WPS4909

POLICY RESEARCH WORKING PAPER 4909

Risks, Ex-ante Actions and Public Assistance

Impacts of Natural Disasters on Child Schooling in Bangladesh, Ethiopia and Malawi

Futoshi Yamauchi
Yisehac Yohannes
Agnes Quisumbing

The World Bank
Sustainable Development Network
Global Facility for Disaster Reduction and Recovery Unit
April 2009

Policy Research Working Paper 4909

Abstract

This paper examines the impacts of natural disasters on schooling investments with special focus on the roles of ex-ante actions and ex-post responses using panel data from Bangladesh, Ethiopia, and Malawi. The importance of ex-ante actions depends on disaster risks and the likelihood of public assistance, which potentially creates substitution between the two actions. The findings show that higher future probabilities of disasters increase the likelihood of holding more human capital and/or livestock relative to land, and this asset-portfolio effect is significant in disaster prone areas. The empirical results support the roles of both ex-ante and ex-post responses (public assistance) in coping with disasters, but also show interesting variations across countries. In Ethiopia, public assistance plays a more important role than ex-ante actions to mitigate the impact of shocks on child schooling. In contrast, households in Malawi rely more on private ex-ante actions than public assistance. The Bangladesh example shows active roles of both ex-ante and ex-post actions. These observations are consistent with the finding on the relationship between ex-ante actions and disaster risks. The results also show that among ex-ante actions, human capital accumulated in the household prior to disasters helps mitigate the negative effects of disasters in both the short and long runs.

This paper—a product of the Global Facility for Disaster Reduction and Recovery Unit, Sustainable Development Network Vice Presidency—is part of a larger effort in the network to disseminate the emerging findings of the forthcoming joint World Bank-UN Assessment of the Economics of Disaster Risk Reduction. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The team leader—Apurva Sanghi—can be contacted at "asanghi@worldbank.org", and the author of this paper at "f.yamauchi@cgiar.org". We thank Apurva Sanghi and participants at the World Bank for useful comments.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

Produced by the Research Support Team

Risks, Ex-ante Actions and Public Assistance: Impacts of Natural Disasters on Child Schooling in Bangladesh, Ethiopia and Malawi[1]

Futoshi Yamauchi, Yisehac Yohannes and Agnes Quisumbing[2]

[1] This paper was prepared as a background paper to the joint World Bank - UN Assessment of the Economics of Disaster Risk Reduction. Funding from the Global Facility for Disaster Reduction and Recovery is gratefully acknowledged. We would like to thank Harold Alderman, Alejandro De la Fuente, John Hoddinott, Apurva Sanghi and seminar participants at the World Bank for their useful comments. Special thanks to Wahid Quabili¥ for excellent assistance on Bangladesh data. We are responsible for any remaining errors.

[2] Yamauchi (corresponding author), Yohannes, Quisumbing: International Food Policy Research Institute, 2033 K Street, NW, Washington DC 20006. Email: f.yamauchi@cgiar.org, Phone: 202-862-5665.

1. Introduction

It has been increasingly recognized that economic agents attempt to smooth consumption by managing risks associated with natural and social hazards in low-income countries through both formal mechanisms and informal arrangements (e.g., Townsend, 1994; Rosenzweig, 1988; Binswanger and Rosenzweig, 1986). In many low-income settings, since formal insurance and government supports are limited, they tend to rely on informal insurance such as remittances from relatives to secure their livelihoods. For example, marriage arrangements with households in other villages would diversify income risks among relatives (Rosenzweig and Stark, 1989). These mechanisms can be quite effective to smooth the impacts of idiosyncratic shocks but if the risks are aggregate or correlated across agents (e.g, large-scale natural hazards), these strategies cannot be so useful since the risks cannot be pooled to offset each others.[3]

When agents perceive the high likelihood of large-scale hazards in the near future, they have to employ strategies that differ from the informal arrangements described above since cross-sectional diversification and pooling of such risks are difficult. That is, the scope of insurance arrangements (whether they are formal or informal) against large-scale natural disasters is quite limited (see also the review by Dercon, 2002; Morduch, 1999; Skoufias, 2003). Instead of pooling risk across individuals or households, agents need to reallocate resources intertemporaly.[4]

The relationship between natural hazards and investment behavior provides interesting insights. Most of natural disasters damage physical capital. For instance, climatic disasters such as floods and droughts damage crops on farm land. Earthquakes suddenly destroy buildings and landscapes. The immediate loss of human capital is typically much smaller than that of physical capital, though the loss largely depends on not only the nature and magnitude of events but also the suddenness and unexpectedness of the events. Impacts on human capital seems more gradual due to potential repercussions from physical destructions as well as economic impacts.

The above observations suggest the possibility of a poverty trap. Once a disaster destroys productive assets and public goods (such as schools), the expected income in subsequent periods will be lower than that in the past. For example, when an earthquake destroys schools, human capital investments (and its quality) drop, decreasing the expected income in the future. This point clearly distinguishes between disasters and income fluctuations.

Recent macroeconomic studies report that high likelihood of natural hazards can increase economic growth in the long run (e.g., Skidmore and Toya, 2002; Tol and Leek, 1999). However, more careful studies on developing countries recently show that technology inflow, positively related with growth, increases with natural disasters only among wealthier countries (Crespo Curaresma et al., 2008). Disasters also have

[3]In informal insurance arrangements, not only the correlation structure of risks but imperfect information on actual realizations of shocks limit the effectiveness. The latter creates a limited commitment (self-enforcing) problem unless agents can reduce monitoring cost through strong personal ties (Ligon, 1998; Coate and Ravallion, 1993; Ligon, Thomas and Worrall, 1997). In correlated risks such as large-scale natural hazards, this problem is mitigated as agents can easily observe states facing other agents, as it is opposed to indiosyncratic risks. In the case of highly correlated risks, however, they cannot pool and cancel the shocks.

[4]Agents could also diversify against risk spatially, through migration of entire households or of individual household members, as pointed out above. But spatial diversification against risk is limited in the case of large-scale natural disasters.

negative impacts on growth in the short run, and such negative effects are larger if the country has low levels of human capital (Noy, 2008). However, these studies only discuss the loss of physical and human capital due to disasters and the impacts of post-disaster investments and capital inflow (reconstruction efforts) on economic growth. The impacts on ex-ante investment behavior are outside the scope of these papers.

The likelihood of damages due to natural hazards affects the expected returns to investments, and can therefore determine investment behavior in the long run. Dercon and Christiaensen (2007) show that the high likelihood of harvest failure discourages the application of fertilizer in Ethiopian agriculture, causing inefficiency in production choices.

If household activities go beyond agriculture, the implications of high disaster probabilities may encourage transition to non-agricultural activities that require human capital. For example, if physical capital such as land (agriculture) is often exposed to natural hazards, agents will be better off by investing in human capital as human capital is portable and less affected by natural hazards. Educated workers can find work in urban labor markets that can be distant from the affected areas. Porter (2008) recently showed that hurricane risks increase education and the effect is largest among the landless. Our study will also show empirical results in the similar line.

Similarly, investments in financial capital and livestock are also more robust to natural hazards than land. Under certain conditions, agents increase precautionary savings with increased risks (Deaton, 1991, Kimbal, 1990). Micro studies show that in the empirical setting where formal financial intermediation is not available, the accumulation of livestock buffers income shocks, helping smooth consumption (Rosenzweig and Wolpin, 1993).

However, the importance of ex-ante actions such as investing in certain assets highly depends on how agents perceive actual risks as well as their expectation of the likelihood of public assistance in the post-disaster period. The first question is also analogous to whether or not we can assume stationarity in risk structure and the agent's rational expectations in the risks. These are empirical matters - it is challenging to identify dynamics of the risk structure and the agent's learning behavior and information set (e.g., see Gine, Townsend and Vickery, 2007; Dercon and Christiaensen, 2007). In the analysis of this paper, we do not address the above issues but simply use the empirical frequency of natural hazards (flood and/or drought) from data under the assumption of rational expectations and risk structure stationarity. Similarly we assume that risk preference is homogeneous.[5] Other things being equal, the importance of ex-ante actions should increase with the frequency of natural hazards in the future.

To decide ex-ante actions, households potentially face a trade-off between income augmentation and income risk mitigation. For example, a large family may help diversify risks but also decrease per-child investments in schooling. However, investment in education seems to achieve the above two goals: increasing income and reducing risk. However, whether or not there are returns to schooling investment largely depends on the development of the non-agriculture labor market (including the possibility of migration).

[5]Wealthy households may be less risk averse than poor households. However, with imperfect credit market, wealthy households can self-insure against risks by utilizing their assets, and therefore take more risky choices than poor households.

The relationship between ex-ante actions and ex-post responses is more delicate. Some of ex-post responses such as private transfers (e.g., remittances and borrowing) are already incorporated in the decision making on ex-ante actions. For example, educated labor in the household can migrate to urban sectors to remit money to the household. Holding livestock enables them to get cash income by selling some of the livestock and/or using them as collateral. What is more exogenous to agents is the availability and accessibility of public assistance. Even if such ex-post assistance is available in the economy, its targeting efficiency critically matters in determining how likely the affected areas and agents therein receive aid (see, e.g., Coady, Grosh and Hoddinott, 2004; Quisumbing, 2005a, 2005b). If such public actions are fast enough, they can create substitution between private actions (as a function of ex-ante actions) and public responses. Owens and Hoddinott (2003) investigated the trade-off between the ex-ante interventions that increase capital accumulation and ex-post assistance. They showed that (i) intensive agricultural extension services and the accumulation of trained oxen mitigated the reduction of net crop income during a drought, and (ii) private and public transfers are substitutable. In the empirical analysis, we use actual data on public assistance to investigate how likely these aids affect the role of ex-ante actions in human capital formation.

In this paper, we examine the impacts of flood and drought on child human capital formation using data from Bangladesh, Ethiopia and Malawi. The empirical analysis uses schooling investment measured by grade progression (change in grades) to examine the above issue. As Ferreira and Schady (2008) summarizes, aggregate shocks such as economic recession can have two offsetting effects on schooling investments: a negative income effect and a positive substitution (time allocation) effect.[6] Large income losses may encourage a shift of resources from investments in child schooling to consumption smoothing. But if the opportunity cost for schooling investment (i.e., child wage) decreases, this creates an incentive to keep children in school. In theory, therefore, disaster impacts on schooling investment could be ambiguous. The empirical strategy adopted in this paper controls for area fixed effects, in order to account for labor-market effects uniformly affecting households in each area.[7] Furthermore, since our interest is to know the roles of ex-ante and ex-post actions that affect disaster impacts on human capital formation, we do not think that the above issue is a problem.

The paper is organized as follows. The next section describes a simple model that concisely summarizes our hypotheses on sequential decision making. The importance of ex-ante actions depends on the risk of future natural hazards (disasters) and the likelihood of public assistance. Section 3 discusses econometric framework, and Section 4 describes our data.

The empirical results, summarized in Section 5, show that the likelihood of holding more human capital and/or livestock relative to land is positively associated with the future disaster probability. Interestingly, this asset-portfolio effect is significant in disaster prone areas. Our results support the roles of both ex-ante and ex-post responses (public assistance) to disasters but also show interesting variations across countries. In Ethiopia, public assistance plays a more important role than ex-ante actions to mitigate the shocks on child schooling. In contrast, Malawi relies on private ex-ante actions, with public aid being largely insignificant. The Bangladesh example

[6]For example, Jacoby and Skoufias (1997) showed from ICRISAT India data the contrast between the two effects.
[7]With village fixed effects, we may underestimate the impacts of natural disasters, especially drought.

shows active roles of both ex-ante and ex-post actions. These observations are consistent with our finding on the relationship between ex-ante actions and the disaster risks. Our results show that among ex-ante actions, human capital accumulated in the household prior to disasters helps mitigate the negative effects of disasters in both the short and long run.

2. A Simple Model

In this section we construct a simple model to clarify the intuition for the relationship between ex-ante and ex-post actions to respond to disasters. The importance of ex-ante actions depends on the likelihood of receiving external assistance such as public emergency relief. If targeting of public assistance is perfect, households do not have to undertake ex-ante actions such as reallocating their assets to mitigate the adverse impacts of disasters.

Assume four sequential stages. In the first stage, agents decide on asset allocation with the expectation of future disasters and possible public assistance that is conditional on actual disaster incidence. Assume that agents know the correct probability distribution of future disasters (though they cannot predict the actual occurrence in the future). Disaster can randomly occur in the second stage. In the third stage, the availability of public assistance is determined exogenously to agents. Therefore, events in the second and third stages are random to the agents. In the final stage, agents will act so as to mitigate the disaster impacts based on their pre-committed asset portfolio in the first stage.

Let $e \in \{0, z\}$ denote disaster impact on income, with probability $p(e = z)$ following the binomial distribution. If disaster occurs, it causes a reduction of income with z. Conditional on the disaster incidence, agents can have an access to public assistance x with probability $p(x \mid e)$. For simplicity, assume that $x \in \{0, x^*\}$, and $z \geq x^* > 0$. That is, even if they receive public assistance, it does not recover the income loss perfectly.

In the first stage (period), agents allocate some portion of their asset K to a means H, human capital, that is not directly productive at least in the short run. Therefore, agents can use $K - H$ for income generating activities. For example, H can be migrants who work in towns distant from the original village, who can provide support to the original family in the case of disasters. Allocating some resources to H is analogous to purchasing insurance against future disaster risks.

In the second stage, agents have risk averse utility from consumption in the second period (second and third stages). Consumption is determined as $K - H - e + x + t - ph$ where t is private transfers and ph is the total cost for child schooling investment (h: schooling investment and p: unit price for the investment). In the end of the second period, they receive financial returns to schooling investment $R(h)$ and pay the costs of private transfers $r(H)t$. Assume that the human-capital return function $R(h)$ is strictly increasing and concave, and $r(H)$ is strictly decreasing and convex. Investment in child schooling has returns in the future, and the allocation of resources to human capital in the initial stage means a lower unit cost for private transfer.

Note that disasters can destroy production assets (such as land), which may

lower production levels in subsequent periods. The consequence of asset destruction is different from that of income fluctuation in the sense that asset destruction decreases the expected income in subsequent periods, potentially creating a poverty trap. Income fluctuations, however, do not change the expected income. In the context of human capital accumulation, school destruction is particularly regarded important. In our model, we do not capture poverty trap since our focus is placed on the substitution between ex-ante actions and ex-post public responses.
Agents have the following problem.

$$\max_{H}\left\{(K-H)+\beta\int\left[\max_{t,s}u(K-H-e+x+t-ph)+[R(h)-r(H)t]\right]dF(e,x)\right\}$$

where $\beta\in(0,1)$ is discount factor. We solve this through backward induction. In the second period, agents know the realization of (e,x). Based on this information, they will decide (t,h). In the first period when they decide asset allocation H, agents incorporate this (re)action responding to disaster incidence and public assistance. In the above formulation, we ignore time allocation of children between work and school.

Our modeling strategy is different from that of the consumption smoothing literature. We rather focus on intergenerational aspects of the disaster impacts on human capital investments. Ex-ante actions (asset portfolio) are taken by the parents' generation. Human capital investment in children has financial returns, which increase the household income. Therefore, discount factor also means the degree of altruism to the children's generation.

At this stage, it is meaningful to compare different scenarios: (i) disaster without public assistance when $e=z>0$ with $x=0$, (ii) disaster but mitigated through public assistance when $e=z>0$ with $x=x^{*}$, and (iii) no disaster when $e=0$. We can rank income levels in the beginning of the second period, which depend on the probabilities of disaster occurrence and (conditional) public assistance. Income level is the highest in case (iii), followed by (ii) and (i). That is, the demand for private transfers is the largest in case (i), which also implies that potential need for reserving human capital is the largest in this case.

First order conditions for child schooling s and private transfer t give $pu'=R'$ and $u'=r(H)$ respectively. Here the unit cost of private transfers $r(H)$, which decreases with human capital, determines the utility price for private transfer. Thus in stage 2 when (e,x) are realized, large H makes it easy to increase t (human capital H and private transfers t are positively related, other things being equal). The availability of private transfers increases investment in child schooling.

In the first period, given the optimal behavior for (t,h), agents decide H with the expectations of disaster occurrence and public assistance. The first order condition for the first-period asset allocation gives $\beta[-r+Eu']\frac{\partial t(e,x,H)}{\partial H}=1+\beta E[u'+r'(H)t]$. With the Envelope condition, we obtain

$$-\beta r'(H)Et(e,x,H)=1+\beta Eu'.$$

That is, the marginal gain (a reduction in the cost of private transfers) on the left-hand

size is equal to the expected marginal cost (production loss in the two periods, part of which depends on Eu') on the right-hand side. Intuitively, we have a trade-off between income and risk reduction, in which the expected marginal utility and the expected demand for private transfers matter. By reducing H, the household increases current income, but this increases the cost of private transfers (say, borrowing), which may decrease the expected utility if a disaster occurs. Therefore the optimal decision on H depends on the likelihood of disasters and public assistance as well as risk aversion.[8]

Note that H does not have to be narrowly defined. For example, a large household size enables agents to diversify and pool risks, which enables agents to ensure post-disaster private transfers to smooth consumption. Holding livestock is also known to increase production as well as enhance income smoothing (selling bullocks when income drops, which however decreases the next-period production).

We summarize results in the proposition below.

Proposition 1:
(i) An increase in disaster probability increases the share of assets that promote post-disaster private transfers (e.g., human capital).[9]
(ii) Good targeting of public assistance conditional on a disaster reduces the incentive to hold transferrable assets and increases investment in child schooling.
(iii) Disaster decreases schooling investment unless disaster is perfectly insured.

In the next section, we will discuss the empirical strategy to test the above hypotheses.

3. Econometric Framework

In this section we describe an econometric framework to clarify the hypotheses to test regarding ex-ante and ex-post actions. We use schooling progression - the number of years completed during a period to investigate how disasters affect human capital formation in the affected and unaffected areas. As discussed more carefully in the next section, the analysis utilizes data on actual natural disaster occurrences: the 1998 flood in Bangladesh, and 2001 droughts in Ethiopia and Malawi.

Strictly speaking, the use of child schooling to measure disaster impacts may be problematic since disasters may affect not only marginal utility (due to income reduction) but also the opportunity cost for schooling investment (i.e., a decrease in labor-market wage). The former decreases schooling investment in order to smooth consumption over time, but the latter increases investment since a decrease in wage reduces opportunity costs of schooling, thereby increasing the incentive to allocate more

---

[8] If $p(e=z)$ is high and $p(x \mid z)$ is low (i.e., disaster is likely to occur but public assistance is small), Eu' increases and H^* is larger ($-r'(H)$ becomes larger). If $\left|r''(H)\right|$ is sufficiently large, the change in the right-hand side (Eu') is small, and the left-hand side increases. In this case, agents will increase human capital in the initial stage. Good targeting, represented by higher $p(x \mid z)$, will substitute for private transfers, and therefore decreases the proportion of total assets allocated to human capital.

[9] *Note that private transfer $t(e,x,H)$ is dependent on disaster occurence, public assistance and ex-ante asset allocation. In the empirical analysis, we do not directly use the information on private transfers, but rather infer the effects from how ex-ante assets alter the impact of disasters on child schooling investment.*

time to schooling. However, many disasters are different from economic recessions. For example, floods can destroy school facilities to disrupt normal school activities. Severe droughts - those analyzed in the Ethiopian and Malawi examples in this paper - cause a substantial decrease in crop production, which threatens food security and human survival and therefore increases the real necessity for children to earn for their families. Hence, in the case of severe disasters such as those examined in this paper, it is likely that income effect dominates substitution effect.

The above observations suggest that disasters can cause poverty trap, by destroying productive assets and public goods such as schools and therefore lowering the income generating capacity in subsequent periods. Unfortunately we do not have information on the destruction of local public goods. In the empirical analysis, therefore, we can only estimate the aggregate effect of disasters on child schooling through both income reduction and asset destruction at the household level and the destruction of public goods at the community level.

We estimate the first-differenced equation for child schooling, which is the schooling progression equation where the dependent variable is differenced grades between two points in time. By doing this, we can difference out unobserved fixed component of the error terms.

$$\Delta h_{ijl(t,t+1)} = \alpha + \beta_1 D_{jl} + \sum_k \beta_2^k D_{jl} a_{jl0}^k + \beta_3 D_{jl} m_{ijl1} + area + age_i + gender_i + \Delta\varepsilon_{ijl(t,t+1)} \quad (1)$$

where $\Delta h_{ijl(t,t+1)}$ is change in grades from time t to $t+1$ for child i in household j and village l, D_{jl} is disaster/exposure indicator or its continuous measure such as depth of water, a_{jl0}^k is pre-disaster asset of type k, m_{ijl1} is post-disaster public assistance, $area$ is area fixed effect, age_i denotes a set of age dummies to control for age-specific trends, $gender_i$ is gender indicator (male or female) that controls for gender-specific trend and $\Delta\varepsilon_{ijl(t,t+1)}$ is differenced error terms. In the above notations, we use time 0 and 1 for pre-disaster asset (before t) and post-disaster public assistance (before $t+1$) respectively.

We assume that $E[\varepsilon_{ijl,t} D_{jl}] = 0$. In other words, the disaster is unexpected so that agents do not adjust schooling investment in t, and/or shocks to child schooling in t do not cause disasters. In theory, the perceived disaster probability could be correlated with pre-disaster asset allocation (portfolio), which may include human capital investment in children. Though agents can estimate disaster probability which affects their behavior, the actual occurrence of disaster is unpredictable in each year.

It is also assumed that $E[\varepsilon_{ijl,t} a_{jl0}^k] = E[\varepsilon_{ijl,t+1} m_{ijl1}] = 0$. Pre-disaster assets and post-disaster public assistance are also uncorrelated with shocks to schooling investment. Note that they only enter the specification through the interactions with disaster measures. In other words, we assume that in the grade-level equations (both t and $t+1$), parameters are the same for assets (if there is no disaster), but the disaster introduces changes in the parameters in the post-disaster period (this point is analogous to the way we estimate complementarity between new technology and schooling). Also public assistance is provided only when the disaster affects the household. Finally

$E[\varepsilon_{ijl,t+1} D_{jl}] = 0$, implying that disaster was observed in $t+1$ and actions taken in $t+1$ are conditioned on this information.

Including area fixed effects in the above specification may underestimate the impacts of disaster if shocks are perfectly correlated within an area. However, there is a cost of not including area fixed effects since unobserved area-specific time-varying factors often jointly affect child schooling in the same area. For example, change in school availability and local wage (due to increased labor demand in the local labor market) affect changes in human capital investments. Actual costs of flood and drought are not evenly distributed in an area.

Note that the labor market (substitution) effect is relatively short in time. During a natural disaster, the wage decreases due to the reduction of labor demand. However, it is also expected that the wage will eventually go back to the normal level after the disaster. Therefore, if our panel data are collected with the interval of several years, we cannot capture the labor market effect. We can only observe the total effect, that is, the income effect net of the substitution effect.

To clarify our theoretical insight, we also estimate pre-disaster asset allocation equations.

$$a^k_{jl0} = \alpha' + \gamma^k_1 \Pr[D_l] + \gamma^k_2 \Pr[D_l] K_{jl} + area_l + \xi^k_{jl} \qquad (2)$$

where $\Pr[D_l]$ is the estimated village-level disaster probability conditional on the information from t to $t+1$, and K_{jl} is landholding of household j in village l. We focus on human capital and livestock allocation in the analysis. For human capital, we use the maximum level of schooling (years) achieved among the household members. If agents correctly perceive the future disaster probability and pre-disaster asset allocation is effective to mitigate potential disaster impacts, they will adjust asset portfolio prior to the actual occurrence of disasters.

To construct a measure of $\Pr[D_l]$, first, we use time series data of disaster incidences at the household level. This first-stage estimate of the disaster probability contains idiosyncratic errors. We then take the average within village to average out the idiosyncratic errors.

Comparison of Eqs (1) and (2) provides some integrated hypotheses on ex-ante actions and disaster impacts. That is, if γ_1 and/or γ_2 are positive for k in Eq (2), we should expect positive β^k_2 in Eq (1). In other words, if some assets play a role in mitigating the impacts of disasters, agents would try to allocate more to those assets before the actual disaster happens: a higher future probability of disasters increases incentives to do so.

4. Data

This section describes the data from Bangladesh, Ethiopia and Malawi that we use to test our hypotheses. The International Food Policy Research Institute has conducted panel household surveys in the three countries with corresponding local collaborators. The period covered in the panel data includes the occurrence of major natural hazards such as flood and drought.

In Bangladesh, the initial survey round was fielded in late 1998, immediately after the onset of the 1998 flood, followed by two subsequent rounds until the middle of

1999 (del Nino et al. 2001). In 2004, a follow-up survey was conducted in April-May, coinciding with the season of the previous survey round, April-May 1999 (Quisumbing 2005a, 2005b).

In Ethiopia, the panel data set builds on the Ethiopian Rural Household Survey, which began in a smaller sample of villages in 1989, then was expanded to 15 villages in 1994. Several rounds were conducted before 1999. A large drought occurred in 2001, followed by the 2004 survey. Similarly, in Malawi, the initial round occurred in 2000, followed by the 2001 drought and the subsequent round in 2004. Therefore, combining the panel data and the information on these natural hazards, we have an ideal setting to assess the impacts of natural hazards and disasters on human capital formation and the roles of ex-ante actions and ex-post responses.

However, the exact timing of occurrence of the natural hazards and surveys matters in interpreting our empirical results, although we adopt the unique approach described in the previous sections. In Bangladesh, the 1998 flood was immediately followed by the initial round. Though the impact of disaster was realized gradually after the flood, the initial round would already have captured some short-term impact of flood exposure. The subsequent two rounds conducted within a year captured dynamic changes of the impacts. This issue is especially important in analyzing child anthropometry. However, we think that our measure of human capital investment, years of schooling completed is more robust to idiosyncratic shocks, particularly health and illness shocks that typically accompany floods.[10] For pre-flood assets, however, the data were constructed to reflect the pre-flood situation.

By contrast, the initial survey rounds in Ethiopia and Malawi were conducted before the 2001 droughts. Thus, the information on child schooling does not contain the potentially confounding influences of the droughts (except the parts explained by ex-ante actions). However, potential problems arise from the interval between the 2001 droughts and the 2004 follow-up survey. Given the actual impacts on income that are supposed to have occurred in 2001-2002, the interval between drought occurrence and the 2004 survey was rather short. This means that we may not capture the complete recovery process of human capital investment in the two-year period.

Malawi had a large flood in 2001-2002 after the 2001 drought. However, our preliminary analysis indicates that the impacts of the flood were rather small, compared to the drought. Therefore, we focus on the 2001 drought in Malawi for the empirical analysis. The above concern on the interval between natural hazards and the follow-up survey is also relevant.

Differences in the time structure of the hazards and the initial and follow-up rounds change the way in which we interpret empirical results. In Bangladesh, first, we may underestimate the initial impacts on child human capital since the first round, immediately after the flood, already contains some of the impacts. However, this survey is ideal to capture the recovery dynamics of human capital starting immediately after the flood. Second, in Ethiopia and Malawi, the setting is suitable to investigate the short-run impacts on human capital investment as the interval between the droughts and the follow-up survey was rather short.

Third, in Bangladesh, using the three rounds conducted in a year after the flood, we can reveal short-term changes of school attendance after the flood, though the initial

[10]For example, water-borne diseases are common after floods, and diarrheal disease in particular would affect weight for height measures. In the analyses, we use the height-for-age z scores in the range of -6 to 6.

round could include some of immediate adverse impacts of the flood. Overall, the Bangladesh setting provides both long-term and short-term dimensions.

The 2004 surveys conducted in the three countries have retrospective information on past disasters. This is useful for knowing the probability of disasters. The probability is defined as the empirical average of incidences in the period from the initial to the last round. Therefore, it is the probability of disasters in the future from the standpoint at the initial round. This preliminary work showed that Ethiopia and Malawi experienced several droughts between the initial and follow-up rounds. In Bangladesh, however, the 1998 flood was the single and most devastating incident for many households in our sample.[11] We have the following distributions for the three countries (Table 1).[12]

Table 1 to be inserted

In Bangladesh, we also use the flood exposure index that measures the severity of the flood (Del Ninno, et al. 2001). In this measure, households were classified into categories depending on flood exposure: no exposure, moderately exposed, severely exposed and very-severely exposed. Given that the 1998 flood was the single and most severe disaster experienced by many households in the sample, it is appropriate to use this exposure measure, rather than the frequency. In addition, the Bangladesh data provides some details of the flood impacts such as the depth of water, the number of days covered by water, repair cost and the number of days evacuated from home. The former two measures are objective, but the latter two could be endogenous. Repair cost is an actual expenditure, so this involves household decisions and also depends on their asset holdings. The number of days evacuated is correlated with number of days submerged, but it also measures the duration of staying safely away from the disaster, so it is higher among those who had resources to keep them away from the flood (e.g., evacuating to other regions). Though these measures principally capture the disaster impacts, we may need to be careful in interpreting the results.

5. Empirical Results

In this section we summarize empirical results on (i) disaster impacts on schooling progression, (ii) ex-ante actions and ex-post public responses, and (iii) pre-disaster asset allocation (ex-ante actions) and disaster risks. In the following analyses, we use the sample of children aged 6 to 12 in the initial rounds.

[11]Floods are a normal part of the agricultural cycle in Bangladesh. However, the 1998 floods were exceptional both for their severity and duration. Unlike normal floods, which cover large parts of the country for several days or weeks during July and August, the 1998 floods lastes until mid-September in many areas, covering more than two-thirds of the coutry, causing over 2 million metric tons of rice crop losses (equal to 10.45 percent of target production in 1998/99) (del Nino et al. 2001).

[12]Alternatively we can use historical meteorological data to construct some measures of too-little and too-much rain. In this way, however, we must define drought and floods with some thresholds in rainfall amount. The proposed method using actual drought (or flood) incidences between the intial and final rounds has an advantage that households were not able to know the future disaster incidences at the time of the initial round. Though historical data reduce the noise in the frequency estimates, both actual incidences and the disaster probability are in the agent's information set. However, our estimates should have relatively large measurement errors.

5.1. Disaster Impacts and Pre-Disaster Assets

5.1.1. Bangladesh

In Bangladesh we have three-round panel data in 1998-1999 collected immediately after the 1998 flood with information on both the number of school days and days actually attended in school. Therefore we can construct the proportions of days attended in rounds 1 to 3 (within a year). In the analysis we investigate changes in the proportion of days attended in school in a year. Age and female dummies are included in all specifications. Union fixed effects and age and female dummies control for variations in trend.

Table 2 to be inserted

Table 2 reports estimation results on the change in school attendance over a year using alternative flood exposure measures such as water depth, the number of days covered by water, repair cost, and the number of days evacuated from home.[13] Columns 1 to 4 show that repair cost significantly reduces school attendance, but other measures are insignificant. In Columns 5 to 8, we include interaction terms with land size and the maximum education in the household, to take into account the possibility that households with higher levels of physical and human resources are better able to cushion the effects of flood. In the estimations with water depth, the number of days covered by water and repair cost, holding land helps to mitigate the negative impacts of the flood. In the specification using repair cost, household education significantly mitigates the impacts of flood. The direct effect on school attendance is significantly negative only in the case of repair cost. Overall the impact seems smaller among girls, but the effect is insignificant in many specifications.

Table 3 to be inserted

From Table 3, we summarize empirical results on school progression measured by change in years of grades completed from 1998 to 2004, which captures long-term impacts of the 1998 flood. In Table 3, we use the four measures of the 1998 flood separately to assess the impacts. Results show that the number of days evacuated from home has a significant and negative effect on change in school attendance. This is in contrast to the finding on transition from pre-school to school stages (Yamauchi, Yohannes and Quisumbing, 2008).

Tables 4 and Figure 1 be inserted

Columns 1 to 4 in Table 4 include interactions with total asset value. Consistent with the notion that households with more resources are better able to weather shocks, asset holding helps mitigate the negative impact of the 1998 flood on school progression

[13]Potentially repair cost and the number of days evacuated from home are endogenous, being correlated with schooling shocks and asset holding. In preliminary analysis, instrumenting these by water depth and the number of days covered by water did not singnificantly change the results. This is because we use the first differenced specification, wiping out the time-invariant effect of household assets.

(Columns 1 and 2: water depth and the number of days water covered). The number of days evacuated from home significantly decreases school progression (Column 4).

In Columns 5 to 8, we disaggregate the household asset portfolios into four measures: the maximum education in the household (years of schooling), land size, household size and livestock (value). First, except for the number of days evacuated, the flood measures have significant and negative effects on school progression. Second, in these cases, maximum education significantly mitigates the negative impacts. In two cases, we also find significant effects of household size and livestock. Therefore, though the flood had negative impacts on schooling investments in the subsequent six years, households with more asset holdings were better able to mitigate the impacts of flood.

Figure 1 shows the flood impacts on schooling progression (based on the estimates in Columns 5 to 7). We use the sample mean of water depth, the number of days covered by water and repair cost to quantify the impacts. Case 1 shows direct effects (without asset). Though the estimate in repair cost effect is relatively small, the water-depth and day effects show nearly a reduction of 0.6-0.7 year due to the flood. In Case 2, we assume that someone in household has attained 8 years of education. Our estimates suggest that the impact is substantially reduced. Case 3 supposes household size of 10 members to assess how the effect of the number of days covered by water changes. This effect is almost equivalent to the education effect in Case 2. Case 4 shows livestock effect using the effect of repair cost. Using the mean value of livestock, we confirm that the mitigation effect is nearly the same as what was found in Cases 2 and 3. These exercises demonstrate the effectiveness of human capital accumulation: both quality and quantity, and livestock in mitigating the flood impact on child schooling.

Table 5 and Figure 2 to be inserted

Next, we use the flood exposure measure constructed by the IFPRI team, that is categorized into not exposed, moderately, severely and very severely exposed (Del Nino et al., 2001). The results are summarized in Table 5. Column 1 includes only the flood exposure index, all of which are insignificant. Columns 2 and 3 include interactions with household assets. Consistent with the previous findings, we confirm that the total asset value, and maximum education and household size (severely exposed case) significantly mitigate the adverse impacts of the 1998 flood.

Figure 2 evaluates the impact of very-severe flood exposure on schooling progression (based on the estimates in Column 3). We use the same assumptions for Cases 2 and 3. The direct impact of very-severe exposure is a reduction of 1.5 years. The simulation shows that maximum education of 8 years and household size of 10 members substantially decrease the impact.

5.1.2. Ethiopia

Table 6 summarizes estimation results on grade progression in Ethiopia. In the case of Ethiopia, we investigate the impact of the 2001 drought on child schooling, using 1997 as the initial round.[14][15] In all specifications, age and male dummies are

[14]The 1997 round is the fourth round of the full Ethiopian Rural Household Survey Sample (three rounds were fielded between 1994 and 1995, and a fifth round was fielded in 1999). In the analysis of dynamic human capital production, we also use information on child anthropometry from the fourth round (Yamauchi, Yohannes and Quisumbing, 2008).

included. Region fixed effects and age and male dummies control for trends.

Table 6 to be inserted

First, Column 1 shows that the 2001 drought has a negative effect on school progression, but it is not statistically significant. Column 2 includes its interaction with total asset value. Interestingly, the drought has a significant negative effect on grade progression (about 0.37 year reduction), but asset holdings significantly mitigate the impact of the drought.

In Column 3, similar to Bangladesh, we use disaggregated measures of the household assets. None of them are shown to be significant. In the Ethiopian survey, we have information on distance to the nearest town, with which we can test the market and institutional effects on the effectiveness of the ex-ante actions.[16] In Column 4, interestingly, the effects of maximum education and household size (both capturing human capital) become significantly positive when the village is distant from towns. Though it is not statistically significant, this is also observed for livestock. This result implies that human capital may play a more important role in mitigating disaster impacts in distant villages.

Figure 3 to be inserted

Figure 3 shows simulation results based on the above estimates in Column 4. Similar to the Bangladesh case (Figure 2), a large family has more advantage than education in Ethiopia. This could be due to the fact that schooling level is generally very low in the rural areas. Risk diversification by having a large family may be more effective in mitigating the effect of droughts.

5.1.3. Malawi

For Malawi, we also use the 2001 drought to investigate the disaster impact on school progression. Since the drought was followed by a flood in 2001-2002, we also analyze the confounding effect. In all specifications, age and male dummies are included. Region fixed effects and age and male dummies control for trends.

Table 7 to be inserted

Table 7 reports the results on school progression in Malawi. Column 1 only includes the 2001 drought indicator and its interaction with the male indicator, both of which are found insignificant. In Column 2, the total asset value was interacted with the drought indicator, which shows that household asset accumulated prior to the 2001 drought mitigated the negative impact, though the direct effect of the drought is not statistically significant (with a negative coefficient).

Column 3 includes the interactions with maximum education in the household, land size, household size and livestock value. First, we find that the 2001 drought significantly decreases school progression (by nearly a year, which is more than twice

[15]Due to a problem in matching children in the two rounds in peasant association no.7, we did not include this peasant association in the analysis. Therefore, the total number of peasant associations is 14.
[16]Note, however, that we have only 14 peasant associations in the analysis.

as large as that found in Ethiopia. Second, the maximum education within the household significantly mitigates the negative impact of drought. This finding is similar to that of Ethiopia and Bangladesh. In fact, junior high school completion (nine years of schooling) almost offsets the negative effect of the drought.

In Column 4, we include the 2001 flood indicator to know the confounding effect. First, the previous results remain robust. Second, household size significantly mitigated the adverse impact of the 2001 drought. Thus, it appears that both quality (maximum education) and quantity (household size) work to mitigate the adverse impacts of the 2001 drought on school progression in Malawi. Third, the 2001 flood had a weakly negative impact on schooling progression.

Figure 4 to be inserted

Figure 4 quantifies drought impacts on schooling progression (based on the estimates in Column 3). Case 1 shows that the direct effect (without assets) is a reduction of about 1 year. Cases 2 and 3 suggest that the effectiveness of education is larger than a large family size in Malawi (compared to Ethiopia). The results are comparable to those of Bangladesh.

5.2. Ex-Post Responses

This section summarizes our findings on ex-post public assistance and ex-ante asset holdings. We are interested in the effectiveness of ex-post public assistance and whether the possibility of receiving public assistance affects ex-ante actions taken by households.

Table 8 to be inserted

Table 8 reports estimation results on Bangladesh. In Bangladesh, we highlight three types of assistance: Gratuitous Relief (GR), Vulnerable Group Feeding (VGF) and assistance from non-government organizations since the preliminary analysis showed that these three sources have large shares in the public assistance (see also Quisumbing, 2004). Columns 1 to 4 use disaggregated measures of the flood exposure, interacted with total amounts of each type of public assistance in 1998-1999 and the household asset value. First, the VGF aid is shown to be most effective in mitigating the flood impacts (three out of four cases). Second, the total asset value also significantly mitigates the impacts (two cases). In Column 4, we also found that GR and NGO assistance mitigated the flood impact.

Columns 5 to 8 use a more disaggregated specification of household assets. The VGF aid significantly mitigates the flood impact (three out of four cases). Among the asset measures, maximum education and household size seem to effectively mitigate the disaster effects. However, land size and livestock have only limited roles in Bangladesh. The above results show that the availability of effective public assistance does not substitute for ex-ante actions taken by households: in Bangladesh, both ex-post public actions and ex-ante private actions coexist, playing active roles in mitigating the flood impacts on schooling investments.

Interestingly, the flood impact was smaller among girls than boys. There seems to be some qualitative difference between genders. One possible answer is that boys may

need to work outside to earn more than girls during and after the flood disaster.

Figure 5 to be inserted

In Figure 5, we simulate the flood impacts by assuming the sample mean of VGF receipt (in 1998-1999) and maximum education of 8 years. The simulations use the estimates in Columns 5 and 6. We found that public assistance can only mitigate the flood impact marginally (Case 2). However, human capital measured by the maximum education seems more effective in mitigating the impact (Case 3).

Table 9 to be inserted

Table 9 reports our results on Ethiopia and Malawi. Columns 1 to 3 summarize findings from the Ethiopian case. First, the 2001 drought has a significant negative effect on grade progression in all estimations. Second, the availability of public work programs (indicator) has two effects: decreasing school progression per se, while increasing it when drought hits the area.[17] However, this result might have been caused by endogenous allocation of such a program to, for example, areas (or households) prone to droughts. We will check this possibility in Table 10. As the second possibility, adult members tend to work in the programs and demand for child labor in own production or domestic work may increase.

Interestingly, we do not find any significant effects of the household assets once public assistance variables are included. Therefore, in Ethiopia, we conclude that the role of public assistance is more important than that of private ex-ante actions.

Results for Malawi are summarized in Columns 4 to 6. In contrast to Ethiopia, our results indicate that receipt of food aid played only a small role in mitigating disaster impacts. Instead, total asset value and maximum education significantly mitigate the drought impacts.

Table 10 to be inserted

Next we check the robustness of the above results by restricting our sample to areas that severely exposed to the 1998 flood in Bangladesh, or high risk disaster areas in Ethiopia and Malawi. High risk areas are defined if the estimated probabilities of drought are greater than 0.4 and 0.5 respectively in Ethiopia and Malawi (see Table 1). Results summarized in Columns 1 to 4 support the previous findings, and also prove that the effects of public assistance are more significant and greater than those in Table 9. The role of public assistance is large in areas severely exposed to the flood.

Columns 5 and 6 report results on Ethiopia and Malawi respectively. In Ethiopia, the negative direct and disaster mitigating effects of public work are also confirmed in high-risk areas. However, the risk mitigation effect is found larger than the direct negative effect, implying that there seems to be bias from the endogenous allocation of public work programs, but still substitution effect among children is also not denied.

[17]In this analysis, we have not controlled for endogeneity of program allocation except by differencing schooling equations over time. Thus, as long as the initial period shock to schooling is uncorrelated with the allocation of public work programs, the estimate should be unbiased. Additional efforts to homogenize the sample using matching techniques are not adopted in this paper.

Interestingly, similar results are found in Malawi. The direct effect of food aid is negative, while food aid mitigates the adverse impact of drought. However, small sample prevents us from reaching a clear conclusion.

5.3. Risks and Asset Portfolio

In this section, we examine how natural hazard risks affect household's asset portfolio. In theory, the importance of ex-ante actions in determining portfolio allocation among different assets depends on the perceived future risks of disasters as well as the likelihood of receiving public assistance. Disaster risk was computed from actual realizations of disasters in the period from the initial round to the final round. In the case of Bangladesh, we computed the probability of having floods in 1998-2004. For Ethiopia and Malawi, it is 1999-2004 and 2000-2004 respectively. The 1998 flood in Bangladesh was a single severe incidence for many households in the sample: as noted earlier, while floods are a normal part of the agricultural cycle in Bangladesh, a flood of such severity and extended duration was extremely unlikely. In Ethiopia and Malawi, droughts occurred rather frequently in our sample villages.

As discussed in Section 3, we focus on maximum education in household and livestock value relative to land. The literature and our previous results suggest that bullocks can cushion negative income shocks since farmers can sell or use them as collateral. However, transactions in land markets are relatively uncommon owing to missing or imperfect land markets in our study countries. Educated household members are more mobile and the returns to schooling are not directly correlated with farm income fluctuations caused by floods and/or droughts.

The roles of assets in mitigating disaster impacts (found in the previous section) are thought to be associated with ex-ante asset allocation. For example, if human capital in the household is important for reducing disaster shocks, individuals have an incentive to invest in and hold human capital prior to disasters. This incentive must be higher if the future disaster risk is larger.

Tables 11 to be inserted

Table 11 summarizes estimation results from the three countries. We use the village average of the household-level disaster probability estimates. The probability of drought or flood was estimated from the information on incidences during the period from the initial to final rounds. We took average of the estimates within a village. This method reduces idiosyncratic errors. In the estimation below, we control for land effect, as human capital stock (measured by maximum education) and livestock are usually positively correlated with total asset holding (here proxied by land size). The future disaster risk estimates are interacted with landholding.

Columns 1 to 4 show results from Bangladesh. In all columns, land has a significant positive effect on maximum years of education and cattle value. In the interaction terms with landholding in Columns 1 and 2, the effect of flood probability on maximum years of education is convex. There exists a threshold probability above which flood probability increases maximum years of education in the household (0.082 in Column 1 and 0.074 in Column 2). For the value of cattle, we do not find any jointly significant effects.

In Ethiopia, we do not find any significant effects on maximum years of

education. In contrast, Columns 7 and 8 show that the value of cattle increases with the probability of drought above some threshold probability (0.189 in Column 7 and 0.159 in Column 8).

In Malawi, results support threshold probabilities above which the probability of drought significantly increases maximum years of education (thresholds: 0.238 in Column 9, and 0.123 in Column 10) and the value of cattle (0.248 in Column 12).

The above finding is theoretically interesting. In the above results, threshold probabilities are relatively small. First, the environment of no disaster risk seems to encourage investments in human capital and livestock. Second, as disaster risk increases, precautionary motives to invest in assets with the expectations of future disasters will offset the above risk-aversion effect. In the environment in our sample, the incentive to hold human capital (Bangladesh and Malawi) and livestock (Ethiopia and Malawi) is positive in a reasonable range of the future disaster probability.

Interestingly, the above findings are consistent with our previous findings on the risk mitigating effects of household education. In Bangladesh (Tables 4 and 5) and Malawi (Table 7), we found that maximum education significantly mitigates the negative impact of flood and drought on schooling investment respectively. For Ethiopia (Table 6) we did not find significant effects of maximum education. Therefore, the positive association between pre-disaster household human capital and the future risk of drought is consistent with the actual impacts of droughts on child schooling investments.

6. Conclusion

This paper examined the impacts of natural disasters on schooling investments with special emphasis on the roles of ex-ante actions and ex-post responses using panel data from Bangladesh, Ethiopia and Malawi. The importance of ex-ante actions depends on disaster risks and the likelihood of public assistance.

Empirical results show interesting heterogeneity in both asset portfolio as well as ex-ante and ex-post responses. In Bangladesh and Malawi, a higher future disaster probability increases the likelihood of holding more human capital relative to land. However, in Ethiopia, investments in human capital are not systematically related to the future disaster probabilities. The likelihood of holding livestock is positively associated with a higher probability of drought in Ethiopia and Malawi.

In all cases, we found an interesting non-linearity: the effect of future disaster risk on asset holding becomes positive when the disaster probability goes above some threshold (relatively small). There seem to be two offsetting effects of the disaster risk. The future risk discourages investment since it makes returns uncertain, while it encourages investments for the need of mitigating disaster impacts. In disaster prone areas, the latter effect offsets the former effect.

Our results confirm that both ex-ante private and ex-post public responses, working mostly through emergency assistance programs in the latter case, help to mitigate disaster impacts, but the balance between ex-ante and ex-post actions varies across countries.

In Ethiopia, public assistance plays a more important role than ex-ante actions to mitigate the shocks on child schooling. In contrast, Malawi relies on private ex-ante actions while public assistance, by and large, is insignificant. The Bangladesh example shows active roles of both ex-ante and ex-post actions. Interestingly, these observations

are consistent with our finding on the relationship between ex-ante actions and the disaster risks.

These findings have important implications for the design of public safety net policies, and raise several questions that deserve further investigation. For example, are ex-post actions unimportant in Malawi owing to ineffectiveness of the public assistance scheme? On the other hand, the importance of ex-post public assistance in Ethiopia could be correlated both with better program effectiveness in terms of targeting emergency assistance as well as with greater difficulties faced by poor Ethiopian households in undertaking ex-ante risk-mitigating actions. In Bangladesh, do different types of households benefit from ex-post and ex-ante actions, with better-off households better able to undertake ex-ante actions, and poorer households benefiting from well-targeted emergency assistance?

All in all, our results show that among the ex-ante actions considered, the accumulation of human capital within the household prior to disasters helps mitigate the negative effects of disasters in both the short and long run. Our results suggest that efforts to increase investment in human capital in disaster-prone countries should be strengthened to mitigate the disaster impacts (i.e., income variance), despite the appeal of urgency and emergency assistance once disaster strikes.

References

[1] Binswanger, H.P. and M.R. Rosenzweig, 1986. "Behavioural and material determinants of production relations in agriculture," *Journal of Development Studies*, 22: 503-539.

[2] Coady, D., P. Dorosh and J. Hoddinott, 2004, *Targeting of transfers in developing countries: Review of lessons and experience*, Washington, D.C: World Bank.

[3] Crespo Cuaresma, J., J. Hlouskova and M. Obersteiner, 2008, "Natural disasters as creative destruction? Evidence from developing countries," *Economic Inquiry*, 46: 214-226.

[4] Coate, S. and M. Ravallion, 1993, "Reciprocity without commitment: Characterization and performance of informal insurance arrangements," *Journal of Development Economics*, 40: 1-24.

[5] Deaton, A., 1991, "Saving and liquidity constraints," *Econometrica*, 59: 53-73.

[6] Del Ninno, C., P.A. Dorosh, L. C. Smith, and D.K. Roy. 2001. The 1998 Flood in Bangladesh: Disaster Impacts, Household Coping Strategies, and Response. Research Report 122. Washington D.C: International Food Policy Research Institute.

[7] Dercon, S., 2002, "Income risk, coping strategies and safety nets," *World Bank Research Observer*, 17: 141-166.

[8] Dercon, S. and L. Christiaensen, 2007, "Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia," World Bank Policy Research Working Paper No.4257.

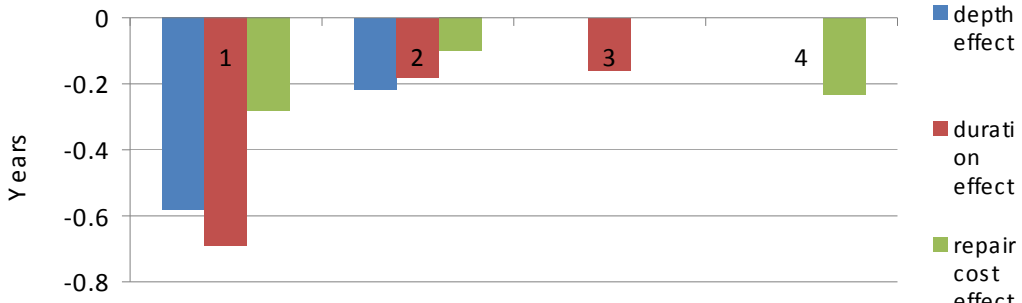
[9] Ferreira, F. and N. Schady, 2008, "Aggregate economic shocks, child schooling and child health," Manuscript, World Bank.

[10] Gilligan, D. and J. Hoddinott. 2005. Using community targeting to provide drought relief: Evidence from Ethiopia. Unpublished manuscript, International Food Policy Research Institute, Washington D.C.

[11] Gine, X., R. Townsend, and J. Vickery, 2007, "Rational expectations: Evidence from planting decisions in semi-arid India," Manuscript, World Bank.

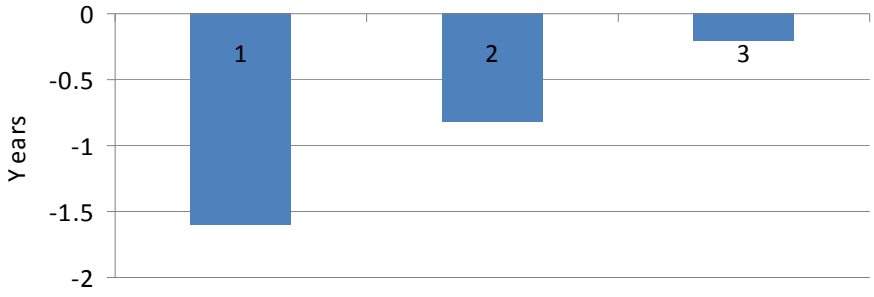
[12] Skidmore, M. and H. Toya, 2002, "Do natural disasters promote long-run growth?," *Economic Inquiry*, 40: 664-687.
[13] Tol, R. and F. Leek, 1999, "Economic analysis of natural disasters," in *Climate Change and Risk* eds by T.E. Downing, A.J. Olsthoorn and R.S.T. Tol. London: Routledge.
[14] Jacoby, H.G. and E. Skoufias, 1997, "Risk, financial markets and human capital in a developing country," *Review of Economic Studies*, 64: 311-335.
[15] Kimball, M.S., 1990, "Precautionary saving in the small and in the large," *Econometrica*, 58: 53-73.
[16] Ligon, E., 1998, "Risk sharing and information in village economies," *Review of Economic Studies*, 65: 847-864.
[17] Ligon, E., J.P. Thomas and T. Worrall, 1997, "Informal insurance arrangements in village economies," CUDARE Working Paper 825, University of California at Berkeley, Department of Agricultural and Resource Economics.
[18] Morduch, J., 1999, "Between the state and the market: Can informal insurance patch the safety net?," *World Bank Research Observer*, 14: 187-207.
[19] Noy, I., 2008, "The macroeconomic consequences of disasters," *Journal of Development Economics*, 88: 221-231.
[20] Owens, T. and J. Hoddinott, 2003, "Ex-ante actions and ex-post public responses to drought shocks: Evidence and simulations from Zimbabwe," *World Development*, 31: 1239-1255.
[21] Porter, C.C., 2008, "Gone with the Wind?: Hurricane Risk, Fertility and Education," Manuscript, University of Washington.
[22] Quisumbing, A., 2005a, "Targeting and fairness of emergency food assistance: The 1998 floods in Bangladesh," Manuscript, International Food Policy Research Institute.
[23] ————, 2005b, "A drop in the bucket? The impact of food assistance after the 1998 floods in Bangladesh," Manuscript, International Food Policy Research Institute.
[24] Rosenzweig, M.R., 1988, "Risk, implicit contracts and the family in rural areas of low-income countries," *Economic Journal*, 98: 1148-1170.
[25] Rosenzweig, M.R. and O. Stark, 1989, "Consumption smoothing, migration, and marriage: Evidence from rural India," Journal of Political Economy, 97: 905-x.
[26] Rosenzweig, M.R. and K. Wolpin, 1993, "Credit market constraints, consumption smoothing and the accumulation of durable production assets in loq-income countries," *Journal of Political Economy*, 101: 223-244.
[27] Sharma, M. 2005. The Impact of Food Aid on Consumption and Asset Levels in Rural Malawi. Unpublished paper, International Food Policy Research Institute.
[28] Skoufias, E., 2003, "Economic crisises and natural disasters: coping strategies and policy implications," *World Development*, 31: 1087-1102.
[29] Townsend, M., 1994, "Risk and insurance in village India," *Econometrica*, 62: 539-591.

Figure 1 Flood impacts in Bangladesh



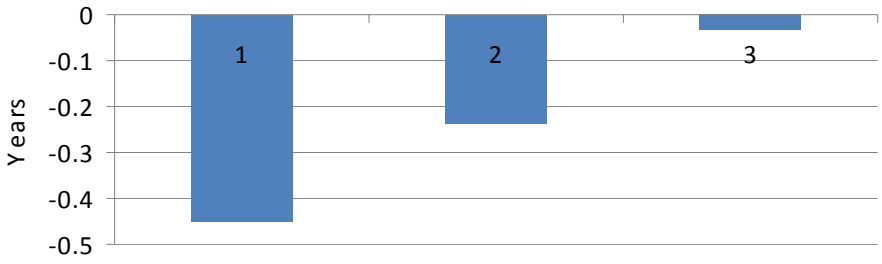
Case 1: Direct effect, Case 2: Maximum educ = 8 years
Case 3: Household size = 10, Case 4: Livestock = 4148 (mean)

Figure 2 Impacts of very-severely flood exposure in Bangladesh 2



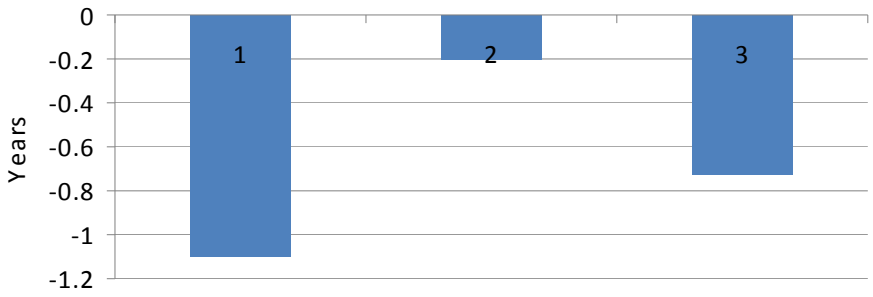
Case 1: Direct effect; Case 2: Maximum educ = 8 years;
Case 3: Household size = 10

Figure 3 Drought impact in Ethiopia



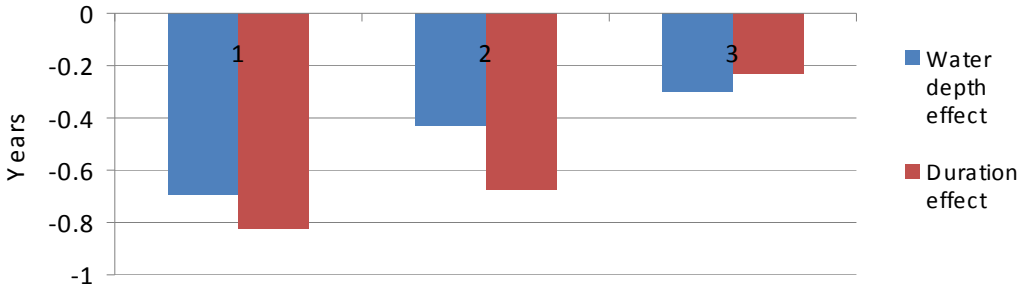
Case 1: Direct effect;
Case 2: Maximum educ = 8 years and Distance from town = 9 km;
Case 3: Household size = 10 and Distance from town = 9 km

Figure 4 Drought impacts in Malawi



Case 1: Direct effect; Case 2: Maximum educ = 8 years;
Case 3: Household size = 10

Figure 5 Public assistance and ex-ante actions in Bangladesh



Case 1: Direct effect; Case 2: VGF = 761.4974;
Case 3: Maximum education = 8 years

Table 1 Estimates of future disaster probabilities

Number of incidences:	None	Once	Twice	Three times
Bangladesh: Flood	0	0.14	0.29	
	(453)	(323)	(7)	
Ethiopia: Drought	0	0.20	0.40	0.60
	(594)	(394)	(215)	(54)
Malawi: Drought	0	0.25	0.50	0.75
	(389)	(228)	(101)	(36)

Numbers of households are shown in parentheses. Probabilities are defined as the empirical average of disaster incidences (measured yearly) in the period between the initial round and the final round.

Table 2 Short-run effects of Bangladesh flood on school attendance

Dependent: Change in proportion of days attended from round 1 to 3								
Flood variable:	Depth	Days	Repair cost	Outhome	Depth	Days	Repair cost	Outhome
Flood	-0.0125	-0.0004	-0.00002	-0.0006	-0.0170	-0.0011	-0.00006	-0.0009
	(1.500)	(0.720)	(2.480)	(0.880)	(1.490)	(1.080)	(3.930)	(0.870)
Flood * land					0.00009	2.29-E-06	1.55E-08	4.06E-07
					(2.700)	(2.900)	(0.940)	(0.050)
Flood * max educ					-0.0001	0.00004	4.94E-06	0.00004
					(0.110)	(0.420)	(3.270)	(0.490)
Flood * female	0.0163	0.0002	0.00002	0.0013	0.0183	0.0002	0.00002	0.0013
	(1.620)	(0.490)	(1.730)	(1.530)	(2.040)	(0.410)	(1.610)	(1.430)
Union FE	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	630	630	630	630	584	584	584	584
Number of unions	21	21	21	21	21	21	21	21
R squared (within)	0.0226	0.0191	0.0431	0.0209	0.0370	0.0292	0.0713	0.0226

Numbers in parentheses are absolute t values using robust standard errors with union clusters. Age and female dummies are included in all specifications.

Table 3 Dynamic effects of Bangladesh flood on schooling progression

Dependent: Change in grades from 1998 to 2004				
Flood variable:	Depth	Days	Repair cost	Outhome
Flood	-0.1352	-0.0005	-0.00007	-0.0164
	(1.510)	(0.110)	(1.210)	(2.250)
Flood * female	0.0777	0.0074	0.00006	0.0131
	(1.140)	(1.530)	(1.410)	(1.250)
Union FE	yes	yes	yes	yes
Number of observations	489	489	489	489
Number of unions	21	21	21	21
R squared (within)	0.0488	0.0474	0.0457	0.0591

Numbers in parentheses are absolute t values using robust standard errors with union clusters. Age and female dummies are included in all specifications.

Table 4 Dynamic effects of Bangladesh flood on schooling progression

Dependent: Change in grades from 1998 to 2004								
Flood variable:	Depth	Days	Repair cost	Outhome	Depth	Days	Repair cost	Outhome
Flood	-0.1586	0.0015	-0.00006	-0.0141	-0.3359	-0.0271	-0.0005	0.0072
	(1.790)	(0.310)	(0.910)	(2.490)	(3.820)	(3.450)	(3.260)	(0.260)
Flood * asset	1.50E-06	3.71E-08	-2.50E-10	-1.01E-07				
	(2.940)	(1.870)	(0.680)	(0.620)				
Flood * max educ					0.0263	0.0025	0.00004	0.0003
					(2.560)	(4.070)	(3.040)	(0.180)
Flood * land					0.0005	6.56E-06	-2.57E-07	-0.0002
					(1.690)	(0.620)	(1.310)	(1.310)
Flood * household size					0.0211	0.0014	0.00002	-0.0032
					(1.130)	(1.870)	(1.260)	(0.950)
Flood * livestock					-1.98E-06	2.77E-07	2.14E-08	-1.23E-06
					(0.660)	(0.830)	(2.930)	(0.940)
Flood * female	0.0892	0.0072	0.00007	0.0128	0.0406	0.0084	0.0001	0.0032
	(1.300)	(1.480)	(2.290)	(1.240)	(0.640)	(1.890)	(2.250)	(0.400)
Union FE	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	489	489	489	489	458	458	458	458
Number of unions	21	21	21	21	21	21	21	21
R squared (within)	0.0564	0.0508	0.0462	0.0595	0.0947	0.1080	0.0827	0.0801

Numbers in parentheses are absolute t values using robust standard errors with union clusters. Age and female dummies are included in all specifications.

Table 5 Dynamic effects of Bangladesh flood on schooling progression: flood exposure measure

Dependent: change in grades from 1998 to 2004			
Flood index 1	0.2411	0.1414	-0.6037
	(0.560)	(0.310)	(0.720)
Flood index 2	0.1049	-0.0438	-0.0444
	(0.280)	(0.110)	(0.090)
Flood index 3	-0.1241	-0.1950	-1.6021
	(0.280)	(0.440)	(3.000)
Flood index 1 * total asset		2.49E-06	
		(1.130)	
Flood index 2 * total asset		5.66E-06	
		(1.110)	
Flood index 3 * total asset		3.20E-06	
		(2.930)	
Flood index 1 * max edu			0.1301
			(2.820)
Flood index 2 * max edu			0.1321
			(3.570)
Flood index 3 * max edu			0.0978
			(1.950)
Flood index 1 * land			0.0002
			(0.240)
Flood index 2 * land			-0.0004
			(0.650)
Flood index 3 * land			0.0017
			(1.310)
Flood index 1 * household size			0.0025
			(0.020)
Flood index 2 * household size			-0.0715
			(1.010)
Flood index 3 * household size			0.1396
			(1.500)
Flood index 1 * livestock			-9.20E06
			(0.270)
Flood index 2 * livestock			-0.00002
			(1.210)
Flood index 3 * livestock			-3.75E-06
			(0.260)
Flood index 1 * female	0.0081	-0.0625	0.0776
	(0.020)	(0.170)	(0.210)
Flood index 2 * female	-0.2688	-0.2655	-0.1639
	(0.900)	(0.930)	(0.570)
Flood index 3 * female	0.4349	0.4535	0.4869
	(1.060)	(1.110)	(1.260)
Village FE	yes	yes	yes
N obs	492	492	468
N villages	21	21	21
R squared (within)	0.0513	0.0596	0.1269

Numbers in parentheses are absolute t values, using robust standard errors with village clusters. Age and female dummies are included in all specifications.

Table 6 Dynamic effect of Ethiopia drought on schooling progression

Dependent: Change in grade from 1998 to 2004				
Drought 2001	-0.1903	-0.3731	-0.3060	-0.4497
	(0.950)	(1.860)	(1.200)	(2.240)
* Total asset		0.0007		
		(4.290)		
* max edu			0.0157	-0.1462
			(0.390)	(2.160)
* max educ * distance				0.0192
				(2.490)
* land			0.0500	0.3836
			(0.250)	(1.890)
* land * distancee				-0.0461
				(2.260)
* household size			0.0020	0.1181
			(0.050)	(4.880)
* household size * distance				-0.0085
				(3.050)
* livestock			-0.00003	-0.0001
			(1.270)	(1.380)
* livestock * distance				0.00001
				(1.960)
* male	0.2690	0.2827	0.3053	0.3138
	(0.760)	(0.810)	(0.950)	(1.040)
Region FE	yes	yes	yes	yes
Number of observations	846	842	815	721
Number of regions	6	6	6	6
R squared (within)	0.0456	0.0507	0.0494	0.0671

Numbers in parentheses are absolute t values using robust standard errors with region clusters. Age and male dummies are included in all specifications. Distance is kilometers to the nearest town.

Table 7 Dynamic effects of Malawi drought on schooling progression

Dependent: Change in grade from 2000 to 2004				
Drought 2001	-0.0172	-0.1328	-1.0057	-1.1000
	(0.130)	(0.980)	(4.440)	(7.500)
* total asset		0.00002		
		(3.460)		
* max edu			0.1107	0.1120
			(6.160)	(5.070)
* land			0.0082	0.0109
			(0.190)	(0.240)
* household size			0.0366	0.0373
			(1.470)	(2.420)
* livestock			-3.28E06	-2.90E06
			(1.020)	(1.210)
* male	-0.0540	-0.0683	-0.0707	0.0119
	(0.300)	(0.410)	(0.410)	(0.060)
Drought 2001 * flood 2001				0.5657
				(0.980)
Flood 2001				-0.2861
				(1.510)
* max edu				-0.0104
				(0.320)
* land				0.0342
				(0.410)
* household size				0.0152
				(0.140)
* livestock				-6.26E06
				(1.030)
* male				0.3250
				(2.600)
Region FE	yes	yes	yes	yes
Number of observations	449	435	433	433
Number of regions	4	4	4	4
R squared (within)	0.0520	0.0849	0.1176	0.1287

Numbers in parentheses are absolute t values, using robust standard errors with region clusters. Age and male dummies are included in all specifications.

Table 8 Dynamic effects of Bangladesh flood on schooling progression: Pre-flood assets and ex-post public assistance

Dependent: Change in grades from 1998 to 2004								
Flood variable:	Depth	Days	Repair cost	Outhome	Depth	Days	Repair cost	Outhome
Flood	-0.2347	-0.0035	-0.00002	-0.0318	-0.4001	-0.0323	-0.0005	0.0209
	(2.170)	(0.660)	(0.240)	(5.670)	(4.440)	(4.480)	(2.760)	(0.650)
Flood * GR	0.00005	-7.05E-06	-4.24E-08	0.00003	0.0001	9.95E-06	2.44E-07	0.00003
	(0.370)	(0.930)	(0.230)	(2.990)	(1.000)	(1.160)	(0.680)	(1.390)
Flood * GFV	0.0001	8.04E-06	1.13E-07	0.00002	0.0002	7.98E-06	4.46E-08	0.00002
	(1.800)	(2.150)	(1.540)	(4.090)	(1.780)	(2.130)	(0.710)	(4.370)
Flood * NGO	0.0001	-2.72E-06	-2.50E-07	0.00002	0.0002	-1.78E-06	-5.98E-08	0.00006
	(1.330)	(0.440)	(1.450)	(2.830)	(1.160)	(0.210)	(0.280)	(3.090)
Flood * asset	1.77E-06	4.34E-08	-5.64E-10	-2.33E-07				
	(3.550)	(1.970)	(1.100)	(1.510)				
Flood * max educ					0.0284	0.0026	0.00004	0.0007
					(2.480)	(4.310)	(2.520)	(0.330)
Flood * land					0.0006	0.00001	-2.55E-07	-0.00008
					(1.950)	(0.890)	(1.070)	(0.810)
Flood * household size					0.015 5	0.0015	0.00003	-0.0121
					(0.730)	(1.780)	(1.040)	(2.630)
Flood * livestock					-1.50E-06	3.46E-07	1.61E-08	-6.93E-07
					(0.490)	(1.040)	(1.320)	(0.590)
Flood * female	0.0831	0.0067	0.0001	0.0173	0.0320	0.0089	0.0001	0.0165
	(1.310)	(1.400)	(3.160)	(2.320)	(0.560)	(1.910)	(1.970)	(2.790)
Union FE	yes	yes	yes	yes	yes	yes	yes	yes
Number of observations	489	489	489	489	458	458	458	458
Number of unions	21	21	21	21	21	21	21	21
R squared (within)	0.0675	0.0618	0.0533	0.0865	0.1084	0.1191	0.0840	0.1069

Numbers in parentheses are absolute t values using robust standard errors with union clusters. Age and female dummies are included in all specification. GR, GFV and NGO are the sum of transfers received in 1998-1999 from respective sources.

Table 9 Dynamic effects of drought on schooling progression in Ethiopia and Malawi: Pre-flood assets and ex-post public assistance

Dependent: Change in grades						
	Ethiopia			Malawi		
Drought 2001	-0.2168	-0.4370	-0.2776	-0.1077	-0.2083	-1.1084
	(1.100)	(2.520)	(0.890)	(0.600)	(1.050)	(3.840)
Public work	-0.7253	-0.7673	-0.7563			
	(1.970)	(2.170)	(2.230)			
Food aid	0.2390	0.2638	0.3538	-0.1912	-0.1921	-0.2057
	(0.850)	(0.980)	(0.980)	(1.430)	(1.340)	(1.380)
Drought * public work	0.5498	0.6392	0.6143			
	(1.910)	(2.480)	(1.770)			
Drought * food aid	-0.5224	-0.4860	-0.6428	0.3554	0.3093	0.3824
	(1.090)	(1.050)	(0.990)	(1.420)	(1.230)	(1.630)
Drought * asset		0.0006			0.00002	
		(3.560)			(3.790)	
Drought * max educ			0.0150			0.1112
			(0.360)			(6.150)
Drought * land			0.0539			0.0112
			(0.290)			(0.280)
Drought * household size			-0.0056			0.0354
			(0.130)			(1.440)
Drought * livestock			-0.00004			-3.70E06
			(1.430)			(0.860)
Drought * male	0.2390	0.2522	0.3020	-0.0627	-0.0786	-0.0744
	(0.670)	(0.710)	(0.930)	(0.300)	(0.390)	(0.360)
Region FE						
Number of observations	842	838	813	447	433	431
Number of regions	6	6	6	4	4	4
R squared (within)	0.0670	0.0724	0.0685	0.0553	0.0875	0.1214

Numbers in parentheses are absolute t values using robust standard errors with region clusters. Age and gender dummies are included in all specifications.

Table 10 Robustness: High-risk and severely exposed areas

Dependent: Change in grades						
	Bangladesh flood				Ethiopia	Malawi
Disaster variable:	Depth	Days	Repair cost	Outhome	Drought	Drought
Sample:	Severely exposed				High risk	High risk
Disaster	-0.4125	-0.0260	-0.0009	-0.0118	-1.2152	-2.2863
	(2.350)	(2.420)	(2.510)	(0.310)	(1.790)	(29.47)
Public work					-1.1361	
					(2.160)	
Food aid					-0.2049	-1.8825
					(0.570)	(13.39)
Disaster * GR	0.0003	0.00001	6.76E-07	0.00006		
	(1.950)	(1.330)	(0.630)	(3.500)		
Disaster * GFV	0.0003	0.00001	3.71E-07	0.00002		
	(5.800)	(2.940)	(1.280)	(2.380)		
Disaster * NGO	0.0004	0.00001	6.68E-07	0.00005		
	(2.740)	(0.860)	(0.870)	(1.260)		
Disaster * public work					1.6314	
					(3.960)	
Disaster * food aid					-0.0264	2.2333
					(0.050)	(15.41)
Disaster * max educ	0.0227	0.0014	0.00005	0.0030	0.0085	0.1635
	(1.760)	(1.500)	(2.230)	(1.740)	(0.550)	(3.520)
Disaster * land	0.0012	0.00003	4.12E-07	-0.0001	-0.4038	-0.0094
	(2.360)	(1.310)	(0.410)	(0.370)	(1.760)	(0.300)
Disaster * hh size	0.0044	0.0010	0.00003	-0.0115	-0.0128	0.0524
	(0.180)	(0.700)	(2.990)	(1.590)	(0.270)	(1.040)
Disaster * livestock	-5.82E-06	1.84E-07	5.64E-09	1.68E-06	0.00008	-0.00002
	(0.960)	(0.650)	(0.160)	(0.990)	(1.530)	(1.450)
Disaster * female	0.0955	0.0130	-0.00008	0.0338		
	(0.650)	(0.720)	(0.600)	(3.610)		
Disaster * male					0.5068	0.3377
					(0.640)	(0.700)
Union FE	yes	yes	yes	yes		
Region FE					yes	yes
Number of observations	121	121	121	121	168	96
Number of unions	17	17	17	17		
Number of regions					5	4
R squared (within)	0.2926	0.2066	0.1640	0.1974	0.1655	0.3048

Numbers in parentheses are absolute t values using robust standard errors with union clusters. Age and female (or male) dummies are included in all specification. GR, GFV and NGO are the sum of transfers received in 1998-1999 from respective sources. Severely exposed sample is used in Bangladesh. In Ethiopia and Malawi, high risk sample is defined if the drought probability is greater than 0.40 and 0.50 respectively (see Table 1).

Table 11 Asset portfolio prior to disaster

	Bangladesh				Ethiopia				Malawi			
	Max edu	Max edu	Cattle	Cattle	Max edu	Max edu	Cattle	Cattle	Max edu	Max edu	Cattle	Cattle
Disaster probability	28.54		20650.8		1.183		-17157.4		-19.10		100788.7	
	(1.76)		(0.58)		(0.07)		(3.38)		(3.28)		(1.10)	
Squared probability	-172.55		-26499.9		-11.20		45430.8		40.08		-183276.6	
	(1.50)		(0.14)		(0.17)		(1.93)		(3.35)		(0.93)	
Land	0.019	0.0134	66.21	57.99	0.3508	0.3650	1026.9	1361.1	-0.079	205023	8953.3	7492.4
	(3.76)	(4.49)	(2.93)	(3.71)	(1.67)	(3.23)	(4.35)	(5.55)	(0.68)	(2.00)	(2.62)	(2.82)
Land * disaster probability	-0.267	-0.134	-875.10	-711.15	-0.775	1.170	-7060.6	-12979.2	1.781	-1.323	-70400.7	-55855.5
	(2.13)	(1.82)	(1.66)	(1.95)	(0.38)	(0.10)	(0.89)	(1.97)	(1.11)	(1.19)	(1.85)	(1.91)
Land * squared probability	1.633	0.908	3061.12	2408.45	-7.730	-17.39	25910.3	40762.7	-1.471	5.382	139949.3	112502
	(1.51)	(1.86)	(1.28)	(1.14)	(0.69)	(0.39)	(0.89)	(1.83)	(0.35)	(2.12)	(1.49)	(1.53)
Number of observations	603	603	602	602	1361	1361	1376	1376	636	636	664	664
Number of thana	7	7	7	7								
Number of regions					4	4	4	4	4	4	4	4
R squared (within)	0.1721	0.1666	0.2516	0.2462	0.0464	0.0438	0.1691	0.1575	0.0559	0.0422	0.2105	0.2003

Numbers in parentheses are t value using robust standard errors with thana clusters (Bangladesh) and region clusters (Ethiopia and Malawi). Disaster probability is the village average of the household-level probability estimates (see Table 1). In Ethiopia, regions are redefined.