (341.75)	-544.34 (477.96)	-504.76 (416.3)	-17.83 (460.2)	-78.54 (229.46)	-612.53 (656.06)	26.79 (815.52)	-256.96 (325.67)
EPoor	512.77 (624.13)	-314.55 (354.73)	-123.03 (361.89)	36.89 (286.61)	-313.31 (521.1)	-259.33 (336.06)	133.88 (423.92)	544.93 (770)	-132.71 (306.55)	-238.6 (613.97)	-847.52 (1374.19)	-513.94 (494.5)
Constant	869.39* (527.29)	949.83*** (287.57)	956.22*** (354.52)	1439.56*** (242.99)	812.5*** (260.92)	1277.6*** (411.06)	1389.02*** (375.93)	799.81** (339.16)	871.87*** (195.65)	1575.01*** (518.6)	939.32 (618.98)	1084.87*** (298.66)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.14	0.25	0.10	0.97	0.36	0.37	0.82	0.46	0.53	0.89	0.46	0.59
Harvest Losses	25.62 (18.2)	-12.10 (22.91)	4.14 (15.63)	34.15 (29.76)	-21.98 (25.47)	4.95 (19.3)	21.12** (9.15)	-21.99 (25.94)	-3.61 (14.62)	23.18 (14.61)	-9.27 (22.55)	3.26 (14.62)
Female	79.85 (669.17)	70.23 (342.12)	55.37 (361.31)	205.9 (841.88)	357.84 (516.99)	250.8 (502.05)	448.91 (875.12)	535.65 (763.74)	519.01 (600.7)	715.28 (1270.26)	1157.4 (1238.26)	951.86 (903.32)
Poor	32.9 (702.91)	-131.99 (282.84)	-93.95 (382.6)	-1013.41 (1191.28)	58.76 (293.94)	-436.61 (563.16)	73.21 (519.86)	-9.47 (362.93)	26.7 (308.31)	-138.89 (651.05)	-121.55 (525.84)	-144.35 (404.06)
Epoor	163.85 (714.69)	-221.34 (302.32)	-38.12 (406.8)	-979.04 (1161.84)	-171.29 (383.33)	-479.47 (533.85)	52.89 (417.7)	-312.91 (506.6)	-101.88 (310.5)	-391.92 (553.34)	-503.19 (754.87)	-458.29 (448.97)
Constant	1074.82* (626.13)	855.77*** (248.78)	985.96*** (363.89)	1951.11 (1335.28)	574.05 (229.53)	1213.51 (620.16)	943.27** (418.17)	606..81** (270.93)	758.09*** (220.51)	1188.62** (550.43)	891.44** (392.81)	1016.04 (301.36)
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.01	0.01	0.01	0.02	0.03	0.01	0.03	0.04	0.02	0.05	0.06	0.04
Hhold Comp	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	160	161	321	98	104	202	69	78	147	46	55	101

* Significant at 10% ** Significant at 5% *** Significant at 1%.

Table 3.21: OLS Regression of Official Aid on Hurricane Shocks with Village Fixed Effects
Dependent Variable: Official Aid Received (in cordóbas)

	Long-term Losses			Days Homeless			Wall Damage			Water Supply Damage		
Shock Coeff	0.08 (0.09)	0.003 (0.003)	0.003 (0.005)	48.6* (25.89)	0.15 (4.49)	33.92 (21.52)	1292.69* (757.26)	121.18 (116.06)	741.25* (404.27)	909.91 (809.86)	7.04 (139.16)	581.25 (460.29)
Female	-662.94 (667.75)	-181.74 (199.01)	-361.04 (276.10)	-359.35 (505.04)	-98.68 (138.29)	-151.24 (206.73)	-461.79 (531.03)	-113.73 (140.69)	-188 (212.81)	-195.01 (424.93)	-112.56 (145.56)	-60.57 (167.58)
Poor	-104.34 (534.59)	-18.05 (284.66)	-192.55 (346.13)	181.32 (479.73)	93.29 (183.92)	-1.61 (309.57)	116.03 (469.7)	122.73 (184.46)	-33.75 (312.73)	116.96 (474.98)	128.57 (190.58)	-36.68 (320.1)
EPoor	412.68 (604.7)	-147.14 (292.02)	-210.93 (340.93)	217.75 (332.17)	158.42 (175.04)	76.51 (228.85)	492.35 (473.07)	183.31 (175.84)	94.66 (268.46)	534.97 (449.26)	188.46 (176.12)	146.15 (255.25)
Constant	985.41** (461.23)	693.27*** (206.57)	960.56*** (314.45)	423.38 (376.08)	327.13** (131.3)	401.91 (260.17)	258.38 (251.29)	268.51** (130.63)	370.38** (179.3)	384.21 (259.21)	292.9** (127.8)	415.38** (179.16)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.15	0.27	0.11	0.23	0.24	0.15	0.18	0.25	0.11	0.16	0.25	0.10
Shock Coeff	-0.001 (0.003)	0.05* (0.03)	0.004 (0.004)	55.46 (24.33)	3.29 (3.01)	36.16 (22.04)	1262.28* (676.32)	111.41 (140.75)	753.68** (374.32)	911.61 (737.56)	-65.98 (147.76)	470.41 (411.03)
Female	-192.02 (153.94)	-564.23 (375.45)	-374.98* (200.32)	-94.6 (329.10)	-115.39 (114.21)	-139.74 (172.81)	-256.55 (358.42)	-129.36 (111.38)	-194.22 (180.31)	21.06 (278.53)	-139.01 (116.28)	-85.69 (146.34)
Poor	81.4 (237.42)	-117.89 (668.51)	-48.17 (360.86)	54.77 (431.25)	64.77 (158.66)	13.13 (242.05)	-58.87 (440.16)	110.09 (159.83)	-8.90 (252.68)	11.82 (431.31)	126.68 (158.11)	27.85 (251.21)
EPoor	35.68 (250.73)	300.24 (712.04)	148.4 (396.45)	-70.14 (378.89)	90.4 (161.79)	54.97 (217.16)	105.51 (560.38)	132.17 (157.68)	120.59 (293.37)	371.31 (522.4)	139.19 (159.34)	211.9 (284.33)
Constant	598.52*** (193.6)	991.01* (593.14)	807.15** (331.90)	449.94 (366.53)	344.65*** (133.45)	388.33* (226.14)	377.86 (245.27)	292.10** (134.47)	352.65** (160.04)	420.18* (225.45)	325.61** (141.2)	403.02*** (153.61)
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.01	0.01	0.01	0.01	0.01	0.08	0.04	0.01	0.03	0.02	0.01	0.01
Hhold Comp Type	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	160	161	321	227	218	445	229	216	445	229	216	445

Robust standard error in parenthesis. * Significant at 10% ** Significant at 5% *** Significant at 1%.

Table 3.22: OLS Regression of Family Aid on Hurricane Shocks with Village Fixed Effects
Dependent Variable: Family Aid Received (in córdobas)

Shock	Long-term Losses			Days Homeless			Wall Damage			Water Supply Damage		
Shock Coeff	-0.01 (0.01)	0.01 (0.01)	-0.0004 (0.01)	0.76 (0.53)	-0.64 (2.14)	0.12 (0.89)	-38.66 (48.55)	41.42 (57.02)	-26.09 (38.59)	-26.53 (59.04)	-109.55 (133.16)	-73.88 (57.33)
Female	756.07 (566.25)	235.11 (301.14)	451.19 (312.21)	326.82 (319.97)	168.81 (185.94)	242.66 (182.47)	342.35 (327.48)	174.94 (189.32)	247.95 (185.96)	334.49 (331.48)	159.56 (184.7)	235.22 (187)
Poor	372.7 (336.35)	-133.38 (134.52)	188.66 (186.74)	177.16 (248.42)	-6.13 (94.6)	114.51 (144.17)	169.27 (241.82)	7.97 (94.22)	123.93 (143.4)	169.2 (239.29)	23.22 (100.64)	128.75 (142.11)
EPoor	189.52 (193.9)	-177.36 (196.78)	86.37 (122.79)	63.64 (144.23)	-108.62 (139.05)	25.73 (105.03)	61.97 (140.84)	-94.08 (139.92)	33.24 (104.75)	60.73 (142.38)	-89.97 (140.7)	31.06 (103.89)
Constant	-160.75 (200.34)	271.97 (125.84)	-3.25 (119.52)	-0.36 (144.08)	182.21** (92.52)	63.48 (93.39)	15.16 (133.6)	154.31 (97.98)	61.91 (90.9)	11.24 (148.28)	181.62* (94.88)	71.18 (95.57)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.32	0.35	0.21	0.18	0.23	0.13	0.23	0.19	0.13	0.19	0.23	0.14
Shock Coeff	-0.02 (0.02)	-0.001 (0.004)	-0.003 (0.004)	-0.52 (0.66)	-0.52 (2.23)	-0.64 (0.95)	-148.54 (99.7)	34.31 (92.29)	-63.56 (63.9)	-109.82** (53.55)	37.11 (99.26)	-44.8 (53.44)
Female	630.16 (569.49)	260.57 (330.65)	429.36 (313.17)	299.27 (277.44)	108.57 (169.64)	207.28 (159.96)	326.34 (291.24)	110.2 (173.23)	216.58 (165.29)	293.24 (278.25)	115.98 (171.36)	206.59 (160.87)
Poor	148.88 (210.92)	-242.43 (180.4)	-43.1 (126.21)	75.87 (153.19)	-131.75 (120.67)	-16.26 (94.92)	85.43 (156.79)	-121.94 (123.84)	-5.98 (96.46)	77.3 (150.39)	-122.39 (126.6)	-8.66 (95.29)
EPoor	-132.23** (65.09)	-273.03 (189.84)	-187.27** (93.72)	-91.01 (56.86)	-155.59 (126.72)	-110.75* (64.28)	-67.89 (60.33)	-145.82 (130.44)	-100.4 (64.44)	-99.2* (56.28)	-144.82 (131.25)	-108.10 (64.57)*
Constant	24.6 (81.13)	323.85** (147.15)	163.93** (78.17)	79.39 (73.72)	257.96** (100.2)	154.92*** (58.64)	107.40* (64.81)	237.27** (105.64)	158.78*** (57,98)	-99.2* (56.28)	237.19** (100.89)	155.58*** (58.35)
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.07	0.04	0.04	0.03	0.01	0.02	0.03	0.01	0.02	0.03	0.01	0.02
Hhold Comp	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	160	161	321	227	218	445	229	216	445	229	216	445

* Significant at 10% ** Significant at 5% *** Significant at 1%.

Table 3.23: OLS Regression of Total Aid on Hurricane Shocks with Village Fixed Effects
Dependent Variable: Total Aid Received (in cordóbas)

Shock	Long-term Losses			Days Homeless			Wall Damage			Water Supply Damage		
Shock Coeff	0.07	0.01	0.003	49.36**	-0.49	34.04	1254.04*	162.59	715.16*	883.37	-102.51	507.37
	(0.09)	(0.01)	(0.007)	(25.58)	(4.63)	(21.3)	(764.55)	(123.46)	(408.23)	(819.28)	(195.73)	(467.36)
Female	93.13	53.37	90.15	-32.53	70.13	91.41	-119.44	61.21	59.95	139.48	47	174.65
	(897.65)	(363.77)	(426.69)	(600.49)	(244.52)	(279.41)	(630.39)	(250.24)	(286.78)	(539.47)	(248.59)	(254.16)
Poor	268.36	-151.43	-3.89	358.48	87.16	112.9	285.3	130.7	90.17	286.16	151.79	92.07
	(645.37)	(319)	(397.36)	(545.48)	(207.13)	(343.64)	(534.5)	(208.21)	(347.15)	(537.21)	(217.82)	(353.48)
EPoor	602.2	-324.5	-124.56	281.39	49.8	102.24	554.32	89.23	127.9	595.7	98.49	177.21
	(632.65)	(357.51)	(362.66)	(361.24)	(227.28)	(254.35)	(493.01)	(227.82)	(291.18)	(471.93)	(228.89)	(278.25)
Constant	824.67	965.24***	957.31***	423.01	509.34***	465.4*	273.54	422.82***	432.29**	395.44	474.52***	486.56**
	(507.13)	(247.42)	(339.81)	(406.32)	(161.48)	(278.38)	(286.26)	(163.86)	(203.47)	(299.6)	(160.43)	(205.65)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.14	0.25	0.10	0.22	0.24	0.14	0.17	0.25	0.10	0.15	0.24	0.09
Shock Coeff	0.04	-0.001	0.001	54.95**	2.77	35.51	1113.73	145.73	690.12*	801.79	-28.87	425.61
	(0.03)	(0.006)	(0.006)	(24.66)	(4.05)	(22.27)	(688.44)	(174.01)	(381.56)	(745.18)	(187.05)	(417.13)
Female	65.93	68.55	54.38	204.67	-6.82	67.54	69.79	-19.16	22.36	314.3	-23.04	120.91
	(671.74)	(349.68)	(362.25)	(422.12)	(213.16)	(235.81)	(461.97)	(214.98)	(246.03)	(385.58)	(214.73)	(216.69)
Poor	30.99	-161.02	-91.27	130.64	-66.99	-3.13	26.57	-11.85	-14.88	89.13	4.3	19.19
	(703.47)	(291.98)	(382.01)	(459.03)	(197.79)	(260.23)	(470.98)	(201.96)	(271.5)	(459.49)	(203.1)	(269.58)
EPoor	168.01	-237.34	-38.87	-161.15	-65.19	-55.78	37.63	-13.65	20.2	272.10	-5.62	103.79
	(719.29)	(311.65)	(408.38)	(384.69)	(216.28)	(229.85)	(567.87)	(216.41)	(303.8)	(527.21)	(218.22)	(294.23)
Constant	1015.61*	922.37***	971.08***	529.33	602.61***	543.24**	485.27*	529.37***	511.43***	523.18**	562.8***	558.6***
	(603.65)	(240.97)	(342.81)	(376.99)	(166.73)	(234.95)	(257.27)	(171.45)	(171.83)	(238.98)	(173.37)	(165.39)
Fixed Effects Included	No	No	No	No	No	No	No	No	No	No	No	No
R^2	0.01	0.01	0.01	0.12	0.01	0.07	0.03	0.01	0.02	0.01	0.01	0.01
Hhold Comp Type	Static	Change	Both	Static	Change	Both	Static	Change	Both	Static	Change	Both
N =	160	161	321	227	218	445	229	216	445	229	216	445

* Significant at 10% ** Significant at 5% *** Significant at 1%.

Two theories may explain the lack of any statistically significant relationship between inter-household transfers and hurricane losses. In the first case, it is possible that inter-household transfers are made on the basis of unobservables, which are not easily quantifiable and poorly correlated with income group, hurricane damage, or gender of the household head. Such factors could include reputation and the strength of the relationship between donor-recipient households, size and quality of the affected household's networks, and the donor's perception of the afflicted household's need of aid.

Finally, it is possible (but unlikely) that post-Mitch, inter-households transfers were simply distributed randomly and not significantly related to any observable or unobservable household characteristics. A minimal role for family transfers is not without precedent in the developing world. For example, Park (2001) did not find evidence to support an altruistic linkage for family household transfers in Bangladesh. Among surveyed Bangladeshi households consumption was closely correlated to household income even after controlling for pooled income of the donor and recipient households. Unfortunately, data is not available on the donor households in Nicaragua, which makes additional analysis of these explanations difficult.

Overall, the following statements can be made about post-Mitch aid: (i) official aid played a larger role than inter-household aid; (ii) official aid was sensitive to two observable factors: harvest losses and wall damage; (iii) having a female household head was not a statistically significant determinant of either aid type; and (iv) official aid was targeted away from the wealthiest households.

IV. E. Household Reformation as a Coping Mechanism

One possibility is that in addition to aid, households exercised other coping strategies. These could be cash-based activities such as loans or activities such as adding or dropping household members, which would not show up as a direct monetary inflow. Although post-Mitch survey data does not allow for statistical analysis of the credit market after the hurricane, survey results do not indicate that loans played a vital role in post-Mitch cash flow for surveyed households.

A possibility raised earlier is that household reformation (composition change) is a coping mechanism. It is possible that household reformation is driven by changes in household consumption or that it is sensitive to specific Mitch damages, or to other factors entirely such as poverty level or gender of the household head. To test this hypothesis we use the regression modelled in equation 4 below.

(4) $COMP_i = a + \beta_1 CONS + \beta_2 SHOCK + \beta_3 FEMALE + \beta_4 POOR + \beta_5 EPOOR$

Where COMP is the net number of household members lost or added from 1998 to 1999, CONS is the change in consumption in thousands of córdobas, SHOCK is the shock metric used in Section III, FEMALE is a dummy for female-headed households, and POOR and EPOOR represent households classified as poor and extremely poor, respectively. Regression results (Table 3.24) suggest two interesting trends. The first is that consumption change is a strong determinant of composition change. With the exception of long-term losses, the shocks are inconsequential as determinants of composition. Secondly, with the exception of households affected by harvest losses and long-term losses, having a female-headed household is always significant for the change in composition at 1% or higher. Where all other coefficients are negative, the female dummy coefficient is always positive which indicates that having a female household head is a significant determinant of household composition change and that female households were, on average, net recipients of household members. It is interesting to note that female-headed households appear marginalized by official aid allocations, but nevertheless added members after Mitch. One possibility is that the bias of family transfers towards female-headed households is related to their acceptance of new members. This sounds like a plausible theory which would explain the bias of official aid towards female-headed households. However, there is no statistical evidence to suggest a relationship between family and received and household composition change.[20]

A household's poverty status also appears to play a role in changing household size. Being classified as poor was not a significant determinant of household composition change, however being classified as extremely poor was significant at 1% or higher for all shocks. The coefficient is always negative and indicates that extremely poor households experienced a net loss of household members. The role of changing household size as a coping mechanism is fully explored in the next chapter.

[20] Regression results with the number of household members added as the explanatory variable were insignificant in explaining the amount of family transfers received ($p = 0.8$).

Table 3.24: OLS Regression of Household Size Change on Mitch Shocks Results by Shock Type with Village Fixed Effects Dependent Variable: Change in Household Size 1998 - 1999

	Shock				
(1)	Harvest Losses (2)	Long-term Losses (3)	Days Homeless (4)	Wall Damage (5)	Water Supply Damage (6)
Consumption Change ('000 cordóbas)	-0.13*** (0.05)	-0.12*** (0.05)	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)
Shock (Shown in Col 2 – 6)	-0.02 (0.02)	-0.04*** (0.01)	-0.001 (0.01)	-0.10 (0.17)	-0.12 (0.18)
FEMALE	0.40 (0.29)	0.40 (0.29)	0.55*** (0.21)	0.61*** (0.21)	0.59*** (0.21)
POOR	-0.08 (0.26)	-0.12 (0.26)	-0.06 (0.16)	-0.08 (0.16)	-0.07 (0.16)
EPOOR	-0.70*** (0.29)	-0.70*** (0.29)	-0.64*** (0.23)	-0.62*** (0.23)	-0.63*** (0.23)
Constant	0.30 (0.20)	0.33* (0.18)	0.16 (0.11)	0.16 (0.11)	0.17 (0.12)
Fixed Effects Included	Yes	Yes	Yes	Yes	Yes
R^2	0.34	0.36	0.22	0.23	0.23
Consumption Change ('000 cordóbas)	-0.12*** (0.04)	-0.12*** (0.04)	-0.09 (0.02)	-0.09*** (0.02)	-0.09*** (0.02)
Shock (Shown in Col 2 – 6)	-0.01 (0.01)	-0.05*** (0.004)	0.002 (0.005)	0.03 (0.16)	-0.22 (0.17)
FEMALE	0.42 (0.29)	0.46 (0.29)	0.52*** (0.2)	0.56*** (0.21)	0.53** (0.21)
POOR	-0.07 (0.24)	-0.04 (0.23)	0.008 (0.14)	-0.01 (0.14)	0.01 (0.14)
EPOOR	-0.59** (0.23)	-0.55** (0.23)	-0.49** (0.20)	-0.48** (0.19)	-0.48** (0.19)
Constant	0.29 (0.19)	0.24 (0.18)	0.09 (0.10)	0.08 (0.10)	0.13 (0.10)
Fixed Effects Included	No	No	No	No	No
R^2	0.08	0.13	0.10	0.10	0.11
N =	321	321	445	445	445

*Significant at 10% **Significant at 5% ***Significant at 1%

V. Conclusion

Covariate risk is a real concern for households in the developing world. In order to assess household response to covariate risk we exploited the LSMS dataset to analyze several key aspects of household response to Hurricane Mitch. At the outset we presented three questions concerning the shock-consumption and aid- shock relationships. First, which shocks proved most disruptive to consumption, and to what extent? Second, what was the role of aid in mitigating the disruption introduced by the shocks? Finally, was household composition change a coping mechanism?

In Section III, we examined the relationship between Mitch damages and household consumption. We divided the sample to isolate households with no composition change, and eliminate the impact of preference shifts on the results. Of the five shocks surveyed, harvest losses and long-term losses are significant for consumption. Although the coefficients on these shocks approximate zero, we rejected risk pooling due to co-movement in consumption which would arise with a highly covariate shock.

In Section IV we addressed the possibility that aid-financed consumption would impact the regression results modelled in Section III. We explored the counter-factual: What would the relationship between shocks and consumption have been if no aid had been received? The results of this exercise were mixed. Harvest losses in excess of 1,000 cordóbas became more significant, while the significance levels for most other shocks were unaffected or affected only for the full sample. The increase in significance for harvest losses should tell us that we may expect to find a significant relationship between harvest losses and aid. Indeed this is exactly what we found. Harvest losses, days homeless and wall damage were significant determinants of official aid, but no shock or control variable was a significant determinant of family aid. The data also showed that family transfers were more generous towards female-headed and wealthier households while official aid was comparatively stingy towards female-headed and less poor households.

Given that the shocks tested in Section III were frequently not significant of consumption of households with a composition change, we returned to explore whether household reformation may have served as a coping strategy after the hurricane and whether it impacted net aid received. These results showed that consumption change and a household's classification as being extremely poor was significant for household composition change across all shocks.

In isolation each question gives a piece of information about the relationship between household consumption, shocks and aid after Hurricane Mitch. When viewed together we can begin to assemble a more complete story of Mitch's impact on Nicaraguan households. Overall, the story is remarkably consistent. Nicaraguan households were unable to smooth consumption against Hurricane Mitch damages using existing insurance mechanisms. Harvest losses and long-term losses caused by Mitch disrupted consumption. The disruption to consumption caused by these shocks was fortunately mitigated by post-disaster aid. Official aid was appropriately targeted using harvest losses, while the distribution of family aid is more ambiguous.

An underlying theme is how female-headed, poor and extremely poor households fared throughout this process. It appears that while female-headed and poor households were not inherently more vulnerable to shocks, these characteristics influenced their receipt of post-disaster aid and household reformation. Female-headed households were less fortunate recipients of official aid, but were also net recipients of new household members after Mitch. This generosity was not statistically associated with family aid received.

Overall, the results show that, as expected, households can not rely on informal insurance networks to mitigate damage from covariate risk. Beyond this however, they illustrate the vulnerability of agricultural households to Mitch damages and underscore the vital role of effective aid targeting in the post-disaster period. Official aid played an important role and appears to have been better targeted and more generous than family transfers. Despite these successes future post-disaster aid allocations can benefit from considering the plight of female-headed households and ensuring equal access to aid resources.

Unfortunately, exogenous disaster aid can not always be counted on in such quantities in afflicted regions. The value of the analysis here lies in its illumination of household economic response to covariate risk. But it would be a mistake not to extend the analysis and derive policy implications to safeguard human welfare. Given that informal insurance networks do break down, we have shown that agricultural households are the most vulnerable to disasters damages. Their crops serve as their principle income-generating assets and coping assets and often serve as an important source of consumption. These crops play such a critical role in these households welfare and are also at high risk to destruction. Sound disaster planning must account for this vulnerability using either ex-ante preventive measures or allocating sufficient ex-post resources.

Before concluding, it should be emphasized that the results deal exclusively with the short-run impact of specific shocks. It is unclear if post-hazard transfers are sufficient to prevent declines in household welfare over the long-term. The afflicted areas in Nicaragua were largely agricultural and Mitch removed topsoil and caused flooding, which will impact future farming. If households long-run income generation was reduced it is possible that funds would be diverted from human capital investments (e.g. education, healthcare, vocational training) to meet current needs (McKenzie 2003).

Chapter 4

The Impact of Hurricane Mitch on Nicaraguan Household Size

I. Introduction

In developing countries households frequently use coping strategies to smooth consumption in the wake of unexpected shocks. Coping strategies may take the form of financial transactions such as commercial borrowing, inter-household transfers or asset sales. Recent work on Bangladesh, for example, (del Ninno et al. 2003) following the 1998 floods found that private sector borrowing was an instrumental household coping strategy. Alternatively households may engage in non-market coping strategies to mitigate the impact of unanticipated shocks. One method of accomplishing this is to add or remove household members. Some scholars have investigated the impact of disasters or crises on household structure (McKenzie 2003) although the empirical literature on this topic remains relatively sparse. In the steady state however, economic theory offers an extended discussion of household formation and the intra-household allocation of resources.

Economic theory indicates that household size is heavily influenced by the cost of public and private goods consumed by members. It is intuitive to see that there are economies of scale to be derived from increasing household size thereby allowing the costs (per member) of public goods to be reduced from *n* for individual residence to *n*/household size for a joint residence. In theory this relationship should allow larger households to enjoy higher per capita consumption of private goods such as food. This is particularly true for poor households that operate close to subsistence since their consumption of food is not easily substitutable to other goods. Assuming proportional increases in household size and household resources we would anticipate that a larger household, particularly in a developing country, would facilitate a higher per capita level of food consumption.

In practice evidence from both the developed and developing world indicates the opposite of what theory would predict (Deaton and Paxson 1998). In Thailand, Pakistan and South Africa the authors find that not only do larger households have a lower per capita food consumption – but that the effect is greater for households in poorer countries. That is to say that the gap between the predicted per capita food consumption and the observed amount is greatest in poorer countries. This creates a paradox in which "larger households are better off at the same level of per capita resources since they have the option of decomposing themselves into smaller units. Yet by the most obvious indicator of their welfare, per capita food consumption, they are worse off" (Deaton and Paxson 1998: 899). Thus on the one hand, empirical evidence suggests that larger households in developing countries are worse off as measured by per capita food consumption. On the other hand if smaller households are better off that inspires the question of why large households are maintained if smaller ones can achieve higher per capita food consumption.

Work by Lanjouw and Ravallion (1995) explores the notion that larger families in developing countries are poorer on average than smaller ones. In the economic literature there exists considerable debate as to the direction of causality. Some argue that larger households are poor because they are large, while a case can also be made that households are large because they are poor. Using data from Pakistan Lanjouw and Ravallion find evidence to caution against too readily assuming a negative correlation between household size and welfare. Given that we can not readily assume a relationship between household size and welfare it is useful to consider motives for household formation and division outside of sharing the cost of household public goods.

Our discussion of the gains from sharing the cost of public goods assumed that all members were adults. Many households in the developing world include children and any discussion of household size and welfare must take the presence of children into consideration. Two of the most pronounced economic effects of having children are the allocation of a higher share of the budget to food and the reallocation of hours from labor or leisure to the children. Additional effects may include an alteration of parental preferences towards risk and insurance (e.g. the purchase of life insurance).

Introducing children also raises questions of comparing welfare levels across households with different composition. This has typically been done through the use of equivalence scales which enable the user to compare different household types relative to the poverty line. There is sufficient variation in the approaches used however that differences in scales can impact conclusions (Atkinson 1987). At a basic level it could be argued that two households of equal size could achieve different levels of welfare by virtue of different amounts of children. The logic is that achieving a given welfare level is much easier for a child than for an adult. One example of this is lower food costs. Thus it is difficult to make inter-household welfare comparisons as households can differ greatly in their composition. We pause to consider how the household makes decisions and allocates resources.

Much of the economic theory of the household rests on work done by Samuelson (1956) and expanded upon by Becker (1981). Becker argued that households form to benefit from economies of scale and to produce non-market goods such as children. Although this chapter is unconcerned with the distribution of resources within a household we quickly review these models as they relate to explaining household division. A large portion of the literature employs a unitary model of the household to explain the distribution of resources within the household. Unitary models treat the household as an individual whose objective is to maximize utility which is expressed as a function of consumption. The unitary household pools resources and information and is governed by a (benevolent) dictator. By contrast, collective models allow for unique preferences by individuals and decisions about intra-household allocation are reached, as the name suggests, collectively. The allocation of resources may be bargained if the household is cooperative. Non-cooperative models, by definition, do not allow bargaining and the household may reach an allocation that is or is not Pareto efficient. The unitary model is powerful in its simplicity, but among other criticisms it is incapable of explaining household breakups.

Foster and Rosenzweig (2003) enumerate additional reasons why households would add members or divide and offer a collective model to analyze household division. They argue that households may add members to realize gains in sharing household-specific public goods as well as to lower barriers to information sharing (e.g. on farming techniques). These gains must be weighed against the amount of the public good that is consumed by household residents (for which some residents may have a negative marginal utility) and the impact on risk-sharing vis-à-vis inter-household transfers. Maintaining separate households provides a more diverse risk portfolio as inter-household transfers can be used as a means of insurance. Other factors which could influence household division include the possibilities of diseconomies to joint production and that residents may derive higher utility from or have a direct preference for independent residence. Finally, the authors indicate that assuming households come together to generate a surplus households will divide when the current surplus is negative.

The work by Foster and Rosenzweig serves as a roadmap to the reduced form equations used in this chapter. To explain household division the authors begin from the premise that the utility (u) if individual (i) in household j is a function of consumption of private goods (x), public goods (z), household structure (r) and a vector of the individual's nuclear family characteristics (n). This is shown in the equation below.

$$u_{ij} = u(x_{ij}, z_j, r_{ij}; \boldsymbol{n}_{ij})$$

Their analysis is founded on three assumptions: 1) Decisions about joint residence in a given period must be made before the income shocks are realized, but consumption allocations in a given period are made afterwards; 2) Intra-household allocations conditional on residence and income realizations must be ex ante efficient (it is not possible for a household to improve the expected utility of one claimant) without reducing the expected utility of some other claimant; 3) Each claimant must be provided an ex ante expected utility level that is at least equal to that which he could obtain if separately resident. The authors assume that households will divide when the third condition is unsatisfied, or when there are no gains to joint residence. As an example, when household per capita income declines the gains from joint residence drop and there is an increased preference towards consumption of the private good.

Foster and Rosenzweig use a probit model to test the determinants of household division using the ICRISAT survey data from India. The authors find that, in accordance with their expectations, intra-household inequality in schooling, marriages and riskiness are associated with an increased probability of household division. This chapter also uses a probit model and the explanatory variables are tweaked to capture relevant Mitch-related factors and their impact on changing household size.

While the work by Foster and Rosenzweig offers methodological guidance on testing for determinants of household division, it is difficult to predict household formation and breakups based upon on the demographic characteristics discussed elsewhere in the literature. We can not say that large households are on average poorer (as defined by higher per capita food consumption) as the veracity of this statement depends heavily on household composition and the elasticity of the cost of living as Lanjouw and Ravallion (1995) show in Pakistan. We must also consider individual utility functions and preferences for separate residences which are not captured in a per person cost analysis of public and private goods. Furthermore, any gains to household separation derived from risk diversification and information sharing are largely constricted to agricultural households.

Despite these constraints which prohibit a generalization we can examine the behavior of Nicaraguan households in the periods surrounding Hurricane Mitch in an effort to understand the factors affecting the decision to alter household size in the wake of a large aggregate shock. There is some precedent in the empirical literature for analyzing household behavior to aggregate shocks. Following the 1995 Mexican Peso Crisis, McKenzie (2003) found that household structure remained relatively stable. There was no evidence to suggest that the young postponed establishing their own households or that the elderly moved in with their children. McKenzie does find that children aged 5 – 14 years were more likely to live with non-parental family members during the crisis, however children aged 0 – 5 and 15 – 19 were more likely to reside with their parents during the crisis period. There is also evidence to suggest that household fertility decisions were impacted by the crisis as households had fewer children during the crisis.

The anthropological literature provides examples of household division in times of crisis. An excellent case to consider is that of the Ngisonyoka Turkana tribe in Kenya who have been observed to adjust their settlement patterns to manage disaster risk (McCabe 1990, 1987). The Turkana are a nomadic people who maintain their assets in the form of camels, cattle, sheep, goats and donkeys. The Turkana area of Kenya is prone to periods of drought, which may last over a year. McCabe focuses on the response to a two-year drought period from 1979 to 1981. To cope with the drought the Turkana separate the human population into the smallest viable units, divide livestock into as many small herds as possible, move into areas considered dangerous because of proximity to tribal enemies and may require non-essential tribal members to seek food elsewhere such as cities or farms (McCabe 1987: 376-7). McCabe observes that these mechanisms were completely effective at preventing human death and that there was no famine relief required by the Turkana. There were significant losses of livestock, but by 1985 large shares of these losses were restored.

The Turkana case illustrates an effective response to drought in which households have adjusted their size to mitigate the shock's impact. Despite the observed success it is unclear to what extent household division may be an effective response in a more sedentary society such as rural Nicaragua. For the Turkana their nomadic lifestyle allows them to move both themselves and their assets (livestock) to more favorable conditions. By contrast a sedentary, agricultural society is constrained by fixed assets (e.g. crops, home, irrigation network, tools, etc.) as well as land ownership or tenancy arrangements which makes relocating with these assets a far less viable option. The Turkana are also able to reduce household size by sending members to less-affected areas. This may be a more viable strategy in a slow-onset disaster where macro-economic factors have sufficient time to adjust to the drought's impact. In the case of a sudden-onset disaster such as Hurricane Mitch the impact will offer virtually no similar adjustment period. Nevertheless, these factors do not preclude the possibility that Nicaraguan households may adjust size to cope with disaster impact over the short or medium term.

In the previous chapter we demonstrated the widespread impact of Hurricane Mitch on Nicaraguan households and in particular the strong impact of Mitch on agricultural households. In addition to more traditional consumption smoothing measures we also briefly investigated the possibility that households added or lost members to cope with Mitch shocks. Results showed that for certain shocks extreme poverty is strongly associated with a net loss of household members while having a female headed household is strongly associated with a net gain of household members.

These results provide a useful starting point upon which to engage the issue of whether Hurricane Mitch shocks were significant determinants of household division. The research focus in this chapter draws together threads from the informal insurance literature in which adjusting household size may be a non-market coping mechanism and economic literature on the household in which the disaster may provide a unique opportunity to observe household division as response to an aggregate shock. This chapter focuses on the following questions: (i) What was the impact of Hurricane Mitch on the probability of household reformation? (ii) What demographic factors affected the probability of Nicaraguan households to alter household size? (iii) Was the adjustment of household size a post-Mitch coping mechanism? (iv) Given the results here and in the first paper, what conclusions can we draw about post-Mitch household reformation?

This chapter is organized as follows. The next section reviews the data used and provides background information. Section III discusses the methodology. Section IV discusses the results and Section V concludes.

II. Data and Background

II. A. Data

This paper draws on three Living Standards and Measurement Surveys (LSMS) supported by the World Bank and executed by the Instituto Nacional de Estadística y Censo (INEC) in Nicaragua. The three surveys were executed in 1998, 1999 and 2001. The 1998 and 2001 surveys were scheduled as part of the LSMS and can be used as panel data with one quarter of the panel rotated off. The 1999 survey was executed in May and June of 1999 and covered 595 households from the 1998 panel. The purpose of the 1999 round was to assess the various impacts of Hurricane Mitch on household indicators. In the previous chapter we established a baseline group of 528 households due to losses from attrition, split households or incomplete interviews. When we account for the households which were rotated off the panel in 2001 this leaves 495 households which appear in all three surveys.

This chapter makes use of the 2001 survey for analysis since it allows us to compare the rate of change. To do three survey periods are required. By contrast the other chapters focus on the impact of Hurricane Mitch on a given dependent variable. Expanding the survey period(s) increases the scope for other exogenous shocks to accumulate and impact the dependent variables (Cochrane 1991). Using only two survey periods (1998 and 1999) restricts the impact of accumulated non-Hurricane shocks to influence the variables of interest.

II. B. Background

The previous analysis offers some insight as to what factors may influence household reformation. The last chapter suggested that household consumption was sensitive to harvest losses and damage to income-generating assets. Given this relationship and the role of aid in sustaining post-Mitch consumption we may expect that these factors may also be significant determinants of the household decision to adjust size. In particular we would expect that harvest losses (and possibly long-term agricultural losses) and aid received would be statistically significant determinants of the decision to alter household size. Harvest losses would, in theory, positively increase the probability of altering household size, while increasing amounts of aid would decrease this probability.

Before proceeding to the econometric analysis it is useful to review observed patterns of household change across the survey group for the two time periods. If Mitch were an important factor in driving changes in household composition we would expect, *ceteris paribus*, a noticeable difference in the pattern of household composition change across survey periods. An initial metric of interest is the change in mean household size over time. For the 495 households mean household size changed from 5.88 in 1998 to 6.04 in 1999 to 5.79 in 2001.[21] These figures suggest a bell shaped pattern in which mean household size increased slightly (3%) in the survey period following Hurricane Mitch and decreased in the following period by a similar amount (4%) to approximate pre-Mitch levels.

Table 4.1 below summarizes percentages of household change across survey periods. It is interesting to note that the ratio of households adjusting size to those not adjusting was 1 to 1 from 1998 to 1999. This is somewhat counterintuitive as we may expect the impact of Mitch (if any) would be most pronounced in the period closest to the event. Yet the data in Table 4.1 shows that the proportion of households adjusting their size increased noticeably in the 1999 – 2001 survey period, which would seem to be a relatively calmer period. Further analysis shows that in the 1998 - 1999 survey period the number of households adding members outweighs those losing members. The converse

[21] Although the data can not be used as part of the panel, mean household size in the 1993 survey was 5.51 members.

is true for the 1999 - 2001 period, which is to be anticipated given the observed movement in mean household size.

Table 4.1: Summary Statistics of Household Change Across Survey Periods

Survey Period	**1998 – 1999**	**1999 – 2001**
Surveyed Household	495	495
Households Adjusting Size (%)	245 (49.5%)	313 (63%)
Households Adding Members	142	152
Households Losing Members	103	161
Mean Change (All Households, in # of members)	0.15	-0.24
Mean Change (Change Households, in # of members)	0.31	-0.39
Highest Net Gain	12	9
Highest Net Loss	-7	-10
N =	495	495

Source: Author's calculations

II. B. 1. Household Size

Further analysis suggests a general trend for larger households to lose members (Table 4.2). In particular those households which dropped members are on average two members larger than households that did not adjust composition or added members. Additional analysis in Table 4.3 indicates changes in household trends by household size. Several trends emerge. The first is that smaller households (1 - 4 members) are the only demographic to be consistently above the mean in terms of the percentage adding household members. During the 1998 – 1999 period only 7% of small households dropped members. By contrast nearly half of large households (9 or more members) dropped members in the immediate post-hurricane period. The percentage of households dropping members steadily increases with household size during both survey periods.

Table 4.2: Mean Household Size by Change Status for Households in 1998 and 1999

	Mean 1998 Household Size	Mean 1999 Household Size
Adding Members	5.32	5.18
Unchanged	5.38	5.39
Dropping Members	7.88	7.58

Source: Author's calculations

Table 4.3: Household Size and Net Household Change Across Survey Periods

	1998 – 1999			1999 – 2001		
Household Size	% Adding Members	% Unchanged	% Dropping Members	% Adding Members	% Unchanged	% Dropping Members
1 – 4	37	56	7	38	43	19
5 – 6	24	59	16	36	41	23
7 – 8	22	48	30	23	38	39
9 – 10	24	31	45	20	24	56
10+	26	25	49	11	11	78
Mean	29	51	20	31	37	32

Source: Author's calculations

The relationship between household size and percentage of households dropping members appears to hold for both survey periods, however there are some interesting distinctions. First, households were much less active in 1998 – 1999 in their modifications of household size. Of the 495 households in the panel 245 (49% of the panel) adjusted size in 1998 – 1999 while 313 (63%) adjusted household size in the 1999 – 2001 period. This behavior is true in both nominal and percentage terms. For example, the trend for the percentage dropping members to rise with household size holds in both periods, but the percentages are always larger for the latter survey period.

We can also observe that the percentage of households leaving size unchanged is always greater in the first period than in the second. This holds true irrespective of household size. If we attempt to explain household reformation as a possible coping mechanism to Mitch damages this pattern is somewhat counterintuitive. We would expect the immediate post-Mitch period to be more active for adjusting household size rather than less. Instead it appears that the dominant response in the post-Mitch period was to leave household size unchanged.

The results in Table 4.3 are inclusive of changes to household size as a result of births and deaths during the survey periods. The decision to have children during the first survey period increases household size and is exogenous of any hurricane impact since the survey concluded before Mitch. Of the 495 households 60 had children between the 1998 and 1999 surveys while 133 had children between the 1999 and 2001 surveys. To gain a more complete picture of household size increase we should factor out births. This information is presented in Table 4.4 below. The figures indicate that some of the increase in household size is explained by births, although the large majority of the increase, 83% for the first survey period and 70% for the second survey period, is explained by non life-cycle reasons.

Table 4.4: Addition of Household Members Explained by Child Birth

Survey Period	Households Adding Members (1)	Households with Births (2)	Number of Households with Births Accounting for Full Increase (3)	% of Households in Column 1 with Births Accounting for Full Increase (4)
1998 – 1999	142	60	24	17%
1999 – 2001	152	133	45	30%

Source: Author's calculations

Households also lost members due to mortality reasons. There were 13 deaths among the sampled households during 1998 – 1999. During the 1999 – 2001 survey period 15 households suffered the death of a family member. Checking the drop in household members against deaths will indicate what percentage of the adjustment in household size is due to mortality reasons. This information is presented below in Table 4.5. From the data in Table 4.5 we see that deaths were much less frequent than births for the surveyed households and in only a small percentage of cases (< 1%) did they completely account for the drop in household size.

Table 4.5: Removal of Household Members Explained by Death

Survey Period	Households Dropping Members (1)	Households with Deaths (2)	Number of Households with Deaths Accounting for Full Decrease (3)	% of Households in Column 1 with Deaths Accounting for Full Decrease (4)
1998 – 1999	103	13	0	0%
1999 – 2001	161	15	3	< 1%

Source: Author's calculations

II. B. 2. Household Characteristics

In addition to life cycle changes it is also useful to consider the relationship between other household characteristics and adjustments in household size. Table 4.6 provides data on the movements in household size by various household types. In the 1998 – 1999 survey period we see that female headed households were very active in adding members. They did so at double the rate of their male counterparts. Most of the other household characteristics are fairly close to the mean percentages for the full sample. One exception is households classified as extremely poor. A third of extremely poor households lost members which is 13 percent higher than that of the mean loss. Only 22 percent of extremely poor households added members which is the lowest percentage for any category except for male-headed households. In the 1999 – 2001 survey period the behavior of female-headed households is much closer to the sample mean. Most noticeably the percentage of female households dropping members increases from 16% to 40%. This suggests that the initial adding of members by some female headed households was a temporary measure.

For most other household types we see a noticeable decrease of typically 10 to 20 percentage points in the number households leaving size unchanged from 1998 – 1999 to 1999 – 2001. One interpretation is that households may have actually intended to adjust household size prior to Mitch but postponed this decision. For the most part it appears that the drop in the percentage of households leaving size unchanged is evenly distributed between the addition and subtraction of members. Most percentages in the 1999 – 2001 period are reasonably close to the mean, which suggests no clear trend specific to any household type.

Table 4.6: Percentages of Household Change by Household Characteristic

Survey Period	1998 – 1999			1999 – 2001		
Household Type	% Adding Members	% Unchanged	% Losing Members	% Adding Members	% Unchanged	% Losing Members
Female Headed	44	40	16	32	28	40
Male Headed	22	53	22	30	39	31
Agricultural	29	51	20	32	36	34
Non-Agricultural	28	50	22	29	39	32
Urban	30	53	17	36	31	33
Rural	28	50	22	29	39	32
Extremely Poor	22	45	33	32	29	39
Poor	35	46	19	26	38	36
Non-Poor	27	59	14	35	40	25
Full Sample	**29**	**51**	**20**	**30**	**33**	**37**

Source: Author's calculations

II. B. 3. Harvest Losses

Given the large role of harvest losses in the previous chapter it is also useful to explore patterns of household change by harvest loss size (Table 4.7). If harvest losses due to Mitch have a significant bearing on the alteration of household size we would expect the percentage of dropped members to increase as the loss threshold increases. Between the 1998 and 1999 surveys the percentage of households dropping members does increase with the loss threshold, but not noticeably. What is more notable are the high percentages of households sustaining agricultural losses that make no change in household size. The tabulated percentages for 1999 – 2001 are closer to our initial suspicions of household adjusting immediately. Those households with losses in excess of 2,000 cordóbas show 38% dropping members compared with only 25% of those with less than 1,000 cordóbas in losses dropping members.

Table 4.7: Percentages of Household Change by Mitch Harvest Loss Size

	1998 – 1999			1999 – 2001		
Harvest Loss (in cordóbas)	% Adding Members	% Unchanged	% Losing Members	% Adding Members	% Unchanged	% Losing Members
< 1,000	30	52	18	35	40	25
1,000 – 2,000	22	61	17	31	38	31
2,001 – 4,000	28	48	24	36	36	28
4,001 – 6,000	31	50	19	28	38	34

Source: Author's calculations

II. B. 4. Aid

Household aid also played a strong role in sustaining consumption in the previous chapter. If altering household size was a response to Mitch damages we may expect that, *ceteris paribus*, households which were recipients of post-disaster aid would be demonstrate a lower frequency of adjusting household size. Table 4.8 shows the percentages of household change by households by aid received. Those which received aid exhibited a slightly greater frequency of adding members (4%) in the immediate post-Mitch period (1998 – 1999) although the difference between the two groups is not particularly large.

Table 4.8: Percentages of Household Change by Total Mitch Aid Received

	1998 – 1999			1999 – 2001		
By Aid	% Adding Members	% Unchanged	% Losing Members	% Adding Members	% Unchanged	% Losing Members
No Aid	26	55	19	31	40	29
Aid	30	48	22	31	35	34

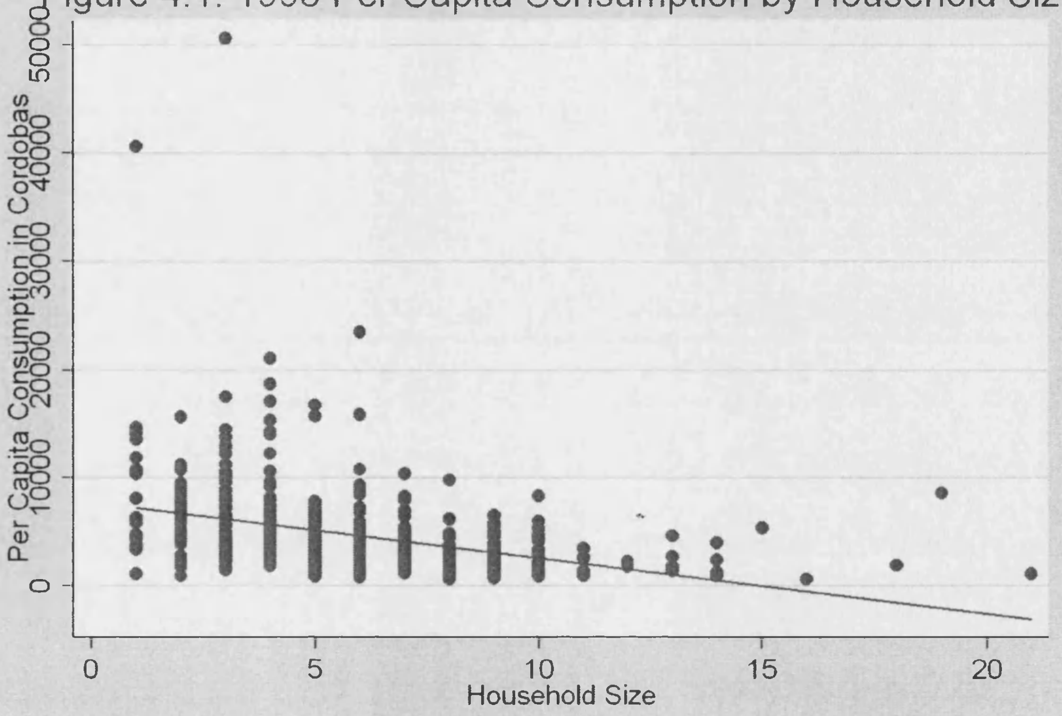
Source: Author's calculations

II. C. Consumption per Capita and Household Size

As discussed earlier the predicted relationship between household welfare (as indicated by per capita consumption) and household size is difficult to define. With the Nicaraguan data we can utilize figures on per capita consumption and changes in household size to test this relationship. Figures 4.1 – 4.3 plot the relationships between household size and per capita consumption.

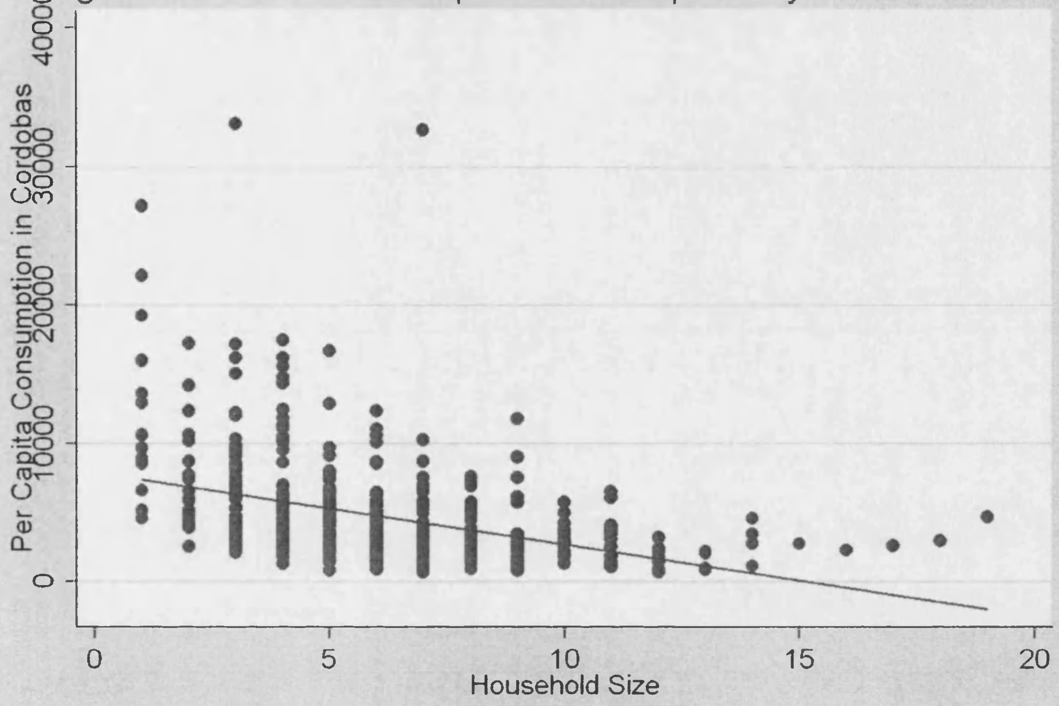
In all three years the plots show a negative relationship between household size and per capita consumption which suggests that larger households on average have a lower per capita consumption. To develop a better understanding of whether households adjusted size as a coping mechanism it would be useful to analyze movements in per capita consumption of those households that change size. In general we would expect that households would drop (add) members to achieve a higher (lower) per capita consumption. We can analyze this pattern in Table 4.9 (below) and graphically in Figure 4.3.

Figure 4.1: 1998 Per Capita Consumption by Household Size

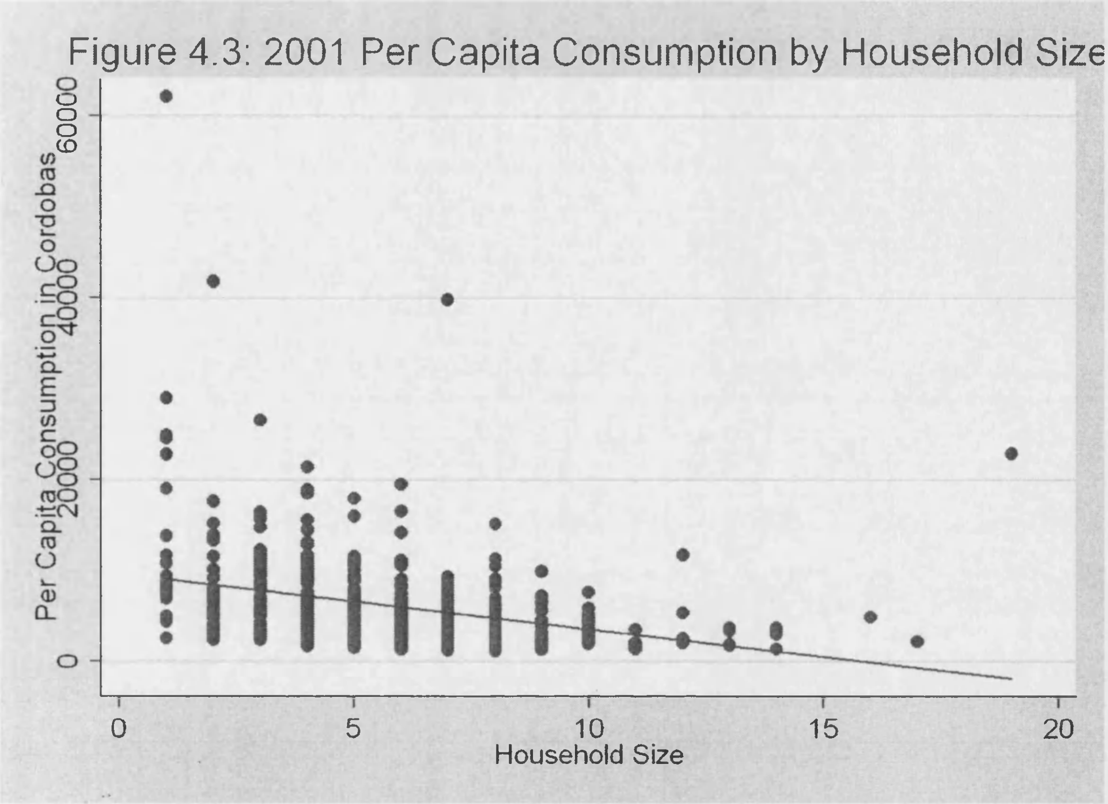


Source: Author's calculations

Figure 4.2: 1999 Per Capita Consumption by Household Size



Source: Author's calculations



Source: Author's calculations

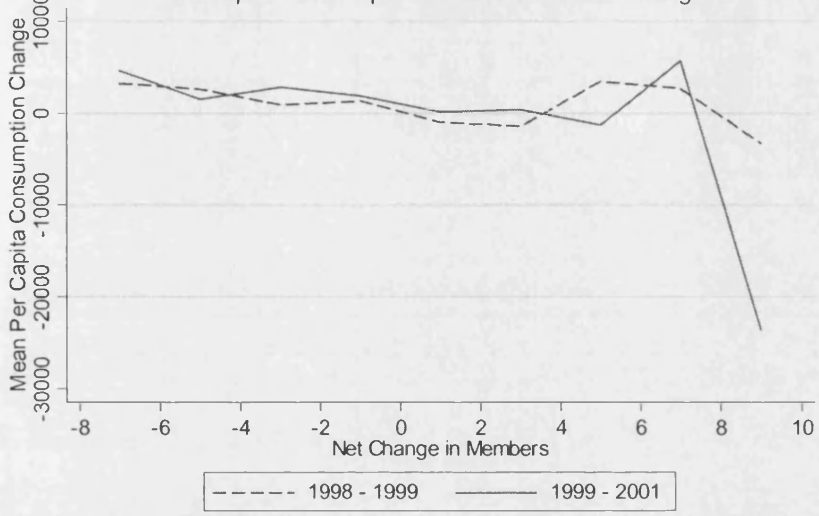
Table 4.9: Mean Change in Per Capita Consumption by Change in Household Size

Change in Household Size	1998 – 1999 Mean Change in Per Capita Consumption (in cordóbas)	1999 – 2001 Mean Change in Per Capita Consumption (in cordóbas)
-7	3260.5	4670.2
-5	2620.7	1550
-3	933.1	2813
-1	1349.7	1922.3
1	-956.2	139.4
3	-1422.2	406.8
5	3492.3	-1286.8
7	2709.8	5722.3
9	-3278.4	-23592

Source: Author's calculations

Figure 4.4

Per Capita Consumption & Household Size Changes



Source: Author's calculations (Table 4.9)

Before drawing conclusions based upon the mean changes in per capita consumption we must caution that some of the values for a change in household size rely on as few as one observation. For households that changed size from 1998 to 1999 (dashed line) there is a pattern of higher per capita consumption growth for households which range between dropping 7 and adding 3 members. However, this relationship breaks down as we move to an addition of 5 and 7 members and then reverses at 9 members. There is no clear relationship in the second period as there is tremendous fluctuation in per capita consumption based upon the net change in size. This information is evident graphically in Figure 4.4 as we see the mean change in per capita consumption in the first period (blue line) begin to *increase* at a net change of 3 members and then decrease again at a net change of 5 members. The second period (solid line) shows an upward trend at a net change of 5 members and then a sharp decline at 7. Based upon these data we would expect to find perhaps limited evidence in the first period of households decreasing size to increase per capita consumption and no evidence of such a relationship in the second period. In the next section we model a relationship to test this hypothesis.

II. D. Summary

A basic review of descriptive statistics suggests some directions for analysis in the next sections based upon the following observations:

- Contrary to initial suspicions it appears that the immediate post-Mitch period was actually less active than the subsequent 1999 – 2001 period for adjusting household size;
- The percentage of households adding (dropping) members decreases (increases) with household size during both periods;

- A higher percentage of households left size unchanged in the first survey period regardless of size;
- A higher percentage of female headed households added members in the first survey period than any other household type;
- The alteration of household size over either survey period appears relatively insensitive to the size of harvest losses;
- There is an inverse relationship between household size and per capita consumption.

The next section sets out our strategy for testing these relationships more rigorously.

III. Methodology

Based upon the descriptive statistics there are a few hypotheses that we can explore. The first is that certain household types are more likely to alter household size. The second and third hypotheses are to evaluate which factors are associated with an increase and decrease in household size, respectively. All three of these hypotheses test for factors that affect the probability of a change in household size. These hypotheses are valuable but do not directly engage the question of whether adjusting household size was a coping mechanism. If households adjusted size as a coping mechanism then households with Mitch damages would have both a decrease in household size and an increase in per capita consumption (all else equal). This forms the basis for a fourth hypothesis: do Mitch-damaged households that decrease size witness an increase in per capita consumption?

III. A. Econometric Background

The discussion of household reformation from the previous chapter can be advanced by several modifications. We modify the model to include household characteristics which were not relevant for risk pooling and aid allocation, but which may be important as the household processes its decision to adjust household size. We also expand the analysis to do a joint significance test for shocks. This allows us to detect the possibility that each individual shock does not exert a strong influence on household reformation, but their aggregate impact does. Finally, we utilize a binary choice model.

Structuring the analysis around a binary choice (dichotomous outcome) model instead of a linear probability model is appropriate when examining dichotomous outcome variable, in this case, the probability of changing household size. In order to model the household decision to adjust composition the variable of interest is defined as a dichotomous outcome variable (Y). Where Y is the decision of household i to not adjust ($Y = 0$) or adjust ($Y = 1$). In the previous chapter we used an OLS regression to test for a statistically significant relationship between the independent and dependent variables. In this case the dependent variable is constrained between 0 and 1 since a traditional linear model could well predict a probability of less than 0 or greater than 1. An additional concern is that a linear OLS model assumes that the error term or disturbance term μ to be normally distributed. However, Y can only take two values (0,1) and this assumption no longer holds as the data takes a different distribution. These are not the only econometric reasons for abandoning the linear model, but two of the most apparent.[22]

To address these concerns a common alternative is to use either a logit or probit model. In brief, these models account for the different distribution of data that the linear model does not adequately handle.[23] In practice the logit and probit models yield similar results although there are certain cases where one may be preferable.

III. B. Modeling the Decision to Adjust Household Size

In the previous section we identified several explanatory variables which are either associated with Hurricane Mitch or which are demographic characteristics. These factors include (but are not limited to) household size, gender of household head, poverty classification, household location, harvest losses due to Mitch and post-disaster aid received. In constructing a model a backwards selection process was used to eliminate variables which do not add explanatory value to the model. The list of variables considered is contained in Table 4.10.

Table 4.10: Potential Determinants of the Decision to Adjust Household Size

Variable	Abbreviation	Variable Type
Household Size in 1998	HH98	Quantitative
Household Size in 1999	HH99	Quantitative
Female Household Head	FEMALE	Qualitative
Rural Household	RURAL	Qualitative
Classified as Poor	POOR	Qualitative
Classified as Extremely Poor	EPOOR	Qualitative
Not Poor	NONPOOR	Qualitative
Children Aged 5 or Younger	KIDS	Qualitative
# of Children Aged 5 or Less	NKIDS	Quantitative
Mitch Harvest Losses	HARV	Quantitative
Mitch Long-Term Losses	LTLOSS	Quantitative
Total Mitch Agricultural Losses (Harvest + Longterm)	AGRLOSS	Quantitative
Days Homeless due to Mitch	DAYS	Quantitative
Home Damaged by Mitch	HDMG	Qualitative
Water Supply Damaged by Mitch	WDMG	Qualitative
Post-Mitch Official Aid	OAID	Quantitative
Post-Mitch Family Aid	FAID	Quantitative
Post-Mitch Total Aid	TAID	Quantitative
Engaged in Agriculture	AGR	Qualitative

[22] For further discussion please refer to Gujarati 2003, p. 580 - 595

[23] Ibid., Chapter 15.

It is somewhat surprising that many of the variables do not add explanatory value to the model. In particular, the literature on household composition and children discussed in the introduction suggested that the number of children may be an important variable to consider. In addition to considering the number of children Browning (1992) finds that it is wise to include a dummy variable for children due to non-linearity in the effects of adding additional children. However neither the number of children nor a dummy variable adds explanatory value to the model.

In the equation 1 we consider the relevant factors enumerated in Table 4.10 with one modification. We first model we consider all households since a significant share of the sample is not engaged in agriculture. Thus including agricultural loss data would prematurely restrict the sample size.

(1) $P_i = F(a + ß_1HH98_i + ß_2FEMALE_i + ß_3AGR_i + ß_4POOR_i + ß_5EPOOR_i + ß_6RURAL_i + ß_7TAID_i + \mu_i)$

P_i is the probability that household *i* will adjust composition, increase size or decrease size (as determined by the relevant equation). P_i is determined by a function (F) which is comprised of several explanatory variables. After different iterations of the model, the following factors were found to be most strongly associated with the probability that a household would adjust composition: household size at the beginning of the survey period (HH98/HH99), have a female household head (FEMALE), whether a household is engaged in agriculture (AGR), whether a household was classified as poor (POOR) or extremely poor (EPOOR), whether a household was located in a rural area (RURAL) and total aid received (TAID). Official aid and family aid were also tested, but their inclusion does not enhance the model and total aid is used instead.

For agricultural households the model is altered slightly to include the agricultural loss variables (AGRLOSS) and the AGR dummy variable is dropped. The amount of agricultural losses is defined as the sum of harvest losses and monetary damages to farming equipment (e.g. livestock, tools, irrigation networks, etc.). During the model selection process total agricultural loss was found to perform better than harvest losses or long-term losses individually. This makes the model more parsimonious without sacrificing loss data and yields the model in equation 2.

(2) $P_i = F(a + ß_1HH98_i + ß_2FEMALE_i + ß_3AGRLOSS_i + ß_4POOR_i + ß_5RURAL_i + ß_6EPOOR_i + ß_7TAID_i + \mu_i)$

In our interpretation of the results we would expect that variables whose coefficients are positive and significant are associated with an increase in the probability of adjusting household size while those variables with negative, significant coefficients are associated with a decrease in the probability of adjusting household size. In other words, a negative significant coefficient indicates an increase in the probability of leaving household size unchanged.

In formulating the model we also tested the possibility that the measured Mitch shocks were jointly significant for household change, additions or subtractions of members. We tested this using a linear probability model, which sacrifices some precision. However as a rule of thumb, if the results of the linear probability model are not statistically significant they are unlikely to be so in a binary choice model. Equation 3 models hurricane damages with various iterations of the dependent variable to reflect a change, increase, or decrease in household size in either of the two periods.

(3) $Y_{it} = a + ß_1 AGRLOSS_i + ß_2 DAYS_i + ß_3 HDMG_i + ß_4 WDMG_i + \mu_i$

In equation 3 Y is the change in household size for household *i* in time period t. The AGRLOSS remains the same from the previous equation and days homeless (DAYS), home damage (HDMG) and damage to the household's water supply (WDMG) are also included. The results of this test reject the hypothesis that all Mitch shocks are jointly significant for any alteration of household size in either period.[24]

III. C. Adjusting Household Size as a Coping Mechanism

The final avenue to explore is that of household size adjustments are a means of coping with Mitch shocks. Based upon the plotted relationship in Figures 4.1 – 4.3 one motive for reducing household size may be to increase per capita consumption. In theory such a relationship would function as follows: a household which suffers Mitch losses would, absent other coping mechanisms, drop members to increase welfare as measured by per capita consumption. However if this hypothesis were true we would expect to see a steady increase (decrease) in per capita consumption as households drop (add) members. The relationship depicted in Figure 4.4 showed that the gains to dropping members begins to reverse when the net change in members reaches a given number. In order to test this relationship more rigorously we use the model in equation 4.

(4) $?C_i = a + ?S_i + ?M_i + ?A_i + DAYS_i + WALL_i + WATER_i + u_i$

The change in per capita consumption (? C) for household *i* from *t* to *t+1* is a function of the net change in household size (? S) across periods as well as the net change in Mitch losses (? M) and aid transfers (? A). Since Mitch losses and aid transfers are zero in time t, this value is equal to the nominal amount for each variable. It is straightforward to see that the changes in Mitch losses and aid will be zero for the second survey period and the equation effectively will simplify to a bivariate regression (not shown). For the same reason household variables across periods demographic characteristics will reduce to zero as nearly all demographic variables remain unchanged between survey periods.

Equation 4 includes a variable for agricultural losses (M) and in doing so excludes non-agricultural households from the sample. Modifying this variable to a dummy (AGRLOSS) which is set to 1 if the household experienced agricultural losses allows us to include non-agricultural households. This modification produces the model in equation 5.

[24] F = 1.72; Prob > F = 0.1469

(5) $? C_i = a + ? S_i + ? M_i + ? A_i + AGRLOSS_i + u_i$

The next section presents regression results for the relationships modeled above.

IV. Results

Results from the models in equations 2 and 3 are presented in Tables 4.11 – 4.16. Each regression is repeated twice: once using the full sample and again excluding observations whose change in household size is fully explained by life cycle reasons. Those households which had changes in size entirely attributable to births and deaths during the survey periods are excluded. Given the relatively small number of households whose size adjustments are fully explained by life cycle reasons, it is reasonable to expect little variation in the results when these are excluded. Nevertheless, in the interest of completeness and for comparative purposes these results are also detailed. Tables 4.11 and 4.12 present the results for the probability of changing household size. Tables 4.13 and 4.14 follow with results for the probability of adding members. Probit results for dropping members are contained in Tables 4.15 and 4.16.

Based upon the probit results we can compute the probability of changing, increasing or decreasing household size for a given value of any variable of interest. Tables 4.17 – 4.19 illustrate the probabilities for changing, increasing or decreasing household size associated with specific variables. Results from the regression model of a change in household size as a coping mechanism (equation 4) are presented in Table 4.20.

IV. A. Probability of Adjusting Household Size

IV. A. 1. 1998 - 1999

During the immediate post-Mitch period three variables are shown in Tables 4.11 and 4.12 to have a statistically significant impact on the probability of adjust household size. The variables of interest are household size in 1998 (significant at 1%), having a female household head (significant at 1%) and being classified as poor (significant at 10%). All three variables have positive coefficients. Households with these characteristics had, *ceteris paribus*, a higher probability of adjusting household size. The results indicate that as household size increases the probability of adjusting size also increases, which supports the descriptive statistics. Female headed households are more likely to adjust size than male-headed ones, which again reinforces the conclusions from the previous section. The same is true for poor households relative to extremely poor and non-poor households.

Narrowing the sample to agricultural households allows us to consider on agricultural losses caused by Mitch. Agricultural losses (harvest losses plus long-term losses) are statistically significant at 5%. This finding is not surprising particularly given the impact of harvets losses on consumption discussed in the previous chapter. As with the full sample, having a female household head and household size in 1998 are also significant (at 10%). One difference compared with the full sample is that the rural household dummy variable is also significant. This is interesting, but not wholly unsurprising as we would expect that agricultural households are also, by definition, rural households as well. Eliminating households whose changes are fully explained by life cycle reasons does not appreciably affect significance levels.

IV. A. 2. 1999 – 2001

During the second period three variables are statistically significant over the full sample. Household size at the beginning of the period (HH99) is significant (at 1%), having a female household head is also statistically significant (at 5%) and a household being rural is significant at 10%. It is interesting to note the inverse relationship between the signs on the coefficients during the two periods. For example, the POOR and RURAL coefficients changes from positive to negative and the AGR and TAID coefficients change from negative to positive. The negative sign on the RURAL coefficient indicates that over the full sample being a rural household had a significant impact on the probability of adjusting household size and that rural households were actually less likely to adjust size.

The significance of agricultural losses appears short-lived as AGRLOSS is no longer a significant determinant of adjusting household size from 1999 to 2001. The rural household dummy variable also loses significance as we move across survey periods. Although none of the other explanatory variables were statistically significant it is interesting to note that the EPOOR coefficient is consistently negative and the FEMALE household is consistently positive. The TAID coefficient and RURAL coefficients both switch signs across survey periods, however total aid is not found to be significant in either instance.

Excluding households with only life cycle changes causes some variation in the statistical significance of certain variables. When are all households are included the rural dummy is significant at 10% for affecting the probability of impacting household change. However, when we remove households with only life cycle changes the rural dummy variables is no longer significant although the coefficient remains negative. The second difference occurs with the female dummy. Over both groups the female dummy increases in significance, from 5% to 1% for the full sample and from not significant to significant at 10% for agricultural households. This is expected as the households which are removed are predominantly male-headed. All three households with deaths were male headed and only 5 of the 45 households with births were female headed.

Table 4.11: Probit Results for Change in Household Size
Dependent Variable: Adjusting Household Size

	Survey Period			
	1998 – 1999		1999 – 2001	
Constant	-0.695*** (0.182)	-1.121*** (0.259)	-0.095 (0.183)	-0.11 (0.253)
Explanatory Variables:				
HH98	0.081*** (0.022)	0.111*** (0.029)	-	-
HH99	-	-	0.08*** (0.023)	0.093*** (0.029)
FEMALE	0.468*** (0.151)	0.508** (0.222)	0.359** (0.156)	0.305 (0.232)
POOR	0.259* (0.136)	0.192 (0.183)	-0.046 (0.137)	-0.214 (0.183)
EPOOR	0.138 (0.166)	-0.225 (0.222)	0.136 (0.167)	-0.039 (0.217)
AGR	-0.082 (0.122)	-	0.073 (0.124)	-
AGRLOSS	-	0.022** (0.011)	-	0.002 (0.01)
RURAL	0.083 (0.13)	0.308* (0.179)	-0.227* (0.134)	-0.072 (0.18)
TAID (in thousands of cordóbas)	-0.035 (0.032)	-0.028 (0.035)	0.006 (0.026)	0.004 (0.028)
Pseudo R^2	0.04	0.07	0.06	0.05
N =	495	298	495	298

Probit coefficients are displayed in the table with robust standard errors in parenthesis.
***Significant at 1% **Significant at 5% *Significant at 10%

Table 4.12: Probit Results for Change in Household Size
Dependent Variable: Adjusting Household Size
(Households with Only Life-Cycle Changes Excluded)

	Survey Period			
	1998 – 1999		1999 – 2001	
Constant	-0.803*** (0.188)	-1.256*** (0.269)	-0.343*** (0.194)	-0.583*** (0.282)
Explanatory Variables:				
HH98	0.09*** (0.023)	0.121*** (0.03)	-	-
HH99	-	-	0.099*** (0.023)	0.12*** (0.03)
FEMALE	0.459*** (0.156)	0.532** (0.23)	0.444*** (0.161)	0.443* (0.239)
POOR	0.233* (0.139)	0.15 (0.189)	-0.055 (0.143)	-0.211 (0.192)
EPOOR	0.112 (0.17)	-0.293 (0.229)	0.084 (0.173)	-0.12 (0.23)
AGR	-0.11 (0.125)	-	0.012 (0.13)	-
AGRLOSS	-	-0.024** (0.011)	-	-0.008 (0.011)
RURAL	0.109 (0.133)	0.314* (0.185)	-0.16 (0.141)	0.091 (0.196)
TAID (in thousands of cordóbas)	-0.03 (0.032)	-0.025 (0.035)	0.012 (0.027)	0.016 (0.029)
Pseudo R^2	0.05	0.07	0.03	0.06
N =	471	282	447	264

Probit coefficients are displayed in the table with robust standard errors in parenthesis.
***Significant at 1% **Significant at 5% *Significant at 10%

IV. B. Probability of Increasing Household Size

By redefining the dependent variable as Y = 1 if the household added members and Y = 0 if the household did not add members we can test which factors significantly affected the probability of adding members. These results are presented below in Table 4.13 for the full sample. Table 4.14 contains the results with increases attributed solely to births factored out.

Table 4.13: Probit Results for Increasing Household Size
Dependent Variable: Increasing Size

	Survey Period			
	1998 – 1999		1999 – 2001	
Constant	-0.565*** (0.19)	-0.804*** (0.265)	0.202 (0.188)	0.569** (0.264)
Explanatory Variables:				
HH98	-0.05** (0.024)	-0.015 (0.029)	-	-
HH99	-	-	-0.118*** (0.026)	-0.11*** (0.032)
FEMALE	0.52*** (0.153)	0.471** (0.223)	0.008 (0.155)	-0.021 (0.232)
POOR	0.328** (0.143)	0.252 (0.189)	-0.12 (0.144)	-0.251 (0.193)
EPOOR	0.012 (0.181)	-0.170 (0.234)	0.23 (0.172)	0.285 (0.223)
AGR	0.146 (0.131)	-	0.187 (0.13)	-
AGRLOSS (in thousands of cordóbas)	-	-0.019* (0.011)	-	0.035** (0.015)
RURAL	-0.035 (0.136)	0.155 (0.188)	-0.209 (0.135)	-0.261 (0.185)
TAID (in thousands of cordóbas)	-0.027 (0.033)	-0.005 (0.032)	0.001 (0.026)	-0.008 (0.028)
Pseudo R^2	0.04	0.04	0.05	0.05
N =	495	298	495	298

Probit coefficients are displayed in the table with robust standard errors in parenthesis.
***Significant at 1% **Significant at 5% *Significant at 10%

Table 4.14: Probit Results for Increasing Household Size
Dependent Variable: Increasing Household Size
(Households with Birth Only Increases Eliminated)

	Survey Period			
	1998 – 1999		1999 – 2001	
Constant	-0.803*** (0.188)	-1.256*** (0.269)	-0.108 (0.206)	-0.008 (0.3)
Explanatory Variables:				
HH98	-0.09*** (0.023)	-0.121*** (0.03)	-	-
HH99	-	-	-0.099*** (0.028)	-0.081** (0.034)
FEMALE	0.459*** (0.156)	0.532** (0.23)	0.127 (0.164)	0.197 (0.242)
POOR	0.233* (0.139)	0.15 (0.189)	-0.167 (0.157)	-0.284 (0.212)
EPOOR	0.112 (0.17)	-0.293 (0.229)	0.119 (0.187)	0.081 (0.0247)
AGR	-0.11 (0.125)	-	0.1 (0.141)	-
AGRLOSS (in thousands of cordóbas)	-	-0.024** (0.011)	-	0.026* (0.015)
RURAL	0.109 (0.133)	0.314* (0.185)	-0.119 (0.15)	-0.06 (0.213)
TAID (in thousands of cordóbas)	-0.03 (0.032)	-0.025 (0.035)	0.007 (0.027)	0.009 (0.028)
Pseudo R^2	0.04	0.06	0.05	0.04
N =	471	282	450	266

Probit coefficients are displayed in the table with robust standard errors in parenthesis.
***Significant at 1% **Significant at 5% *Significant at 10%

IV. B. 1. 1998 - 1999

Over the full sample it is interesting that household size is statistically significant with a negative coefficient. This result supports the earlier descriptive statistics which indicate that larger households are less likely to add members. Having a female household head is significant at 1% and is strongly associated with an increased probability of adding household members from 1998 to 1999. The other variable of interest is the poor dummy variable (POOR) which is significant at 5%. This is unusual as we may anticipate that poor households would be less likely to add members. Instead we find that poor households were in fact more likely to add members over this time. Again we find this relationship is brief as the poor coefficient is both negative and not significant in the subsequent period. Finally, the dummy variable AGR is not significant in either period.

When the sample is restricted to the households engaged in agriculture several results change. During the 1998 – 1999 period the coefficient on household size remains negative, but the variable is no longer statistically significant. The presence of a female household head continues to be significant at 1% with a positive coefficient. Agricultural losses are statistically significant at 10% during the immediate post-Mitch period. As losses increase the probability of household adding members decreases. This relationship sounds intuitive.

IV. B. 2. 1999 – 2001

In the second period household size is also significant (at 1%) with a negative coefficient. We also observe that the increased probability of adding members associated with having a female household head in the first period appears short-lived as the female dummy is no longer significant over the 1999 to 2001 period. Over the full sample none of the other variables are statistically significant however it is interesting to note that the coefficient on poor households has switch signs from positive to negative. This suggests that being a poor household was likely to increase the probability of adding members in the first period, but less likely to do so in the second period.

The negative relationship between harvest losses no longer holds during the second survey period. The amount of agricultural losses due to Mitch is significant at 5% with a positive coefficient. This indicates that as losses sustained due to Mitch increase, affected households had a higher probability of adding members between the 1999 and 2001 surveys. This sounds unusual, but a possible explanation is that the impact of these damages was brief and households are simply adding back members they lost immediately after Mitch. A review of the results in Table 4.14 will allow us to explore this possibility further.

IV. C. Probability of Decreasing Household Size

IV. C. 1. 1998 - 1999

In the immediate post-Mitch period only two variables are statistically significant for the probability of decreasing household size. Household size is significant at 1% with a positive coefficient. Being an agricultural household is significant at 5% with a negative coefficient. Based upon these results it appears that immediately after the hurricane agricultural households were much less likely to drop members relative to urban households. Following this conclusion it is unsurprising that agricultural losses were not significant during the same period. The coefficient on aid received is negative, but never significant. Despite the lack of statistical significance the coefficient's sign suggests that the probability of dropping members decreased as aid received increase. In addition we would not expect a female headed household to be significant for dropping members since they are also significant for adding members in this period. This is indeed what we find. Finally, there are no households whose loss of members is entirely attributable to deaths in this period. Therefore the regression results in Table 4.16 are only for the second survey period.

IV. C. 2. 1999 – 2001

During the second period household size is also significant at 1%. This supports the view that as household size increases the probability of dropping members from the household increases. Having a female household head is significant (at 5%) with a positive coefficient during 1999 – 2001. Female-headed households were more likely to drop members during this time. When we compare this result to the propensity of female headed households to add members in the first period it appears that the addition of members was a temporary measure.

When we restrict the sample to agricultural households, household size continues to be significant at 1%. However, having a female household head is no longer significant, which implies that the female headed households who dropped members in this period may have been predominantly non-agricultural households. The amount of total agricultural loss is also statistically significant at 1%. The negative coefficient indicates the decrease in probability of dropping members associated with agricultural losses sustained during Mitch. Adjusting the sample to exclude the dropping of members for life cycle reasons does not alter the results.

Table 4.15: Probit Results for Decreasing Household Size
Dependent Variable: Decreasing Household Size

	Survey Period			
	All HHs	Agricultural HHs	All HHs	Agricultural HHs
	1998 – 1999		1999 – 2001	
Constant	-1.832*** (0.222)	-2.163*** (0.324)	-1.677*** (0.205)	-2.077*** (0.298)
Explanatory Variables:				
HH98	0.165*** (0.026)	0.172*** (0.033)	-	-
HH99	-	-	0.185*** (0.024)	0.194*** (0.03)
FEMALE	-0.077 (0.185)	0.08 (0.267)	0.38** (0.157)	0.315 (0.237)
POOR	0.139 (0.156)	-0.007 (0.226)	0.154 (0.147)	0.096 (0.198)
EPOOR	0.196 (0.187)	-0.077 (0.256)	0.006 (0.171)	-0.225 (0.228)
AGR	-0.296** (0.144)	-	-0.11 (0.133)	-
AGRLOSS (in thousands of cordóbas)	-	-0.007 (0.012)	-	-0.028*** (0.011)
RURAL	0.139 (0.156)	0.228 (0.216)	-0.034 (0.139)	0.211 (0.194)
TAID (in thousands of cordóbas)	-0.03 (0.045)	-0.079 (0.075)	0.013 (0.026)	0.017 (0.028)
Pseudo R^2	0.11	0.10	0.13	0.16
N =	495	298	495	298

Probit coefficients are displayed in the table with robust standard errors in parenthesis.
***Significant at 1% **Significant at 5% *Significant at 10%

Table 4.16: Probit Results for Decreasing Household Size
Dependent Variable: Decreasing Household Size
(Households with Decrease Explained by Deaths Removed)[25]

	1999 – 2001	
Constant	-1.702*** (0.207)	-2.156*** (0.305)
Explanatory Variables:		
HH99	0.188** (0.024)	0.199*** (0.031)
FEMALE	0.397** (0.157)	0.341 (0.238)
POOR	0.129 (0.148)	0.05 (0.2)
EPOOR	-0.015 (0.171)	-0.237 (0.229)
AGR	-0.114 (0.134)	-
AGRLOSS (in thousands of cordóbas)	-	-0.029*** (0.011)
RURAL	-0.024 (0.14)	0.258 (0.198)
TAID (in thousands of cordóbas)	0.015 (0.026)	0.019 (0.028)
Pseudo R^2	0.07	0.09
N =	492	296

Probit coefficients are displayed in the table with robust standard errors in parenthesis.
***Significant at 1% **Significant at 5% *Significant at 10%

IV. D. Probability of Household Change by Household Characteristics

In addition to tests for statistical significance we can further analyze those factors that are important for changes in household size. Holding all other factors constant, we can test the probability a household characteristic will have on a household changing, increasing or decreasing size. Tables 4.17 – 4.19 indicate the respective changes in probability associated with household size, agricultural losses and gender of the household head.

With household size it is interesting to note that the probability of changing, increasing or decreasing household size is related the number of members. In the case of changing household size, a household with two members in 1998 had, ceteris paribus, a 38% probability of changing household size. This probability increases by 3% per member at which point a household with 10 members in 1998 had a 62% probability of changing size. The relationship for households from 1999 – 2001 is different in two respects. One noticeable difference is that the initial probability of change is higher at 51% for a two person household in this period. A second key difference is that the probability of adjusting size by number of members increases at a more rapid rate. There is not much change as we increase the members from two to four however the probability of change

[25] Regression results are identical to those reported earlier for the 1998 – 1999 period since there were no households which lost members due to death during this time.

increases quite rapidly to 63% for a household of six members. A household of six members is slightly above the mean household size in 1999 and this suggests that a key inflection point during this period lies at mean household size. When households exceed mean household size the probability of changing size increases quite rapidly at a rate of about 2.5% per additional member to a probability of 75% for a household of ten.

The probabilities associated with an increase in household size decrease at about 2% per additional member in 1998 – 1999. There is also a decrease of about 3.5% per member in 1999 – 2001. The difference in the rate of decrease across periods means that smaller households (of less than 6 members) were less likely to add members in 1998 – 1999 than in 1999 – 2001. By the same token larger households (of 6 members or more) were less likely to add members in 1999 – 2001 than in 1998 – 1999.

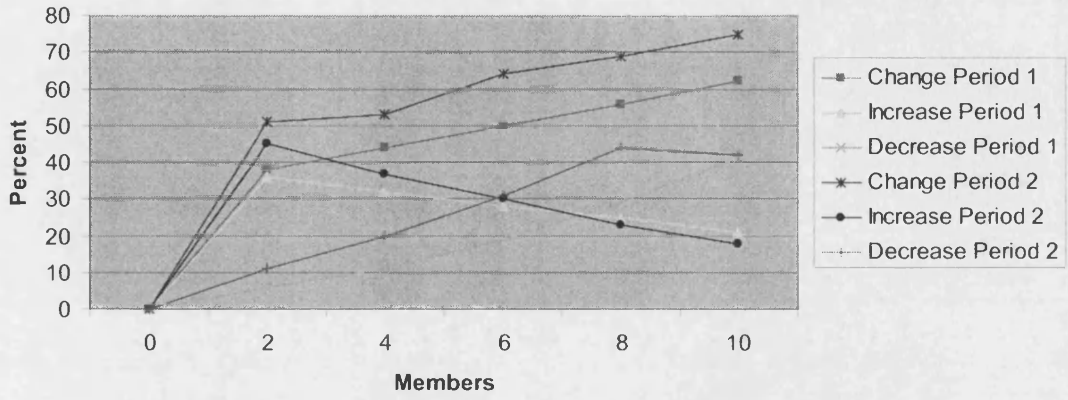
The relationship probability of decreasing household size in both survey periods is shown in Table 4.17. In absolute terms households of any size are less likely to drop members in 1998 – 1999 than in 1999 – 2001 although the probabilities are nearly equal for a household of ten members. All relationships are presented graphically in Figure 4.5.

Table 4.17: Probability of Household Size Adjustment by Number of Members, Ceteris Paribus

1998 – 1999			
# of Members	Changing Household Size	Increasing Household Size	Decreasing Household Size
2	38%	36%	6%
4	44%	32%	11%
6	50%	28%	19%
8	56%	25%	29%
10	62%	21%	41%
1999 – 2001			
# of Members	Changing Household Size	Increasing Household Size	Decreasing Household Size
2	51%	45%	11%
4	53%	37%	20%
6	64%	30%	31%
8	69%	23%	44%
10	75%	18%	42%

Source: Authors's calculations of probability based upon probit coefficients in Tables 4.11, 4.13, 4.15.

Figure 4.5: Probability of Household Size Adjustment



Source: Table 4.17

A second variable of interest in our model is the gender of the household head (Table 4.18). In absolute terms female headed households are both more likely to change household size and increase household size in both survey periods. They are also less likely to decrease household size in either period. In relative terms we see that female headed households were 23% more likely than male headed households to change size in the second period compared to only 13% more in the first period. It appears the greater propensity to adjust size is mostly reflected in decreasing household size. Female headed households were 15% more likely to drop members in the second period compared to their male counterparts versus a difference of only 5% in the first period. Finally, there is a small drop in the difference of the probability of adding members between the genders (16% in the first period versus 12%) although this change is not exceptionally large. Most of the change is reflected in an increased propensity of male headed households to add members.

Table 4.18: Probability of Household Size Adjustment by Gender, Ceteris Paribus

1998 – 1999			
Gender	Changing Household Size	Increasing Household Size	Decreasing Household Size
Female	60%	41%	27%
Male	47%	25%	22%
1999 – 2001			
Gender	Changing Household Size	Increasing Household Size	Decreasing Household Size
Female	84%	42%	46%
Male	61%	30%	31%

Source: Authors's calculations of probability based upon probit coefficients in Tables 4.11, 4.13, 4.15.

When examining the role of agricultural loss size in the probability of changing household size a surprising theme emerges. The results in Table 4.19 suggest that the size of the loss is rather immaterial insofar as probability of household change is concerned. Any loss from 100 cordóbas upwards to 5,000 is associated with only an incremental change in probability. The mean loss is 4,708 cordóbas with a standard deviation of 7,300 cordóbas. Even as we reach loss sizes which are two standard deviations from the mean (approximately 18,000 cordóbas) the associated change in probability is negligible. A loss threshold of 18,000 cordóbas includes 278 of the 298 agricultural households. Extending this threshold by an additional standard deviation to 24,000 cordóbas does not alter the pattern of incremental probabilistic change despite capturing nearly all of the sample. It appears that only in the extreme tail of the distribution for the largest loss sizes (e.g. 63,000 cordóbas) do we observe a large shift in the associated probability.

Table 4.19: Probability of Household Size Adjustment by Agricultural Losses, Ceteris Paribus

1998 – 1999			
Losses in Cordóbas	Changing Household Size	Increasing Household Size	Decreasing Household Size
100	45%	26%	19%
1,000	46%	27%	19%
2,000	47%	27%	19%
3,000	47%	28%	20%
4,000	48%	28%	20%
5,000	49%	29%	20%
11,000	54%	32%	21%
18,000	60%	37%	22%
63,000 (max loss)	88%	65%	29%
1999 – 2001			
Losses in Cordóbas	Changing Household Size	Increasing Household Size	Decreasing Household Size
100	64%	37%	28%
1,000	64%	35%	29%
2,000	64%	34%	30%
3,000	64%	33%	31%
4,000	64%	32%	32%
5,000	64%	31%	33%
11,000	65%	24%	39%
18,000	67%	17%	47%
63,000 (max loss)	73%	1%	88%

Source: Authors's calculations of probability based upon probit coefficients in Tables 4.11, 4.13, 4.15.

The results also reinforce earlier findings that the second survey period was a more active one for adjusting household size. What is particularly striking is that for the large loss households (e.g. those with 11,000 cordóbas or more of losses) the probability of adding members is much lower in the second period than in the first. For households with smaller losses the reverse is true.

IV. E. Changing Household Size as a Coping Mechanism

The results from equation 5 are presented below in Table 4.20. The regression is run three times. The results in the left-hand column for each period use all households including non-agricultural ones. In addition, some null values in the survey limit the sample size to 417 households. The central column in each period contains all agricultural households less those excluded for having null values for other shock variables for a total of 257 households. The right column in each period captures all 298 agricultural households, which comes at the cost of dropping the qualitative Mitch damage indicators. Dropping these variables is not preferable since we decrease our sample size, but none are statistically significant.

If the change in per capita consumption is independent of Mitch losses and purely a function of changing household size we would expect that Mitch losses would not be statistically significant for the change in consumption, while the change in size would be. The household's objective is to maximize per capita consumption we would expect that changing household size would be a significant determinant.

Table 4.20: OLS Regression Results for Per Capita Consumption Change 1998 – 1999

Dependent Variable: Household Per Capita Consumption Change 1998 - 1999

	All Surveyed Households (1)	Households Surveyed with Agricultural Losses and Wall/Water Supply Damage (2)	Households Surveyed with Agricultural Losses (3)
Net Change in Household Size	-666.72*** (131.15)	-564.44*** (161.8)	-457.38*** (113.9)
Agricultural Loss (Dummy)	219 (392.32)	-	-
Days Homeless	8.74 (13.27)	10.84 (13.79)	-
Wall Damage	-142.31 (471.5)	-646.11 (551.92)	-
Damage to Household Water Supply	127.12 (507.61)	371.59 (569.52)	-
Agricultural Losses (in thousands of cordóbas)	-	-48.06 (31.81)	-47.12* (26.85)
TAID (in thousands of cordóbas)	204.66** (84.76)	180.15 (83.24)	187.04** (73.08)
Constant	-179.88 (321.99)	-88.18 (311.73)	-148.76 (244.99)
R^2	0.08	0.08	0.08
N =	417	257	298

***Significant at 1% **Significant at 5% *Significant at 10%

Over the full sample results (Column 1) suggest that the net change in household size was statistically significant at 1% for the change in household per capita consumption between 1998 and 1999. The coefficient is negative which is unsurprising given the distribution of per capita consumption by household size plotted in Figure 4.1. In addition we observe that none of the variables measuring Mitch damages are statistically significant. Based upon this result it would appear that the change in per capita consumption was independent of the indicated Mitch damages. Again this is not wholly unsurprising considering the results in the previous chapter which showed that consumption was relatively unaffected Mitch damages outside of agricultural losses. Finally, we see that aid is statistically significant for the change in per capita consumption (at 5%) with a positive coefficient. Again this is unsurprising given the results in the previous chapter.

The second variant of the model captures as many surveyed agricultural households as possible which were exposed to all measured types of hurricane damages. For this variation of the model the results (Column 2) net composition change is also significant at 1% with a negative coefficient. None of the Mitch damage variables are statistically significant at any level. Aid is also not statistically significant. These results also suggest that the change in per capita consumption was independent of any Mitch damages. One disadvantage of this regression is that in order to capture all Mitch damages we reduce the sample of agricultural households by 41 (from 298 to 257 or roughly 14%). This provides the benefit of capturing additional shock data, however most of these have been shown to be unimportant with the exception of agricultural losses.

Dropping variables without explanatory value from our model allows us to capture the excluded 14% of agricultural households for which we have data on agricultural losses. This variation of the model (Column 3) captures all agricultural households and makes the model more parsimonious by excluding other Mitch damage indicators, which are shown to be not significant for the change in per capita consumption. In this model net change in household size is also significant at 1%. Agricultural losses are statistically significant (at 10%) with a negative coefficient and aid is significant (at 5%) with a positive coefficient. These results indicate that for agricultural households change in size, agricultural losses and aid received were all statistically significant determinants of a change in consumption per capita. The coefficients on all three have the expected sign and suggest that households which experienced agricultural losses, even with aid, adjusted size to realize an increase in consumption per capita among household members.

V. Conclusion

At the outset we enumerated four questions for analysis in order to assess the possible role of household reformation as a coping mechanism to a large aggregate shock - Hurricane Mitch. Specifically, we asked (i) is the rate at which households adjust size in the 1998-1999 pre and post Mitch periods different than in the 1999 – 2001 period? (ii) What impact do Mitch shocks have on the probability of a household's decision to adjust size? (iii) What impact do factors unrelated to Mitch have on the probability of adjusting household size? (iv) Do households adjust size as a post-Mitch coping mechanism?

Prior to any statistical analysis it was suggested that we would expect the 1998 – 1999 period to be an active one in terms of households adjusting size due to the stress placed on traditional household coping mechanisms by Hurricane Mitch. Theory was unclear, however, on whether we would expect households affected by Mitch to add or lose members. The model of household division put forth by Foster and Rosenzweig suggests that households will divide when members derive a negative marginal utility from shared housing. In short, the household will divide when the economic gains from living apart exceed those from living jointly. The converse is true for household addition.

One of the benefits of separate residences is risk diversification. Separate households tend to have income streams that are less correlated. This is particularly true for agricultural households as different plot locations provide some hedge against idiosyncratic variations in yield. Unfortunately for Nicaraguan households, the expansive reach of Hurricane Mitch negated many of the benefits of risk diversification and risk pooling as hurricane damages afflicted entire regions. On one hand it is reasonable to anticipate that affected households would add members in order to reduce the marginal cost of household public goods. On the other hand if households had their income streams and consumption sufficiently disrupted that the costs of leaving household size unadjusted exceeded the gains from adding members we would expect households to drop members.

V. A. Is the Rate at Which Households Adjust Size in the 1998-1999 Pre and Post Mitch Periods Different Than in the 1999 – 2001 Period?

Initially we posited that the period immediately following Mitch would be more active in terms of households adjusting size in response to Mitch's impact. Instead we found that the opposite was true. Roughly 50% of households adjusted household size in the 1998 – 1999 period, while 66% adjusted household size in the 1999 – 2001 period. Further analysis showed that in addition to the second survey period being more active there were also noticeable differences in household adjustments. Perhaps most striking is the tendency of households to leave household size unchanged in the immediate post-Mitch period. Instead of households adjusting rapidly to the impact of Mitch it appears that most household types did not adjust household size until well after the hurricane. In this respect, it appears that a principal impact of Mitch was to delay adjustments in household size by more than 6 months (roughly the amount of time between Mitch and the 1999 survey).

V. B. What Impact Do Mitch Shocks Have on the Probability of a Household's Decision to Adjust Size?

We measured the impact of Mitch shocks while deriving the model presented in section III and the only ones that added explanatory value to the model were total agricultural losses. This makes intuitive sense based upon the results in the previous chapter. Given that agricultural losses did not affect all households we also introduced an agricultural dummy variable. A household's designation as agricultural and the amount of agricultural losses were first tested for their impact on the probability of adjusting size (in either direction) and then for their respective impact on the probability of adding or dropping members.

Results showed that a household being agricultural was associated with a lower probability of changing size in 1998 – 1999 and a higher probability in 1999 – 2001, but was not statistically significant in either period. However, when we isolate households which dropped members results indicate that being an agricultural household was a statistically significant determinant of dropping household members. Agricultural households were much less likely to drop members than non-agricultural households during 1998 – 1999.

When we restrict the sample to agricultural households, we can focus on agricultural losses, which were statistically significant in all periods. The probit results indicate that as losses increased the probability of adjusting household size in 1998 – 1999 also increased. Rising agricultural losses decreased the probability of adding members decreased in 1998 – 1999, but increased it in 1999 – 2001. Agricultural losses did not significantly impact the probability of dropping members in 1998 – 1999, but rising agricultural losses decreased the probability of dropping members in 1999 – 2001.

V. C. What Impact Do Factors Unrelated to Mitch Have on the Probability of Adjusting Household Size?

We surveyed a range of factors and two were consistently significant across the probit analyses: household size at the beginning of the survey period and having a female household head. These factors tend to be significant whether we are considering the probability of household change or the probability of change in a specific direction. From the descriptive statistics and probit analysis we can draw several conclusions about which types of households were most likely to adjust size and add or remove members in a given period.

One factor which is remarkably consistent across all analysis is household size. Both descriptive statistics and econometric results indicate that smaller households are more likely to add members and larger households are more likely to drop members. This relationship holds across the full sample and for the isolated sample of agricultural households. We also found that for two households of equal size, the household in the latter survey period is more likely to change or decrease size. However, with regards to increasing size households of more than six members are more likely to add members in the earlier survey period, while households of less than 6 members are more likely to add members in the latter survey period.

The additional variable which significantly impacted the probability of household change in different sample groups and survey periods was whether or not the household had a female head. In absolute terms, we found that households with a female head were more likely to change, increase and decrease household size in both survey periods. In relative terms we showed that female headed households were more likely to change or decrease household size in the latter period and equally likely to add members in both periods.

V. D. Is Household Change a Coping Mechanism for Mitch Damages?

The response to this question is largely contextual based upon whether we isolate agricultural households. Over the full sample, the answer appears to be no. While we find evidence of a linkage between household size and the change in household per capita consumption, there is limited evidence of a comparable linkage between Mitch shocks and per capita consumption. An analysis of all households shows no relationship, nor does a more narrow analysis of agricultural households. Only when we consider all agricultural households do we find evidence of a relationship between Mitch damages and the change in household per capita consumption. Based upon these results it would appear that a change in household size was a viable non-market coping mechanism for agricultural households, even when we consider the positive impact of post-disaster aid.

V. E. Concluding Remarks

At the outset we raised the issue of adjustments in household size after Hurricane Mitch and the factors which affected the probability of a change. We also introduced the alteration of household size as a possible coping mechanism to aggregate shocks. Based earlier work by Foster and Rosenzweig we discussed potential determinants of household division, however it was unclear what the impact, if any, of Mitch on Nicaraguan households would be as economic theory was unclear as to how households would behave.

Econometric analysis showed that while other sub-themes emerge, agricultural households play an integral role in our analysis. We identified an inverse relationship between household size and per capita consumption and demonstrated differences in patterns of changing household size in the two survey periods after Mitch. In general we observe that households were less likely to adjust household size in the 1998 – 1999 period. We also find that smaller households are more likely to add members while larger households are more likely to drop members. We also show differences in the patterns of changing household size between female and male headed households, with females being more likely to add members in the immediate post-Mitch period.

A constant theme across the analysis is the behavior of agricultural households after Mitch. The descriptive statistics their pattern of household change across survey periods was relatively in line with the entire sample. However, the probit results showed the probability of adding members decreased with agricultural losses in the first period. The probability of dropping members decreased with agricultural losses in the second period. Whether or not a household was engaged in agriculture also reduced the probability of decreasing members in the first period. Further interpretation of the probit results showed that it appears to be the incidence rather than the amount of losses, which was significant for agricultural households changing their household size. Increasing the loss amount by entire standard deviations results in only a negligible increase in the probability of altering size. Regression results also suggest (with the aforementioned caveats) that agricultural losses are the only Mitch related damages that exert are important for changing household per capita consumption – even after controlling for changes in household size and aid received. This suggests a coping relationship in the change in household size and agricultural losses significantly impact household per capita consumption.

In sum, we find evidence to suggest that suffering agricultural losses caused by Mitch strongly affected the probability of adjusting household size and that a coping relationship exists in which the change in harvest losses and household size consequently leads to an increase in household per capita consumption. The findings are consistent with those in the previous chapter and underscore the impact of agricultural losses on Nicaraguan households as well as the difference in response to Mitch by female and male headed households. The next chapter focuses on the impact of Mitch on female headed households and their response.

Chapter 5

Poverty, Vulnerability and Response of Nicaraguan Female Headed Households to Hurricane Mitch

I. Introduction

The development literature has extensively documented the economic, social and political inequalities that women face (UN 2006, World Bank 2002). Within development economics a body of evidence exists to support a relationship between having a female household head and poverty in the developing and developed world. If female headed households (FHHs) are marginalized in everyday economic activities it stands to reason that they are more vulnerable to risk and less equipped to respond to unexpected shocks by using traditional coping mechanisms (both formal and informal).

Despite institutional and political gender discrimination which may negatively influence official transfers to FHHs many studies in the economic literature have found that private, inter-household transfers are positively targeted towards women. In their study of urban households, Cox and Jimenez (1998) show that Colombian inter-household transfers are favorably targeted to FHHs in urban Cartagena. In Peru Cox et al. (1998) find that a disproportionate share of child-to-parent transfers is allocated to female headed households. In El Salvador Kaufman and Lindauer (1986) find that transfers to female headed households are roughly 2.5 higher than those to male headed households even after adjusting for income levels. Evidence from the Philippines (Cox et al. 2004) also shows that female headed households receive higher private transfers than male headed ones. Female headed households are also more likely to receive remittances from abroad which lends support to the theory that these transfer levels are driven by migrant husbands. If these transfers contain a risk sharing component we would expect them to continue to be targeted to female headed households in the post-disaster environment.

Their may be at least two reasons to explain a targeted distribution of inter-household transfers to FHHs. One is a structural function of a divided household when the husband moves abroad or to an urban area and sends remittances. The second is of a behavioral nature and has been noted in intergenerational studies. In these situations transfers are payments for in-kind services such as child rearing or household work (Cox and Jimenez 1998). The authors also indicate that women have fewer opportunities in the labor market and thus have higher income risk.

Women and female headed households can also disproportionately impacted by disasters (ECLAC 2003). Female headed households may incur direct and indirect losses. Direct losses include damage to the home, its furnishings and appliances. The loss of productive appliances that are used in home workshops or small business can be particularly crippling. Indirect losses are classified by four groupings: (i) loss of external productive employment and income; (ii) loss of household production and income; (iii) an increase in women's reproductive work and (iv) other indirect damages (ECLAC 2003). The loss of external productive employment includes becoming unemployed or underemployed following the disaster. Loss of household production and income occurs as a female headed household's home based entrepreneurial activity is disrupted. This activity may often be in the informal sector and estimates are not captured by official statistics. Increased reproductive work refers to time devoted to tasks such as securing food, shelter, medical supplies and survival necessities that entail an opportunity cost. Examples would be time spent seeking aid, preparing meals and household reconstruction and repairs. These tasks do not have a monetary value, but are necessary and are often performed by women even in male headed households. Finally other types of indirect damages may include the loss or destruction of assets the female headed household has borrowed or disruption to income flows the household needs to repay any loans (ECLAC 2003).

This chapter focuses on the allocation of post-disaster aid to FHHs and the behavior of FHHs after Mitch. It explores three questions: (i) whether FHHs, and in particular agricultural FHHs, were disadvantaged in receiving official aid (ii) if FHHs were targeted for inter-household transfers based upon the gender of the household head and (iii) why some FHHs are more likely to increase household size after Mitch.

I. A. Why Are Female Headed Households Poor?

Many studies have found a relationship between female headship and poverty. Buvinic and Gupta (1997) review 61 studies on the relationship between female headship and poverty: only eight of these (13%) found no evidence of greater poverty for FHHs. Buvinic and Gupta cite three factors why FHHs may be poorer. First, although female households are smaller, they have a greater dependency ratio. That is to say that the ratio of non-workers to workers to workers is higher in FHHs. It should be noted that the elderly are not included as dependents since they may have their own savings or assets with which to support themselves (or still be employed). A second factor is existing inequalities within the labor market. If females in general have lower average earnings in the economy having the household head's wages reduced by this amount increases the probability of a female headed household being poor. Finally, household structure and wage differences can combine to contribute to poverty. This is because female household heads must also attend to domestic responsibilities which can lead them to taking jobs which are less than optimal from a wage perspective although they afford working hours or proximity to the home which allows domestic duties to be more easily fulfilled.

In addition to these reasons Vecchio and Roy (1998) propose two additional explanations which have exacerbated the status of FHHs in the developing world over the long-term.

Citing Kottis (1990) the authors indicate that changes in women's participation in the labor force is U-shaped. That is to say as the economy industrializes and grows women are last to be employed in periods of growth and first to be laid off during a contractionary or slow growth period. As industrialization proceeds and the economy expands the relative share of agriculture and the informal sector will decline and it is these latter sectors which are more likely to employ women.

A second theory is that FHHs are vulnerable to negative externalities from the depletion of public goods. This theory draws on work by Dasgupta and Heal (1979) on the importance of recognizing renewable environmental resources as economic goods. In the developing world FHHs are more dependent upon common property resources (CPRs) than men. This is because environmental resources such as drinking water and firewood may hold more relative importance for FHHs. As these resources are depleted or rendered unusable (e.g. through pollution) the impact of this loss is felt disproportionately upon FHHs. The authors find evidence of commercial operators depleting waters in India which deprives women of a primary income source (prawn larvae).

While poverty amongst females and FHHs has received much attention in the development literature an initial lack of empirical data led to a heavy reliance on anecdotal accounts of female poverty (McGuire and Popkin 1990). The United Nations has stated that as much as 70 percent of those in poverty are women (UN 1996). The UN figures assume 1.3 billion in poverty of which 900 million are women. These figures suggest that there are more women in poverty than men (by 500 million), although some scholars have questioned the exact size of this gap (Quisumbing et al. 2001).

Quisumbing et al. investigate whether females and FHHs contribute disproportionately to overall poverty. The authors examine poverty measures and their sensitivity to the use of per-capita and per-adult equivalent units as measures of poverty and different definitions of the poverty line. Poverty measures are generally higher for FHH, but the difference between FHH and male headed households is significant in less than a third of the datasets. FHHs also contribute a low share to aggregate poverty since they represent a smaller share of the population. Only in Ghana and Bangladesh do the authors find significant differences between poverty of male and FHHs.

I. B. What is a Female Headed Household?

Despite empirical evidence over the past decade on the link between FHHs and poverty and no lack of theory as to explain why, we must caution against painting FHHs with too broad of a brush. The classification of FHHs can include widows, divorced women, single women, abandoned women and women whose husbands are migrant workers (Joshi 2004). The reason behind the household's formation may have implications for its welfare. For example, an elderly widow is a female headed household by all counts, but she may have access to bequests from her late husband or transfers from children. By the same token, wives of working migrant husbands often receive remittances. These classifications illustrate the difficulty in defining a female household and caution against assuming homogeneity among FHHs. To complicate matters further disparities in the economic definition of a household and of a household head complicate inter country comparisons of FHHs.

I. C. Targeting Female Headed Households to Reduce Poverty

If FHHs are overrepresented among the poor it is logical to ask if targeting aid transfers to females and, in particular, FHHs may be an effective means of anti-poverty allocation (Buvinic and Gupta 1997). Some arguments for targeting transfers towards FHHs are that FHHs are poorer, they suffer gender discrimination and they do not have a partner to help support the household. In addition to the immediate benefits of poverty reduction there are long-term benefits that are chiefly associated with the welfare of children in the household. For example, if it can be shown that the benefits of anti-poverty transfers extend to the nutrition and education of children in FHHs there is a stronger argument for directing transfers towards FHHs (Buvinic and Gupta 1997).

With any targeting program there are concerns of leakage and missed targeting. In the case of leakage female headship is not always correlated with poverty and there would be screening costs to eliminate non-poor FHHs. It is also possible that FHHs which are poor would be missed due to differences that arise when trying to consistently define female household headship. Another concern is issues of incentives and endogeneity which arise when transfer programs explicitly target FHHs. This creates circumstances in which households could form in order to receive transfer benefits. Recognizing these issues "[u]sing female headship as a targeting criterion is, in principle, attractive because of the association between female headship and poverty. Targeting these households may be especially useful when there are no other reliable ways to identify poor households and when their prevalence is not too high" (Buvinic and Gupta 1997: 270).

Transfer targeting based upon female headship has been implemented in Chile since 1991 with encouraging results. The program was unique in the sense that there were no direct transfers of cash or benefits redeemable for food. The project also entailed participation costs for the members in the form of attending training sessions. Leakages in the project were minimal and results suggest that the benefits of the program were directed to those households in need. The Chile program is notable in that it has minimal screening costs since the households largely self-screen based upon the transaction costs the household incurs by participating (Buvinic and Gupta 1997).

I. D. Female Headed Households and Natural Disasters

Gender roles may also contribute to variations in post-disaster recovery. In a study of the rebuilding process following the 1991 Oakland firestorm Hoffman (1999) finds evidence to support a relatively disadvantaged post-disaster position for females. From her findings she argues that in general "women are more prone to post-disaster disease. Women tend to lose conflicts over scarce resources . . . After disasters, in many societies women are more likely to end up on government handouts or permanently dependent on aid" (Ibid.: 188). Her analysis is supported by the work of Blaikie et al. (1994) who also argue that women are relatively disadvantaged in the post-disaster prevention and response processes. Furthermore, women may be adversely affected by natural disasters in a manner, which may not show up in aid distribution surveys. In Bangladesh, for example, "a particularly damaging flood, however, has more serious consequences for women than for men. In addition to women's work being confined and undervalued by men, wives in poor homes are perceived as a burden and finally deserted by their husbands during the severe impoverishment, which is the long-term consequence of flood disasters for the very poor" (Shaw 1992: 210).

The socio-economic effects of Hurricane Mitch have been analyzed using a gender approach by Bradshaw (2004) and we briefly summarize the key findings here. The most important direct and indirect impacts of Mitch can be classified as time, safety, income and production. Time represents the additional hours devoted to community work which entails an opportunity cost for productive work that could be done. Migration by men after Mitch meant that women's household responsibilities also increased. Bradshaw also cites the emotional impact of Mitch as a factor which raised feelings of fear and insecurity which contributed to higher violence, some of which was directed towards women. Income was also sacrificed by rural households who saw a decline in productive sowing capacity and lost income in the period after Mitch. Finally, hurricane damages may have disrupted the production of homegrown food as well as reproduction decisions.

I. E. Analytical Focus

This chapter builds upon work in the economic literature which identifies linkages between female headship, poverty and aid targeting as well as accounts of FHHs in the post-disaster environment in the anthropological literature. Using panel data from Nicaraguan households we can first test poverty levels of FHHs and analyze their behavior following the hurricane. Based upon field work accounts from disaster anthropologists we would expect that FHHs would be disadvantaged in receiving official post-disaster aid. It is unclear what relationship would hold for family transfers.

In the previous chapters we demonstrated that FHHs responded differently to Mitch than their male counterparts. In the first chapter we showed that FHHs were received less post-disaster aid, but more inter-household transfers. At that time we speculated that FHHs may have been discriminated against or partially excluded from official aid transfers. We will see if this conclusion is accurate. In the second chapter results showed that FHHs were more likely to add members after Mitch. These findings differentiated between male and FHHs. Due to heterogeneity among FHHs it is premature to conclude that any uniformity in behavior existed amongst FHHs. We examine the decision of some FHHs to increase household size, while others of comparable welfare do not.

Before proceeding it is important to state that we are only concerned with economic or otherwise observable indicators of Mitch. There is evidence in the literature (e.g. Bradshaw 2004) which details that FHHs (and women in general) often suffer in non-quantifiable ways after a disaster. Examples include being the victims of violence, the emotional stress of living through the disaster and the demands of maintaining a full household if the male becomes an economic migrant after the storm. This list is not exhaustive, but illustrates factors which are clearly important in completely evaluating welfare comparisons. Bearing these factors in mind, we focus on welfare which is measured using quantifiable economic indicators, recognizing this is likely an imperfect picture of welfare post-Mitch for FHHs.

The chapter proceeds as follows. The next section reviews the data set and relevant descriptive statistics associated with FHHs. Section III details the methodology used to test the behavior of female households after Mitch. Section IV discusses the results. Section V concludes.

II. Data and Background

II. A. Data

This chapter also uses the LSMS data set. The specifics of the data set have been detailed in the previous chapters. We use the 1998 and 1999 surveys for this chapter, which have detailed information on household characteristics. These surveys contain 528 households for analysis. Of the 528 households 103 are female headed.

II. B. Background

In the Nicaragua LSMS the household head is the "head" as defined by the household itself using its own definitional criteria.

II. B. 1. Demographic Characteristics by Gender of Household Head

II. B. 1.1 Poverty

Before we move to an analysis of the impact of Mitch on FHHs and their response it is useful to begin with an analysis of poverty levels among female households. The LSMS classifies households as either poor, extremely poor or non-poor. Table 5.1 gives the percentages of households by poverty classification for the full sample and for FHHs. The initial results are somewhat surprising since FHHs are equally represented among the extremely poor and are underrepresented among the poor.

Table 5.1: 1998 Poverty By Household Type

Poverty Level	All Households (n = 528)	Male Headed Households (n = 425)	Female Headed Households (n=103)
Extremely Poor	24%	24%	24%
Poor	37%	39%	31%
Non Poor	39%	37%	45%
Mean Per Capita Consumption	4,746	4,585	5,410

Source: Author's calculations

Since these classifications are rather broad we can use more specific details on household per capita consumption to compare welfare levels of FHHs against the full sample. Mean per capita household consumption in 1998 was 4,746 cordóbas for the full sample and was 5,410 cordóbas for FHHs. One female household has per capita consumption of 40,000 cordóbas. Even when this outlier is excluded the mean figure is 5,065 cordóbas. In contrast to the common relationship between female headship and poverty, for the surveyed Nicaraguan households no such link appears to hold. FHHs are less likely to be poor and are actually better off (as measured by household per capita consumption).

II. B. 1.2 Household Location

The impact of Mitch was most strongly felt in the Nicaraguan departments of Chinandega and Leon. Table 5.2 shows the percentage of female headed households in these departments compared with less affected areas. Chinandega and Leon have a higher percentage of FHHs than the rest of the country. If differences in aid distribution or patterns of changing household size emerge it is worthwhile considering this may be a regional phenomenon in which FHHs are overrepresented.

Table 5.2: Female Headed Households by Department

Department	Female Headed Households
Chinandega	22%
Leon	23%
Other	17%

Source: Author's calculations

In regards to the differences in welfare levels, urban households have a higher mean consumption per capita (5189 cordóbas) than rural households (4578 cordóbas). One reason for the higher welfare of FHHs may be that a greater proportion of them are urban households. Table 5.3 shows the percentages of urban and rural households for the whole sample and by gender.

Table 5.3: Location of Households by Gender of Head

Location	Full Sample	Male Headed	Female Headed
Urban	27%	26%	34%
Rural	73%	74%	66%

Source: Author's calculations

Thus far we have demonstrated that FHHs actually had higher consumption per capita than those households with male headships. This relationship is associated with a greater percentage of FHHs being located in urban areas and not being engaged in agriculture as rural, agricultural households have lower consumption per capita than urban households. However, it is also worthwhile to compare the welfare of urban households by gender of the household head. It may be that urban households with a female head are indeed worse off (from a welfare perspective) than those with a male head. Instead we find the opposite as shown in Table 5.4. The same is also true for rural households with a female headship.

Table 5.4: Consumption Per Capita* for Household Type by Gender of Head

Location	Male Headed	Female Headed
Urban	4815	6125
Rural	4478	5042
N =	425	103

Source: Author's calculations
*Figures are mean consumption in cordóbas.

Data indicates that female households have a higher consumption per capita than male headed ones regardless of whether the household is located in an urban or rural area. This is somewhat surprising although this discrepancy could be explained if a high percentage of the FHHs have migrant husbands who send remittances or if the household receives some other type of transfer. Unfortunately the 1998 and 1999 surveys do not have data specifically linked to remittances.[26]

II. B. 1.3 Agriculture

Earlier we found that agricultural households were the most vulnerable to Mitch. The lower percentage of rural households among FHHs naturally implies that there will also be a lower percentage of agricultural households with female headships. These data are presented in Table 5.5 and shows that a much lower percentage of FHHs are engaged in agriculture.

[26] Funkhouser (1995) surveys households in the Managua and San Salvador and finds Nicaraguan households remit less than El Salvadoran households. Funkhouser's findings however do not enable us to advance our theory of why FHHs have higher consumption per capita levels.

Table 5.5: Agricultural Households by Gender of Head

	Full Sample	Male Headed	Female Headed
Agricultural	61%	65%	42%
Non-Agricultural	39%	35%	58%

Source: Author's calculations

II. B. 1.4 Household Size

Two other characteristics of FHHs in the literature are that they are typically smaller and have a higher dependency ratio. If these are true for the surveyed households in Nicaragua we would expect that FHHs will be smaller and have more children. In the previous chapter we found that smaller households have a higher consumption per capita than larger ones. Data thus far shows FHHs to have a higher per capita consumption. Evidence from the literature indicates we would expect them to also have smaller households. Using data on household size we can see if this relationship holds.

In 1998 mean household size was 6.05 members for male headed households and 5.04 members for FHHs. FHHs are smaller, by one member on average. Table 5.6 summarizes these figures along with the number of dependents (aged 15 or younger) and the dependency ratio. In contrast to what the literature suggests the number of dependents (defined as children aged 15 or younger) is lower for FHHs by approximately 0.7 per household.

Table 5.6: Household Size and Dependency by Gender of Head

	Full Sample	Male Headed	Female Headed
Mean Household Size	5.85	6.05	5.04
Mean Number of Children Aged 15 or Younger	2.7	2.82	2.18
Dependency Ratio	1.24	1.25	1.21

Source: Author's calculations

II. B. 2. Mitch Damages and Gender of Household Head

When comparing hurricane damages by gender the impacts appear to be fairly mixed based upon gender of the household head (Table 5.7). In the case of agricultural losses (harvest and long-term losses) there are 321 households surveyed. Of these 278 are male headed and 43 are female headed. In comparison to some of the earlier demographic indicators male headed households suffered larger harvest losses, although the difference is negligible. By contrast mean long-term losses for male headed household are more than three times those for FHHs. It is important to note that this figure may simply be a reflection of male headed households having more assets and consequently more to lose. The non-monetary indicators (wall damage, water supply damage and days homeless) are fairly gender neutral with the exception of damage to the water supply. Only seven percent of FHHs experienced damage to the water supply compared with 24 percent for male headed households. This is likely related to a higher percentage of FHHs residing in urban areas. FHHs were homeless 0.7 days less than male headed households.

Table 5.7: Mitch Damages by Gender of Household Head

	Male Headed	Female Headed
Surveyed Households on Agricultural Losses	278	43
% of Households with Agricultural Losses > 0	90	84
Mean Harvest Losses (in cordóbas)	3870	3838
Mean Long-term Losses (in cordóbas)	1507	479
Surveyed Households on Wall / Water Damage	361	84
With Walls Damaged (%)	26	30
With Water Supply Damaged (%)	24	7
Mean Days Homeless	4.91	4.23

Source: Author's calculations

II. C. Post-Mitch Aid

Based upon a review of the literature and the findings of the previous two chapters it was reasonable to expect that FHHs would both be more vulnerable to Mitch damages and be more heavily impacted by the hurricane. Instead we found evidence to the contrary. At worst it appears that female households were equal to male headed ones in nearly all respects.

Given the results in the first chapter we know that harvest losses were a statistically significant determinant of aid. For this reason it is useful to view mean aid received for agricultural and non-agricultural households. If aid was allocated based upon harvest losses we would expect mean aid for agricultural households to be approximately equal for male and FHHs engaged in agriculture.

Table 5.8 provides data on aid by gender of the household head. The difference in mean official aid is 189 cordóbas in favor of male headed households, and 189 in favor of FHHs for family transfers. FHHs received only 71% of the official aid received by male headed households, but received nearly three times as much in family transfers.[27]

[27] The difference in means of official aid received is statistically significant. The z statistic is an enormous 149.75 and the p-value is nearly 0.

Table 5.8: Mean Aid by Gender of Household Head (in cordóbas)

Gender of Household Head	Official Aid	Official Aid for Agricultural Households	Official Aid for Non-Agricultural Households	Family Aid	Family Aid for Agricultural Households	Family Aid for Non-Agricultural Households
Male	648	820	321	106	101	115
Female	459	463	457	295	519	134

Source: Author's calculations

Male headed agricultural households received 77% more aid than female headed ones. This figure is particularly alarming since mean agricultural losses for male headed households (5377 cordóbas) are only 25% greater than those for female headed agricultural households (4317).[28] With a strict distribution of official aid by harvest losses only male and female headed agricultural households should receive approximately equal amounts of aid. Instead there is an "extra" 52% of aid going to male headed agricultural households. Section III explores possible determinants for this discrepancy and whether gender of the household head is a viable explanation.

II. D. Adjusting Household Size Post-Mitch

In the previous chapter we found that FHHs were more likely to add members in the immediate post-Mitch period than male headed households and that the alteration of household size may have been a post-Mitch coping mechanism for certain households. Based upon the descriptive statistics in this section FHHs had a higher welfare and experienced fewer damages (in general) than male headed households. As such social insurance arrangements would dictate that those households with excess resources would add members.

Before proceeding to inferential analysis it is worthwhile to review the data on FHHs and see what patterns emerge. This information is presented in Table 5.9.

Table 5.9: Female Headed Households and Changing Household Size 1998 - 1999

Total HHs	N = 103	HHs in %	Mean HH Consumption	Mean HH Size	HHs in Agriculture	Mean Agricultural Loss	Mean Official Aid	Mean Family Aid
Adding Members	45	44%	5,883	4.1	17	5260	304	231
No Change	41	40%	5,891	4.9	18	4164	648	374
Dropping Members	17	16%	2,997	7.8	8	2565	414	274

Source: Author's calculations

[28] These figures are the summation of mean harvest losses and long-term losses from Table 5.7.

Table 5.9 (Continued)

Total HHs	% of HHs with Wall Damage	Mean Days Homeless	Mean Home Reconstruction Expenditure	Mean Dependents	Dependency Ratio	% With Children (Aged 5 or Younger)
Adding Members	18%	5.09	1755	1.87	1.04	16%
No Change	34%	3.87	944	2.29	1.14	10%
Dropping Members	18%	3.21	1202	2.71	1.86	12%

Source: Author's calculations

From Table 5.9 it is easy to see a gulf between those FHHs dropping members and those adding or remaining neutral. Those households dropping members have a lower per capita consumption, larger household size, more dependents and a higher dependency ratio. What is more striking are the similarities between the groups of households adding members and those leaving household size unchanged. There is no clear distinguishing factor to separate the two groups or identify why one group would add members while the other would not.

FHHs which did not change composition received 113% more official aid and 62% more family aid than those households adding members. This occurs despite comparable welfare levels and lower agricultural loss amounts. Even when considering Mitch damages no clear pattern emerges. Those households adding members were homeless longer and had higher agricultural losses. In the case of wall damage, it could be that those households with structural damage to the home (wall damage) were reluctant to take in additional members on grounds of safety or overcrowding. Households adding members also spent more money on home reconstruction. Households adding members had fewer dependents and a lower dependency ratio. The most distinguishing factors for those adding members are the smaller household size, fewer dependent and the lower dependency ratio. The next section explores why some FHHs added members after Mitch while others with comparable levels of welfare and hurricane damage did not.

III. Methodology

This section details methodology for empirically testing: (i) whether FHHs, and in particular agricultural FHHs, were disadvantaged in receiving official aid (ii) if FHHs were targeted for inter-household transfers based upon the gender of the household head and (iii) why some FHHs are more likely to increase household size after Mitch.

III. A. Post-Mitch Aid Allocations by Gender of Household Head

Based upon the results in the first chapter an initial reaction was that official aid was allocated to male headed households in a discriminatory manner. Since FHHs received less aid this conclusion seemed plausible based upon the disaster anthropology literature which indicates that FHHs may be disadvantaged in the post-disaster environment. However, the descriptive statistics in the previous section give pause for thought. The welfare figures indicate that FHHs had a higher welfare before the hurricane and a conclusion of discrimination seems premature. At the same time an analysis of mean aid (Table 5.8) shows that official aid transfers to agricultural households still favored those with male headship even after we account for the relatively higher losses they incurred.

There are three possibilities that can explain the discrepancy in mean aid received. The first is that aid was directly discriminatory. If this were true we would expect FHHs to receive less aid simply for having a female head. In this case a dummy for having a female head would likely be statistically significant in a regression framework. A second possibility is that aid was indirectly discriminatory. In this case official aid would be targeted based around household characteristics which favor male headed households. Although the gender of the household head may not be statistically significant other explanatory factors have a strong relationship to headship may be statistically significant. The final possibility is that aid was neither directly nor indirectly discriminatory.

From our review of the literature and the results in the first chapter the following factors merit consideration in devising a model:

- Gender of the Household Head;
- Welfare (Per capita household consumption);
- Household Size;
- Children (Aged 5 or Younger);
- Number of Dependents (Aged 15 or Younger);
- Dependency Ratio;
- Size of Agricultural Losses;
- Geographic Location of the Household.

III. A. 1. Agricultural Households

We start with the inclusion of a dummy for a FHH (FEMALE). If having a female household head led to receiving less aid we expect the female dummy will remain statistically significant as we control for other factors. We expand the model to include the explanatory factors enumerated in Table 5.10. This model is presented in equation 1.

Table 5.10: Explanatory Variables Considered

Explanatory Variable	Variable Name	Type
Female Household Head	FEMALE	Qualitative
Total Agricultural Losses (Harvest + Long-term Losses) in thousands of cordóbas	TLOSS	Quantitative
Engaged in Agriculture	AGR	Qualitative
Per Capita Household Consumption in 1998 (in thousands of cordóbas)	CONS98	Quantitative
# Dependents of Aged 15 or Younger	DEP	Quantitative
Children Aged 5 or Younger	KIDS	Qualitative
Members Aged 16 or Older	ADULTS	Quantitative
Ratio of Dependents to Adults in Household	DEPRATIO	Quantitative
Household Size in 1998	HH98	Quantitative
Located in Chinandega	CHIN	Qualitative
Located in Leon	LEON	Qualitative

(1) $OAID_i = a + FEMALE_i + HH98_i + CONS98i + DEP_i + DEPRATIO_i + KIDS_i + TLOSS_i + AGR_i + CHIN_i + LEON_i + \mu_i$

Equation 1 models official aid (OAID) received by household *i* after Mitch as a function of the gender of the household head, household size in 1998, the number of dependents, the dependency ration, the presence of children and residence in Chinandega or Leon. Variables for total agricultural losses and being engaged in agriculture are also included as appropriate. We can also repeat this process with family aid (inter-household transfers, FAID) received as the dependent variable (results are presented in the next section) in equation 2.

(2) $FAID_i = a + FEMALE_i + HH98_i + CONS98i + DEP_i + DEPRATIO_i + KIDS_i + TLOSS_i + AGR_i + CHIN_i + LEON_i + \mu_i$

Some terms in equations 1 and 2 are necessarily excluded as we isolate agricultural and non-agricultural households. These alterations are made clear in the results section.

III. B. Change in Household Size

If home damage (or another factor) is the dominant reason for why some FHHs added members and others did not it is reasonable to assume that this can be shown empirically. Four variables emerged from the descriptive statistics which could explain the decision of otherwise similar FHHs to add members, while others chose not to do so. We use a probit model with the decision to add members set equal to 1 and the decision not to add set to 0 (equation 3).

(3) $Y_i = Z_i(a + HH98_i + KIDS_i + DEPRATIO_i + CONS98_i + OAID_i + WALLDMG_i + \mu_i)$

The sample contains the 86 FHHs that either added members or kept household size the same. Additional variables were considered, but they did not add any explanatory value to the model.

IV. Results

IV. A. Gender of the Household Head and Aid Received

The results of the models in equations 1 and 2 are presented below in Tables 5.11 and 5.12, respectively. The regression results in Table 11 are those with official aid as the dependent variable. Table 12 presents the regression results with family aid as the dependent variable. Each regression is run on three groupings: agricultural households, non-agricultural households and all households. Results from equation 3 are presented in Table 5.13.

IV. A. 1. Official Aid

Having a female household head is the only explanatory factor which is statistically significant for the distribution of official aid to agricultural households. Even after controlling for total agricultural losses, household per capita consumption, other demographic variables and location of the household having a female headship remains significant at 10% with a negative coefficient. These results suggest that among agricultural households those with a female head were disadvantaged in receiving official aid transfers.

For non-agricultural households the gender bias is eliminated and the female coefficient is positive (but not significant). Being located in the Chinandega department is the only factor which is statistically significant (at 10%) for official aid distributions to non-agricultural households. Over the full sample the gender bias is also eliminated even though the female coefficient is negative. For the full sample three factors are statistically significant determinants of aid received. The number of dependents and being engaged in agriculture are both significant at 10% with positive coefficients. Being located in Chinandega is again significant at 10% with a negative coefficient. These findings open several avenues for discussion.

Before discussing the results in Table 5.11 it is important to note that in this regression that neither the total loss (TLOSS) nor the consumption (CONS98) variables are significant. This is in contrast to the findings in Chapter 3 which indicate that family aid was targeted to the hardest hit and poorer households. The difference in these results is driven by the model specification. The model in this section was structured to answer the question of whether household demographic characteristics beyond gender of the household head may impact the receipt of family aid by female headed households. By contrast the aid regression in Chapter 3 was structured (based upon risk pooling theory and literature) whether shock values damages and household welfare were statistically significant determinants of family aid. In response to these questions consumption and agricultural losses are significant in the former but not the latter.

Table 5.11: OLS Regression Results for Determinants of Official Aid Received
Dependent Variable: Official Aid Received (in cordóbas)

	Sampled Households		
Explanatory Variables:	Agricultural	Non-Agricultural	All
FEMALE	-367.21* (216.35)	207.55 (181.96)	-92.73 (146.18)
HH98	-137.04 (89.5)	53.89 (41.06)	-57.31 (54.17)
CONS98 (in thousands)	-13.66 (33.15)	-8.33 (7.26)	-14.94 (12.28)
DEP	155.92 (97.88)	47.21 (54.65)	94.39* (54.45)
DEPRATIO	121.23 (95.54)	-45.58 (36.52)	39.61 (48.9)
KIDS	-102.06 (298.26)	-28.38 (222.14)	-39.44 (186.82)
TLOSS	-7.79 (6.59)	-	-
AGR	-	-	348.76* (186.84)
LEON	269.46 (513.43)	61.73 (196.88)	186.15 (303.48)
CHIN	-247.19 (240.15)	-310.76* (161.38)	-226.47* (136.92)
Constant	1155.12*** (418.56)	87.73 (136.83)	520.98*** (195.49)
R^2	0.01	0.02	0.02
N =	321	207	528

*Significant at 10% **Significant at 5% ***Significant at 1%

Statistics on the distribution of official aid to agricultural households indicated an "extra" 52% of aid going to male headed households. However, based upon higher mean per capita consumption for FHHs it could have been argued that the lack of aid received by agricultural FHHs was in relation to their higher welfare level and independent of their gender. If this were the case we would have expected per capita household consumption to be statistically significant and the female dummy not to be significant. Instead the opposite is true. The regression results indicate a gender bias in the distribution of aid for agricultural households, but results do not tell us why. A subsequent exploration of the anthropological findings may help put the results in Table 5.11 into context.

Work by Bradshaw (2004) draws parallels between the situation of women in post-Mitch El Salvador and Nicaragua. In El Salvador the dominance of men may have played a large role in the disparity in aid received:

> [w]omen in El Salvador also noted differences between the tasks performed by them and by men: women distributed emergency aid, but it was the community board, made up of men, which decided who would benefit from it. In other words, women were involved in the physical distribution, but not in the decision-making process. This situation occurred not only in the communities, where it is perhaps more difficult to envision changes in traditional roles, but also in shelters, new and distinct environs.

In other words, cultural and institutional factors which affect gender relations such as traditional machismo or men's domination of the political or legal institutions can also contribute to an unequal distribution of aid. These factors would not necessarily show up in our regression framework although their effects would be captured.

IV. A. 2. Family (Inter-household) Aid

If the distribution of official aid was male-dominated this provides a more logical reason as to why inter-household (family) transfers to agricultural households favored FHHs (Table 5.8). Family transfers can bypass any formal male dominated allocation authority and also benefit from more complete information. Table 5.12 presents regression results with family aid received as the dependent variable.

Table 5.12: OLS Regression Results for Determinants of Family Aid Received
Dependent Variable: Family Aid Received (in cordóbas)

	Sampled Households		
Explanatory Variables	Agricultural Households	Non-Agricultural Households	All Households
FEMALE	436.61 (311.71)	26.67 (53.42)	218.26 (150.89)
HH98	-9.54 (21.2)	34.37 (28.58)	8.72 (16.18)
TLOSS	6.46 (6.99)	-	-
DEP	35.06 (28.86)	-35.69 (28.61)	3.36 (18.97)
DEPRATIO	152.76 (135.48)	0.56 (22.67)	69.06 (62.97)
KIDS	-117.38 (81.5)	-119.28*** (37.19)	-113.72*** (49.03)
CONS98	17.93 (16.02)	-1.13 (2.31)	5.44 (4.82)
AGR	-	-	88.09 (83.22)
LEON	73.08 (93.32)	59.1 (64.4)	60.67 (62.34)
CHIN	-55.74 (113.05)	-65.47 (49.58)	-38.3 (58.57)
Constant	-220.57 (170.85)	32.03 (99.07)	-119.3 (117.74)
R^2	0.08	0.03	0.04
N =	321	207	528

*Significant at 10% **Significant at 5% ***Significant at 1%

Regression results with family aid as the dependent variable show that having a female head ceases to be a statistically significant determinant of inter-household transfers received. For agricultural households no factor is a statistically significant determinant of inter-household transfers. For non-agricultural households the presence of children aged five or younger was highly significant at 1%. Surprisingly the coefficient is negative. This is also true for the full sample. This relationship is counterintuitive since it indicates that inter-household transfers were directed away from households with children. For all three groupings the female coefficient is positive in all cases.[29]

[29] The results of all regressions are presented using robust standard errors. Using uncorrected standard errors the FEMALE and DEPRATIO variables are statistically significant at 1% for the agricultural and full sample. The large discrepancy in the standard errors suggests heteroscedasticity in the data set.

IV. B. Female Household Size

The results from equation 3 (Table 5.13) are surprising since none of the factors highlighted in the previous section is statistically significant. The explanatory variables are not jointly significant in either regression.[30] With the exception of the presence of children in the household (KIDS) the variables have the expected sign, but leave us no closer to an explanation for the decision of some FHHs to increase household size after the hurricane.

Table 5.13: Probit Results for Female Households Adding Members 1998 - 1999
Dependent Variable: Increasing Household Size

Explanatory Variables:	FHHs with no Decrease in Size (1)	Those in Column 1 Surveyed on Wall Damage (2)
HH98	-0.09 (0.06)	-0.07 (0.07)
DEPRATIO	-0.03 (0.12)	-0.08 (0.14)
WALLDMG	-	-0.4 (0.36)
KIDS	0.54 (0.45)	0.58 (0.49)
CONS98 (in thousands of cordóbas)	-0.02 (0.03)	-0.01 (0.03)
OAID (in thousands of cordóbas)	-0.2 (0.2)	-0.36 (0.33)
LEON	-0.04 (0.36)	-0.42 (0.4)
CHIN	0.37 (0.41)	-0.06 (0.48)
Constant	0.63 (0.41)	0.65 (0.47)
Pseudo R^2	0.04	0.07
N =	86	71

Probit coefficients are displayed in the table with robust standard errors in parenthesis.
* Significant at 10% **Significant at 5% *** Significant at 1%

This conclusion is more surprising given the results of the identical regressions on male headed households (Table 5.14). For male headed households the decision to add members or leave size unchanged is strongly influenced by the presence of children under 5 in the household and the dependency ratio. The presence of a child aged 5 or younger is statistically significant at 1%. The relationship for dependency ratio is weaker (significant at 10%). The sign is positive as expected. As the ratio of workers to non-workers increases the probability of adding members increases as well. Although male headed households were less likely to add members after Mitch identifiable determinants

27 Prob > ?2 = 0.344 for Column 1 and 0.398 for Column 2.

of their decision can be found, but not for FHHs. We considered welfare, various indicators of household composition and hurricane damage as well as post-Mitch aid (both official and family aid). None of these factors significantly affected the probability of FHHs adding members.

Table 5.14: Probit Results for Male Households (MHHs) Adding Members
Dependent Variable: Increasing Household Size

Explanatory Variables:	MHHs with no Decrease in Size (1)	Those in (1) Surveyed on Wall Damage (2)
HH98	-0.0006 (0.03)	-0.003 (0.03)
DEPRATIO	0.12** (0.06)	0.12* (0.07)
WALLDMG	-	0.08 (0.18)
KIDS	0.7*** (0.22)	0.81*** (0.24)
CONS98	-0.004 (0.02)	0.003 (0.02)
OAID	-0.02 (0.04)	0.04 (0.05)
CHIN	-0.24 (0.19)	0.24 (0.22)
LEON	0.31 (0.2)	-0.15 (0.21)
Constant	-0.64*** (0.22)	-0.75*** (0.25)
Pseudo R^2	0.04	0.05
N =	330	279

Probit coefficients are displayed in the table with robust standard errors in parenthesis.
* Significant at 10% **Significant at 5% *** Significant at 1%

V. Conclusion

On the whole, the gender of the household head was not a significant factor in the distribution of official aid after Mitch. Agricultural households were most in need of aid after Mitch. When we focus on agricultural households we find evidence that having a female headship was a significant factor which led to FHHs receiving less aid. This phenomenon appears to be isolated to agricultural households. Regression results tell us that having a female headship was an important contributory factor for receiving less aid. At the same time the results are limiting in that they illustrate the end and not the process of aid allocation. To fill in the gaps we turn to anthropological work after Mitch which emphasizes the role of cultural and institutional factors that marginalized women to the periphery of decision-making of aid allocation following Mitch.

The decision of FHHs to increase household size following Mitch appears to follow no clear pattern. Isolating two comparable groups of FHHs no discernable characteristics emerge to explain why some FHHs added members after Mitch while others did not. By contrast the decision of MHHs to add members is related to the dependency ratio and the presence of children aged five or under in the household. While FHHs are more likely to increase household size after Mitch, it is unclear why certain FHHs do so while others do not.

Chapter 6

Conclusions

Global disaster trends may indicate that the rate of losses over time is not subject to rapid increase. Nevertheless, for millions of the world's poor natural disasters continue to have a profound impact on their livelihood. In addition to potential loss of life, many of the world's poor have incomes that are not captured in official figures which are vulnerable to disaster damage. Development economists have identified many non-market mechanisms that households in the developing world use to cope with risk, uncertainty and unanticipated shocks to income and consumption. The viability of these mechanisms is often predicated upon certain assumptions. For example, the functionality of informal insurance arrangements is conditional upon a low percentage of the risk pooling network being simultaneously affected.

Idiosyncratic shocks such as job loss, illness or injury allow us to observe the workings of non-market mechanisms in their usual environment. The incidence of large-scale disasters creates a covariate shock and places coping mechanisms under increased stress since assets which could ordinarily be used to cope can often be destroyed. Disasters also generate claims for scarce resources in the post-event period, which may lead to allocations based upon existing power relations instead of need. The focus of this dissertation has been to analyze the household response to a covariate shock (Mitch) vis-à-vis non-market mechanisms as well as the distribution of aid in the post-disaster environment, with particular reference to female headed households.

An overview of Mitch damages in Chapter 2 indicated that we could expect agricultural households to be the most strongly affected. Chapter 2 also accentuated the importance of post-disaster aid for affected households and suggested that aid would play an important role in maintaining household welfare post-Mitch. The findings subsequent chapters reiterated these suspicions.

In Chapter 3 we found a strong relationship between household consumption and harvest losses. The principal findings from Chapter 3 are the following:

- As theory would predict households can not rely on informal insurance networks to mitigate damage from covariate risk;
- Agricultural households are particularly vulnerable to Mitch damages;
- The inability of informal mechanisms to cope with damages emphasizes the need for effective aid targeting in the post-disaster period;
- Official aid played was instrumental in sustaining post-Mitch welfare and was better targeted and larger in nominal terms than family transfers.

Chapter 4 shifted focus to adjusting household size as a post-Mitch coping mechanism. Results from this chapter showed noticeable behavioral patterns in the alteration of household size after Mitch. The key observations are summarized below.

- A household suffering agricultural losses was more likely to adjust household size;
- A coping relationship exists in which the change in harvest losses and household size consequently leads to an increase in household per capita consumption;
- Female households were more likely to increase household size after Mitch.

Finally in Chapter 5 analyzed the distribution of official and private, inter-household aid along gender lines. This chapter also examined the decision of female headed households to increase household size after Mitch. Results showed the following:

- Over the full sample having a female household head was not a statistically significant determinant of receiving official aid;
- For agricultural households female headship was a statistically significant determinant of receiving less official aid;
- There was no evidence to indicate why some FHHs increased household size while others kept size constant.

Chapter 5 also specified a model to test whether household demographic characteristics in addition to gender of household head were determinants of family aid. As a result the model in Chapter 3 was expanded to include static household characteristics that were not relevant for risk pooling tests carried out earlier in the dissertation. In Chapter 3 and in our risk pooling tests household consumption (welfare) and agricultural losses (shocks) were significant determinants of family transfers, but not in Chapter 5 due to the difference in model specification detailed in Chapter 5.

On the whole the findings show that informal coping mechanisms were insufficient to safeguard household consumption after Mitch and that relief aid was well targeted and played a key role in maintaining household welfare. Agricultural households were particularly vulnerable to Mitch damages. One coping mechanism for agricultural households was to reduce household size. By contrast other segments of the population such as female headed households were the most likely to increase size, which suggests this may have operated as a risk pooling arrangement of sorts. Official aid was well targeted and used agricultural losses as a determinant for allocation. Although aid was effectively targeted among agricultural households those with a female household head were statistically shown to receive less aid. Overall, the evidence suggests that informal mechanisms were insufficient but aid transfers and non-market coping mechanisms such as adjusting household size played a role in coping with Mitch damages.

The dissertation touches on several topics in the development economics literature including risk coping, aid effectiveness and gender. The dissertation has contributed to the literature by utilizing a data set and shock that has not been previously studied for risk coping implications. Unlike previous studies in the literature which have focused on different shock types we have researched the impact of a natural disaster shock which, unlike other shocks, entails exogenous aid transfers as well as the possible destruction of physical assets which could ordinarily be used as part of a coping strategy. The dissertation has also drawn together threads from the disaster anthropology, gender and development economics literature to analyze non-market coping mechanisms and the role gender played in post-shock recovery. The disaster anthropology literature uses qualitative analysis and the empirical testing here contributes toward theories that being a female headed household is a significant disadvantage in the post-disaster setting.

From a policy perspective the results indicate the impact of hurricanes on agricultural households in developing countries can be potentially quite severe. Since the occurrence of natural disasters can not be prevented these results suggest that increased attention should be given to constructing mitigation measures to minimize flooding associated with heavy hurricane rainfall. Much of the harvest losses were attributable to topsoil washed away. Additional preventive measures may include investing in roads and bridges that are less prone to flooding as well as implementing policies at the macro-level to minimize erosion which often exacerbates flood damage. In addition the establishment of official ex-ante relief funds could facilitate the recovery process for agricultural households. This is particularly important in areas which lack developed credit markets. It is also important to recognize that the impact of natural disasters is heterogenous. For example, the impact of an earthquake on agricultural households would be fairly mild since croplands would be unaffected. Thus it is important to consider the hazard type when formulating an appropriate policy response.

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