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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

Poverty, Health, and Nutrition Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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AUTHORS

Futoshi Yamauchi, International Food Policy Research Institute
Research Fellow, Poverty, Health, and Nutrition Division

Yisehac Yohannes, International Food Policy Research Institute
Research Analyst, Poverty, Health, and Nutrition Division

Agnes Quisumbing, International Food Policy Research Institute
Senior Research Fellow, Poverty, Health, and Nutrition Division

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ABSTRACT

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

Keywords: natural disasters, ex-ante actions, ex-post responses, human capital investment, Bangladesh, Ethiopia, Malawi

1. INTRODUCTION

In low-income countries, it has been increasingly recognized that economic agents attempt to smooth consumption by managing risks associated with natural and social hazards, through both formal mechanisms and informal arrangements (for example, Townsend 1994, Rosenzweig 1988, and Binswanger and Rosenzweig 1986). In many low-income settings, where formal insurance and government support are limited, agents tend to rely on informal insurance (for example, remittances from relatives) to secure their livelihoods. For example, marriage arrangements with households in other villages may be used to diversify income risks among relatives (Rosenzweig and Stark 1989). These mechanisms can be quite effective in smoothing the impacts of idiosyncratic shocks; however, if the risks are aggregate or correlated across agents (for example, large-scale natural hazards), these strategies may be less useful because the risks cannot be pooled to offset each other.[1]

When agents perceive that there is a high likelihood of a large-scale hazard in the near future, they must employ strategies that differ from the informal arrangements described above, since cross-sectional diversification and pooling of such risks are difficult. In other words, the scope of insurance arrangements (either formal or informal) against large-scale natural disasters is quite limited (see, also, the review by Dercon 2002, Morduch 1999, and Skoufias 2003). Thus, instead of pooling risk across individuals or households, agents must reallocate resources intertemporarily.[2]

The relationship between natural hazards and investment behavior provides interesting insights. Most natural disasters damage physical capital; climatic disasters (for example, floods and droughts) damage crops on farmland, while earthquakes can suddenly destroy buildings and landscapes. The immediate loss of human capital is typically much smaller than that of physical capital, although the loss of human capital largely depends on the nature and magnitude of the event, as well as its suddenness and unexpectedness. Disaster impacts on human capital seem to be more gradual, due to potential repercussions from physical destruction and economic impacts.

The above observations suggest the possibility of a poverty trap. Once a disaster destroys productive assets and public goods, 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 their quality) drop, decreasing the expected income in the future. This point clearly distinguishes between disasters and income fluctuations.

Recent macroeconomic studies find that a high likelihood of natural hazards can increase economic growth in the long run (for example, Skidmore and Toya 2002, and Tol and Leek 1999). However, more careful studies on developing countries recently show that technology inflow, which is positively related to growth, increases with natural disasters only among wealthier countries (Crespo Cuaresma, Hlouskova, and Obersteiner 2008). Disasters also have 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, the prior 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 have not previously been examined.

The expected returns to investments will be affected by the likelihood of damages due to natural hazards, which can therefore determine investment behavior in the long run. Dercon and Christiaensen

[1] The effectiveness of informal insurance arrangements is limited by the correlation structure of risks and imperfect information on the actual realizations of shocks. The latter creates a limited commitment (self-enforcing) problem unless agents can reduce monitoring costs 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 because agents can easily observe the states facing other agents, as the situation is opposed to indiosyncratic risks. In the case of highly correlated risks, however, agents cannot pool and cancel the shocks.

[2] Agents may also spatially diversify against risk through the migration of entire households or individual household members, as noted above. However, 'the effectiveness of spatial diversification against risk is limited in the case of large-scale natural disasters.

(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 agents to transition to nonagricultural 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 investing in human capital, which is portable and less affected by natural hazards. Educated workers can find work in urban labor markets, which may be distant from the affected areas. Porter (2008) shows that hurricane risks increase education, and the effect is largest among the landless. The present study shows empirical results in a similar vein.

Consistent with this, 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; Kimball 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 point is analogous to asking whether or not we can assume stationarity in risk structure and the agent's rational expectations in the risks. As these are empirical matters, it is challenging to identify the dynamics of the risk structure and the agent's learning behavior and information set (for example, see Gine, Townsend, and Vickery 2007; Dercon and Christiaensen 2007). In our present analysis, we do not address the above issues, but instead simply use the empirical frequency of natural hazards (flood and/or drought) from our data set, and assume rational expectations and risk structure stationarity. Similarly, we assume that risk preference is homogeneous.[3] Other things being equal, the importance of ex-ante actions should increase with the expected frequency of future natural hazards.

When deciding on ex-ante actions, households face a potential trade-off between income augmentation and income-risk mitigation. For example, a large family may help diversify risks, but it may also decrease per-child investments in schooling. However, investments in education seem to achieve the above two goals by increasing income and reducing risk, although returns to schooling investments largely depend on the development of nonagricultural labor markets (including the possibility of migration).

The relationship between ex-ante actions and ex-post responses is more delicate. Some ex-post responses, such as private transfers (for example, remittances and borrowing) are already incorporated in the decisionmaking on ex-ante actions. For example, educated laborers can migrate to urban sectors and subsequently remit money to their original household. Holding livestock enables agents to gain cash income by selling some of the animals and/or using them as collateral. For agents, a more exogenous element is the availability and accessibility of public assistance. Even if such ex-post assistance is available in the economy, its targeting efficiency is critical to determining the likelihood of aid receipt in affected areas and by agents therein (see, for example, Coady, Grosh, and Hoddinott 2004; Quisumbing 2005a; and Quisumbing 2005b). If such public actions are taken quickly enough, they can create substitution between private actions (as a function of ex-ante actions) and public responses. Owens, Hoddinott, and Kinsey (2003), in investigating the trade-off between ex-post assistance and the ex-ante interventions that increase capital accumulation, show that (1) intensive agricultural extension services and the accumulation of trained oxen mitigate the reduction of net crop income during a drought, and (2) private and public transfers are substitutable. In the present empirical analysis, we use actual data on public assistance to investigate the likelihood of these aids affecting the role of ex-ante actions in human capital formation.

[3] Wealthy households may be less risk-averse than poor households. However, given an imperfect credit market, wealthy households can self-insure against risks by utilizing their assets, and therefore may make more risky choices compared to poor households.

We investigate the impacts of flood and drought on child human capital formation using data from Bangladesh, Ethiopia, and Malawi. Our empirical analysis uses schooling investment, as measured by grade progression (change in grades), to examine this issue. As Ferreira and Schady (2008) summarize, aggregate shocks (for example, economic recession) can have two offsetting effects on schooling investments: a negative income effect, and a positive substitution (time allocation) effect.[4] Large income losses may encourage a shift of resources from investments in child schooling to consumption smoothing. However, if the opportunity cost for schooling investment (that is, child wage) decreases, this creates an incentive to keep children in school. In theory, therefore, the impacts of disaster on schooling investment could be ambiguous. In the present study, our empirical strategy controls for area-fixed effects, in order to account for labor-market effects that uniformly affect households in a given area.[5] Furthermore, since we are examining the roles of ex-ante and ex-post actions in altering the impacts of disaster on human capital formation, we do not think that the above-described issue is a problem.

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

Our empirical results, which are 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 probability of disaster. 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 in mitigating shocks on child schooling. In contrast, households in Malawi rely on private ex-ante actions, with the impact of public aid being largely insignificant. The Bangladesh example 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 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 disaster in both the short and long run.

[4] For example, Jacoby and Skoufias (1997) show the contrast between the two effects, using the International Crop Research Institute for Semi-Arid Tropics data from India.

[5] With village-fixed effects, we may underestimate the impacts of natural disasters, especially drought.

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. The importance of ex-ante actions depends on the likelihood of an agent receiving external assistance, such as public emergency relief. If the targeting of public assistance is perfect, then households do not have to undertake ex-ante actions (for example, asset reallocation) to mitigate the adverse impacts of disasters.

Here, we assume four sequential stages. In the first stage, agents decide on asset allocation based on the expectation of future disasters and possible public assistance that is conditional on actual disaster incidence. We assume that agents know the correct probability distribution of future disasters, even though they cannot predict actual future occurrences. 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, the agents act so as to mitigate disaster impacts based on the asset portfolio they pre-committed in the first stage.

Let $e \in \{0,z\}$ denote the impact of disaster on income, with probability $p(e = z)$ following the binomial distribution. If a disaster occurs, it reduces income by z. Conditional on the disaster incidence, agents can gain access to public assistance x with probability $p(x|e)$. For simplicity, we assume that $x \in \{0,x^*\}$ and $z \geq x^* > 0$. In other words, even if agents receive public assistance, this assistance does not perfectly recover the income loss.

In the first stage (period), agents allocate some portion of their asset K to means H (human capital), which 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 their original village, and are able to provide support to their original families in the case of a disaster. Allocating 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 is the schooling investment and p is the unit price of the investment). At the end of the second period, agents receive financial returns to schooling investment $R(h)$ and pay the costs of private transfers $r(H)t$. We assume that the human-capital return function $R(h)$ is strictly increasing and concave, while $r(H)$ 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 that there is a lower unit cost for private transfer.

Note that disasters can destroy production assets (such as land), thereby potentially lowering production levels in subsequent periods. The consequence of asset destruction differs from that of income fluctuation in the sense that asset destruction decreases the expected income in subsequent periods, potentially creating a poverty trap. In contrast, income fluctuations do not change the expected income. In the context of human capital accumulation, school destruction is regarded as particularly important. In our model, we do not capture the potential for a poverty trap, because we focus 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 a discount factor. We solve this through backward induction. In the second period, agents know the realization of (e,x). Based on this information, they decide (t,h). In the first period, when they decide asset allocation H, agents incorporate schooling investments and private transfers as functions of disaster incidence and public assistance. In the above formulation, we ignore the time allocation of children between work and school.

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

At this stage, it is meaningful to compare the following different scenarios: (1) disaster without public assistance when $e = z > 0$ and $x = 0$; (2) disaster mitigated through public assistance when $e = z > 0$ with $x = x^*$; and (3) no disaster when $e = 0$. We can rank income levels in the beginning of the second period; these levels depend on the probabilities of disaster occurrence and (conditional) public assistance. The income level is highest in case (3), followed by case (2) and case (1). In other words, the demand for private transfers is the largest in case (1), which also implies that the potential need for reserving human capital is the largest in this case.

The 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, when (e,x) are realized in stage two, a 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

$$\beta[-r + Eu'] \tfrac{\partial t(e,x,H)}{\partial H} = 1 + \beta E[u' + r'(H)t] .$$

With the Envelope condition, we obtain

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

In other words, the marginal gain (reduction in the cost of private transfer) on the left-hand side is equal to the expected marginal cost (the production loss in the two periods, part of which depends on Eu') on the right-hand side. Intuitively, we see that there is a trade-off between income and risk reduction, depending on the expected marginal utility and private transfer demand. By reducing H, the household increases its current income, but this increases the cost of private transfers (for example, borrowing), which may decrease the expected utility if a disaster occurs. Therefore, the optimal decision on H depends on the likelihood of disaster, access to public assistance, and risk aversion.[6]

Note that H does not have to be narrowly defined. For example, a large household size allows agents to diversify and pool risks, enabling them to ensure post-disaster private transfers to smooth consumption. Holding livestock is also known to increase production and enhance income smoothing (for example, by selling bullocks when income drops, even though this decreases the next-period production).

We summarize our results in the proposition below.

Proposition 1:

(i) An increase in disaster probability increases the share of assets that promote post-disaster private transfers (for example, human capital).[7]

(ii) Good targeting of public assistance conditional on a disaster reduces the incentive to hold transferable 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 we use to test the above hypotheses.

[6] If $p(e = z)$ is high and $p(x|z)$ is low (that is, disaster is likely to occur but public assistance is small), Eu' increases and H^* is larger ($-r'(H)$ (becomes larger). If $|r''(H)|$ 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 $p(x|z)$, will substitute for private transfers, thereby decreasing the proportion of total assets allocated to human capital.

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

3. ECONOMETRIC FRAMEWORK

Here, we describe the econometric framework to clarify testable hypotheses regarding ex-ante and ex-post actions. We use schooling progression (the number of years completed during the survey period) to investigate how disasters affect human capital formation in disaster-affected and -unaffected areas. As discussed more carefully in the next section, our analysis utilizes data from 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 (by decreasing the labor-market wage). The former decreases schooling investment in order to smooth consumption over time. In contrast, the latter increases schooling investment; a decrease in wage reduces the opportunity costs of schooling and increases the incentive to allocate more time to schooling. However, many disasters differ from economic recessions. For example, floods can destroy school facilities, thereby disrupting normal school activities. Severe droughts (such as those analyzed in the Ethiopia and Malawi examples in this paper) can substantially decrease crop production and threatening food security and human survival; this increases the real necessity for children to earn incomes for their families. Hence, in the case of severe disasters such as those examined herein, it is likely that the income effect dominates over the substitution effect.

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

We estimate the first-differenced equation for child schooling, which is the schooling progression equation where the dependent variable is the difference in grades between two points in time (this allows us to difference-out unobserved fixed components of the error terms). This is given as

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

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 the disaster/exposure indicator or its continuous measure (for example, depth of water), a_{jl0}^k is pre-disaster asset of type k, m_{ijl1} is is post-disaster public assistance, *area* is the area-fixed effect, age_i denotes a set of age dummies we use to control for age-specific trends, $gender_i$ is a gender indicator (male or female) that controls for gender-specific trends, and $\Delta\varepsilon_{ijl(t,t+1)}$ is the differenced error term. In the above notations, we use time 0 and 1 for pre-disasters 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 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 to the agent's portfolio, which may include human capital investment in children. Although agents can estimate disaster probability that affects their behavior, the actual occurrence of disaster is unpredictable in a given 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 $t + 1$), the parameters are the same for assets (if there is no disaster), but the disaster introduces changes in the parameters during the post-disaster period (this point is analogous to the way in which we estimate complementarity between new technology and schooling). Public assistance is provided only when the disaster affects the household. Finally,

$$E[\varepsilon_{ijl,t+1} D_{jl}] = 0,$$

implying that a disaster is observed in $t + 1$ and actions taken in $t + 1$ are conditioned on this information.

Including area-fixed effects in the above specification may cause us to underestimate the impacts of the 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, changes in school availability and local wage (due to increased labor demand in the local labor market) affect changes in human capital investments. Furthermore, the actual costs of flood and drought are not evenly distributed in an area.

Note that the labor market (substitution) effect occurs over a relatively short time frame. During a natural disaster, the wage decreases due to the reduction of labor demand. However, it is also expected that the wage will eventually return to a normal level after the disaster. Therefore, if our panel data are collected over 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 using

$$a_{jl0}^{k} = \alpha' + \gamma_1^k \Pr[D_l] + \gamma_2^k \Pr[D_l] K_{jl} + area_l + \xi_{jl}^k, \tag{2}$$

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 an effective strategy for mitigating potential disaster impacts, then agents should adjust their asset portfolios prior to the actual occurrence of disasters.

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

Comparison of equations (1) and (2) yields two integrated hypotheses on ex-ante actions and disaster impacts: first, if γ_1 and/or γ_2 are positive for k in equation (2), we should expect positive β_2^k in equation (1) (that is, if some assets play a role in mitigating the impacts of disasters, agents will allocate more to those assets before the actual disaster occurs); and second, a higher future probability of disaster will increase the incentive to do so.

4. DATA

This section describes the data we use to test our hypotheses. The International Food Policy Research Institute (IFPRI) and local collaborators conducted panel household surveys in Bangladesh, Ethiopia, and Malawi over periods that include the occurrence of major natural hazards such as floods and droughts.

In Bangladesh, the initial survey round was fielded in late 1998, immediately after the onset of the 1998 flood. This first survey was followed by two subsequent rounds lasting until the middle of 1999 (del Ninno et al. 2001). In 2004, a follow-up survey was conducted in April and May, coinciding with the season of the prior 1999 survey round (Quisumbing 2005a, 2005b).

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

However, although we adopt the unique approach described in the previous sections, the exact timing of the natural hazards with respect to the surveys is critical to the interpretation of our empirical results. In Bangladesh, the 1998 flood was immediately followed by the initial survey round. Although the impact of the disaster was gradually realized after the flood, the initial round captured some short-term impacts of flood exposure. The next two rounds, which were conducted within a year of the flood, captured dynamic changes in the short-term 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 fairly robust to idiosyncratic shocks, particularly the health and illness shocks that typically accompany floods. In the case of pre-flood assets, we address this potential issue by constructing the data to reflect the pre-flood situation.

In 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 surveys. Given that the actual drought impacts on income would be expected to occur in 2001-2002, we may not capture the complete recovery process of human capital investment in the two-year period after the income impact (that is, from 2002-2004).

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

Differences in the time structure of the hazards and the initial and follow-up rounds affect our interpretation of our empirical results. In the case of Bangladesh, we may underestimate the initial impacts on child human capital, since the first round was conducted immediately after the flood, and therefore contains some flood impacts. However, these data are ideal for capturing the dynamics of human capital recovery, which begins immediately after the flood. Furthermore, using the three rounds conducted over the first year post-flood, we can examine short-term changes in school attendance after the flood. Thus, the Bangladesh setting provides both long-term and short-term dimensions. In the cases of Ethiopia and Malawi, the interval between the droughts and the follow-up surveys was rather short, making this data set suitable for investigating the short-run impacts on human capital investment.

The 2004 surveys conducted in the three countries contain retrospective information on past disasters, allowing us to examine the probability of disaster. This probability is defined as the empirical average of incidences in the period from the initial to final survey rounds. Therefore, this metric reflects the probability of future disaster from the perspective of the initial round. Our preliminary work shows 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 of the households in our sample.[8] The disaster distributions for the three countries are shown in Table 1.[9]

Table 1. Estimates of future disaster probabilities

	Number of incidences			
Country/disaster	None	One	Two	Three
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)

Notes: 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 and final survey rounds.

In Bangladesh, we also use a flood exposure index that measures the severity of the flood (del Ninno et al. 2001). In this measure, households are classified into flood exposure categories as follows: 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 of the households in the sample, it is appropriate to use this exposure measure rather than disaster frequency. In addition, the Bangladesh data provide some details on flood impacts, such as the depth of water, the number of days covered by water, repair costs, and the number of days household members were evacuated from their homes. The former two measures are objective, while the latter two could be endogenous. Repair costs are actual expenditures related to household decisions and asset holdings. The number of days evacuated is correlated with number of days submerged, but it also measures the length of time household members were able to stay safely away from the disaster, and is therefore higher among those who had sufficient resources to stay away from the flood (for example, by evacuating to other regions). Thus, while these measures principally capture disaster impacts, some care should be taken in their interpretation.

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

[9] Alternatively, we can use historical meteorological data to construct some measures of too-little and too-much rain. In this case, however, we must define drought and flood using rainfall thresholds. Our method of using actual drought (or flood) incidences between the initial and final rounds has the advantage that households did not know the future disaster incidences at the time of the initial round. Both actual incidences and the disaster probability are contained within the agent's information set. Although historical data reduce the noise in our frequency estimates, our estimates are likely to have relatively large measurement errors.

5. EMPIRICAL RESULTS

In this section, we summarize our empirical results on (1) disaster impacts on schooling progression, (2) ex-ante actions and ex-post public responses, and (3) pre-disaster asset allocation (ex-ante actions) and disaster risks. In the following analyses, we use the sample of children who were aged 6 to 12 in the initial rounds.

Disaster Impacts and Pre-Disaster Assets

Bangladesh

For Bangladesh, we have panel data collected during three survey rounds conducted in 1998-1999, beginning immediately after the 1998 flood. The data set contains information on both the number of school days and number of days the child actually attended school. Therefore we can construct the proportion of days attended in rounds 1 to 3, and investigate changes in this proportion over the course of one year. Age and female dummies are included in all specifications. We use union-fixed effects[10] and age and female dummies to control for trend variations.

Table 2 shows our 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.[11] Columns 1 through 4 (Model 1) show that repair cost significantly reduces school attendance, but the effects of the other measures are insignificant. In Columns 5 through 8 (Model 2), we include interaction terms representing 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 the flood. In estimations with water depth, the number of days covered by water, and repair cost, we find that holding land helps to mitigate the negative impacts of the flood. In the specification using repair cost, we see that household education significantly mitigates flood impacts. The direct effect on school attendance is significantly negative only in the case of repair cost. Overall, this impact seems smaller among girls, and the effect is insignificant in many specifications.

In Table 3a, we summarize our empirical results on school progression; this is measured by change in grades completed from 1998 to 2004, thereby capturing the long-term impacts of the 1998 flood. We use four measures of the 1998 flood to separately assess the impacts. Our results show that the number of days evacuated from home has a significantly negative effect on change in grades. This is in contrast to a previous finding on the transition from preschool to school stages (Yamauchi, Yohannes, and Quisumbing 2009).

Columns 1 through 4 in Table 3b include interactions with total asset value (Model 1). Consistent with the notion that households with more resources are better able to weather shocks, we see that asset holding helps to mitigate the negative impact of the 1998 flood on school progression (Columns 1 and 2—water depth and the number of days water-covered), while the number of days evacuated from home significantly decreases school progression (Column 4).

In Columns 5 through 8 of Table 3b (Model 2), 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. We find that, with the exception of the number of days evacuated, the studied flood measures all have significant and negative effects on school progression. In these cases, maximum education significantly mitigates the negative impacts. In two cases, we also find significant effects of household size and livestock. Therefore, although the flood negatively impacts schooling investments in

[10] Union is an administrative unit directly above village.

[11] Repair cost and the number of days evacuated from home are potentially endogenous, as they are correlated with schooling shocks and asset holding. In our preliminary analysis, we find that instrumenting these measures by water depth and the number of days covered by water did not significantly change the results. This is because we use the first-differenced specification, which wipes out the time-invariant effect of household assets.

the subsequent six years, households with more asset holdings are better able to mitigate the flood impacts overall.

Table 2. Short-run effects of Bangladesh flood on school attendance
Dependent: Change in proportion of days attended from round 1 to 3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model 1				Model 2			
Flood variable	Depth	Days	Repair cost	Out of home	Depth	Days	Repair cost	Out of home
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 × maximum education					-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 fixed effects	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

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

Table 3a. Dynamic effects of Bangladesh flood on schooling progression
Dependent: Change in grades from 1998 to 2004

Flood variable	Depth	Days	Repair cost	Out of home
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 fixed effects	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

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

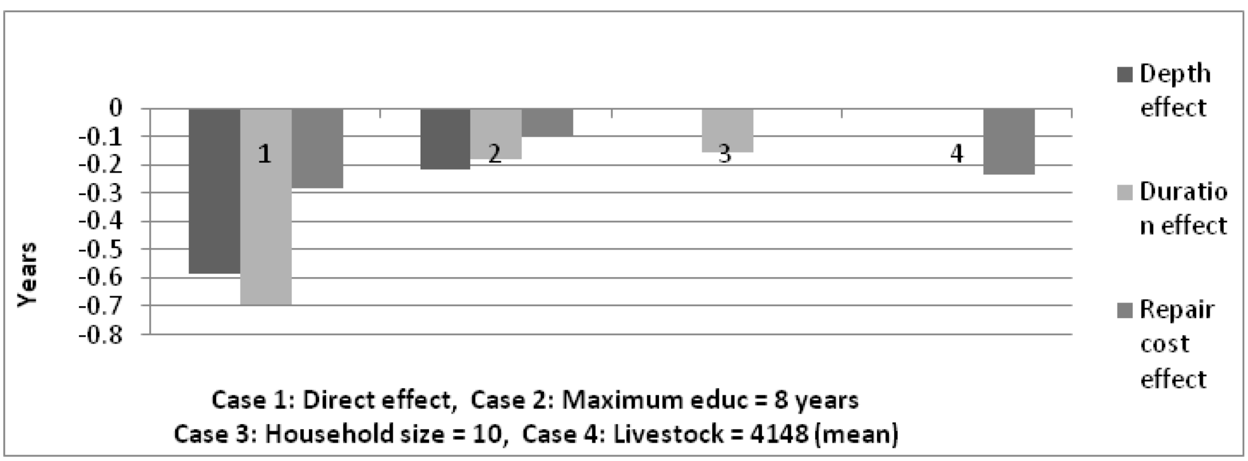
Figure 1 shows flood impacts on schooling progression (based on the estimates in Columns 5 to 7). We use the sample mean of water depth, the number of days covered by water, and repair cost to quantify the impacts. Case 1 shows direct effects (without assets). Although the estimated repair cost effect is relatively small, the water-depth and days-water-covered effects reduce schooling progression by nearly 0.6-0.7 year. In Case 2, where we assume that someone in the household has attained a maximum of eight years of education, our estimates suggest that the flood impact is substantially reduced. Case 3 supposes a household size of 10 members to assess changes in the effect of the number of days covered by water. This effect is almost equivalent to the education effect seen in Case 2. Case 4 shows the effect of livestock holding on the effect of repair cost. Using the mean value of livestock, we confirm that the mitigation effect is nearly the same as that found in Cases 2 and 3. These exercises demonstrate the effectiveness of human capital accumulation (in both quality and quantity) and livestock holding for mitigating flood impacts on child schooling.

Table 3b. Dynamic effects of Bangladesh flood on schooling progression
Dependent: Change in grade from 1998 to 2004

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model 1				Model 2			
Flood variable	Depth	Days	Repair cost	Out of home	Depth	Days	Repair cost	Out of home
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 × maximum education					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 fixed effects	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

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

Figure 1. Flood impacts in Bangladesh



Next, we use the flood exposure measure constructed by the IFPRI team, wherein households are categorized as not exposed, or moderately, severely, and very-severely exposed (del Ninno et al. 2001). The results are summarized in Table 4. Column 1 includes only the flood exposure index, for which all of the tested parameters are insignificant. Columns 2 and 3 include interactions with household assets. Consistent with the above-described findings, we see that total asset value, maximum education, and household size (in the severely exposed case) significantly mitigate the adverse impacts of the 1998 flood.

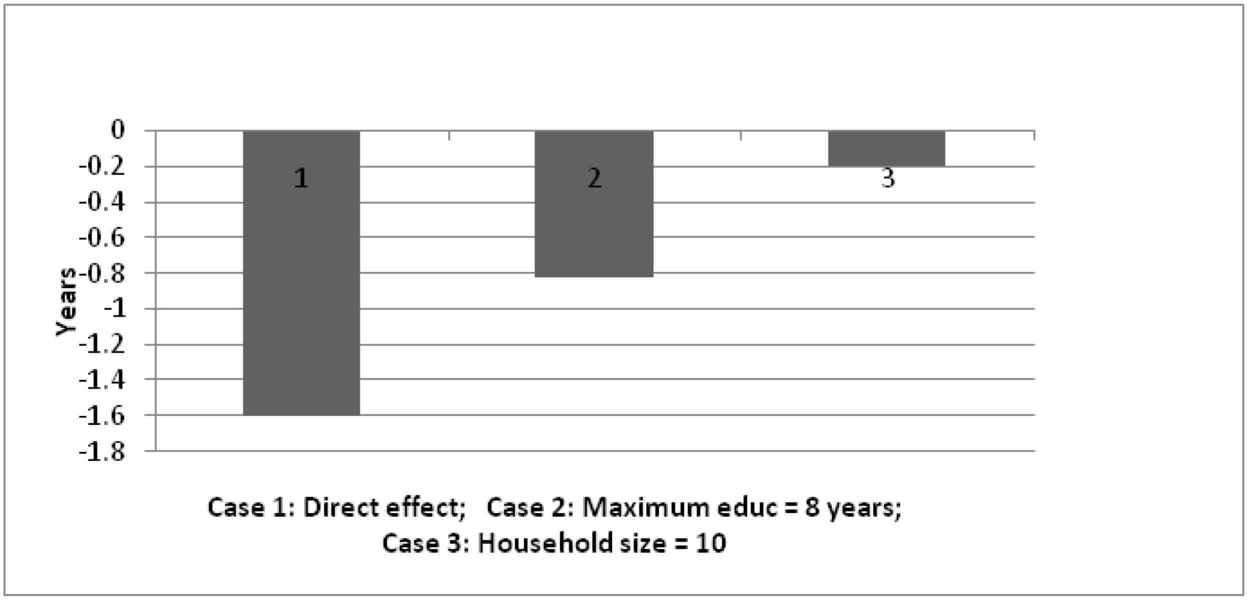
Table 4. Dynamic effects of Bangladeshi flood on schooling progression: Flood exposure measure
Dependent: Change in grade from 1998 to 2004

	(1)	(2)	(3)
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 × maximum education			0.1301
			(2.820)
Flood index 2 × maximum education			0.1321
			(3.570)
Flood index 3 × maximum education			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 fixed effects	Yes	Yes	Yes
Number of observations	492	492	468
Number of villages	21	21	21
R-squared (within)	0.0513	0.0596	0.1269

Notes: Numbers in parentheses are absolute t-values obtained using robust standard errors with village clusters. Age and female dummies are included in all specifications. Flood indexes 1, 2, and 3 stand for moderate exposure, severe exposure, and very severe exposure, respectively.

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 schooling reduction of 1.5 years. Our simulation shows that a maximum education of eight years and a household size of 10 members substantially decrease the negative impacts of the flood.

Figure 2. Impacts of very severe flood exposure in Bangladesh 2



Ethiopia

Table 5 summarizes our estimation results for grade progression in Ethiopia, where we use 1997 as the initial round and investigate the impact of the 2001 drought on child schooling.[12,13] In all specifications, we include age and male dummies, and use region-fixed effects and age and male dummies to control for trends.

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

In Column 3, as discussed above for the Bangladesh data, we use disaggregated measures of household assets, none of which are found to be significant. The Ethiopia survey includes information on distance to the nearest town, which we can use to test the market and institutional effects on the effectiveness of ex-ante actions.[14] Interestingly, Column 4 shows that the effects of maximum education and household size (both capturing human capital) become significantly positive when the village is distant from the nearest town. This is also observed for livestock, although not to a statistically significant degree. These results suggest that human capital may play a more important role in mitigating disaster impacts in isolated villages.

Figure 3 shows simulation results based on the estimates given in Column 4. Similar to the Bangladesh case (Figure 2), we find that a large family is more advantageous than higher education for

[12] 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 2009).

[13] Due to a problem in the between-round matching of children from peasant association no. 7, we excluded this peasant association from the analysis. Therefore, a total of 14 peasant associations are examined.

[14] Note, however, that we include only 14 peasant associations in the analysis.

disaster mitigation in Ethiopia. This could be due to the fact that the schooling level is generally very low in the rural areas of this country, meaning that diversifying risk by having a large family may be more effective in mitigating the effect of droughts.

Table 5. Dynamic effects of Ethiopian drought on schooling progression
Dependent: Change in grade from 1998 to 2004

	(1)	(2)	(3)	(4)
Drought 2001	-0.1903	-0.3731	-0.3060	-0.4497
	(0.950)	(1.860)	(1.200)	(2.240)
× total asset		0.0007		
		(4.290)		
× maximum education			0.0157	-0.1462
			(0.390)	(2.160)
× maximum education × distance				0.0192
				(2.490)
× land			0.0500	0.3836
			(0.250)	(1.890)
× land × distance				-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 fixed effects	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

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

Figure 3. Drought impact in Ethiopia

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 are used to control for trends.

Table 6 shows our results for school progression in Malawi. Column 1 only includes the 2001 drought indicator and its interaction with the male indicator, both of which are found to be insignificant. In Column 2, the total asset value is interacted with the drought indicator, and we see that household assets accumulated prior to the 2001 drought mitigate the negative impact of the drought, although the direct effect of the drought is not statistically significant (with a negative coefficient).

Table 6. Dynamic effects of Malawian drought on schooling progression
Dependent: Change in grade from 2000 to 2004

	(1)	(2)	(3)	(4)
Drought 2001	-0.0172	-0.1328	-1.0057	-1.1000
	(0.130)	(0.980)	(4.440)	(7.500)
× total asset		0.00002		
		(3.460)		
× maximum education			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)
× maximum education				-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 fixed effects	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

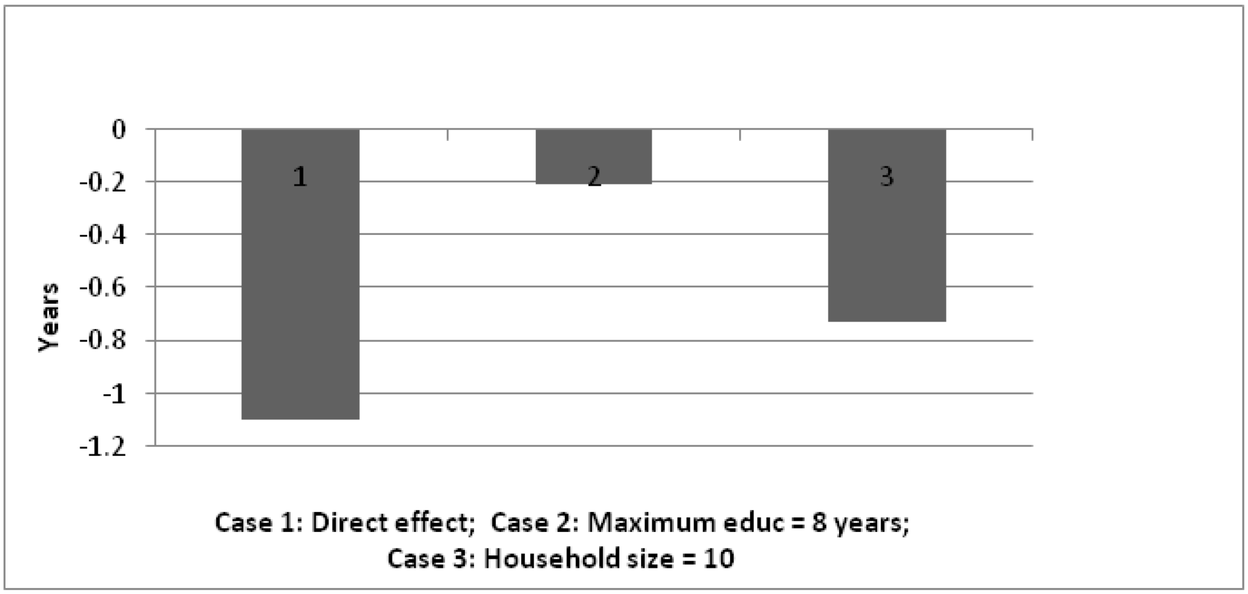
Notes: Numbers in parentheses are absolute t-values obtained using robust standard errors with region clusters. Age and female dummies are included in all specifications.

Column 3 includes the interactions with maximum education in the household, land size, household size, and livestock value. We find that the 2001 drought significantly decreases school progression (by nearly a year, which is more than twice the effect found in Ethiopia). Furthermore, we see that maximum education within the household significantly mitigates the negative impact of the drought. This finding is similar to those in Ethiopia and Bangladesh. In fact, junior high school completion (nine years of schooling) almost entirely offsets the negative effect of the drought in this data set.

In Column 4, we include the 2001 flood indicator to examine its potential confounding effects, but the previous results remain robust. Furthermore, household size significantly mitigates 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. Finally, the 2001 flood had a weakly negative impact on schooling progression.

Figure 4 quantifies the impacts of the drought on schooling progression (based on the estimates in Column 3). Case 1 shows that the direct effect (without assets) is a reduction of about one year. Cases 2 and 3 suggest that education is more effective than a large family size for mitigating disaster effects in Malawi. This is contrary to our findings in Ethiopia, but consistent with those from Bangladesh.

Figure 4. Drought impacts in Malawi



Ex-Post Responses

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

Table 7 reports our estimation results for Bangladesh, where we highlight three types of assistance: gratuitous relief (GR), vulnerable group feeding (VGF), and assistance from nongovernment organizations (NGOs). Our preliminary analysis shows that these three sources have large shares in the public assistance (see, also, Quisumbing 2005a). Columns 1 through 4 (Model 1) use disaggregated measures of flood exposure interacted with the total amounts for each type of public assistance given out in 1998-1999, and the household asset value. We find that VGF aid is the most effective in mitigating flood impacts (in three out of four cases), and the total asset value also significantly mitigates the impacts (in two cases). In Column 4, we further see that GR and NGO assistance mitigates flood impact.

Columns 5 through 8 (Model 2) use a more disaggregated specification of household assets. We find that VGF aid significantly mitigates flood impact (in three out of four cases). Among the asset measures, maximum education and larger household size seem to effectively mitigate the disaster effects. However, land size and livestock appear to play only limited disaster-mitigation 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; ex-post public actions and ex-ante private actions coexist, and both play active roles in mitigating the flood impacts on schooling investments.

Table 7. Dynamic effects of Bangladesh flood on schooling progression: Pre-flood assets and ex-post public assistance

Dependent: Change in grade from 1998 to 2004

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Model 1				Model 2			
Flood variable	Depth	Days	Repair cost	Out of home	Depth	Days	Repair cost	Out of home
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 × VGF	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	4.43E-08	-5.64E-10	-2.33E-07				
	(3.550)	(1.970)	(1.100)	(1.510)				
Flood × maximum education					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					0.0155	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 fixed effects	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

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

Interestingly, the flood impact is smaller among girls than boys. There seems to be some qualitative difference between genders in this regard, potentially because compared to girls, more boys may need to work outside the home to earn incomes during and after the flood disaster.

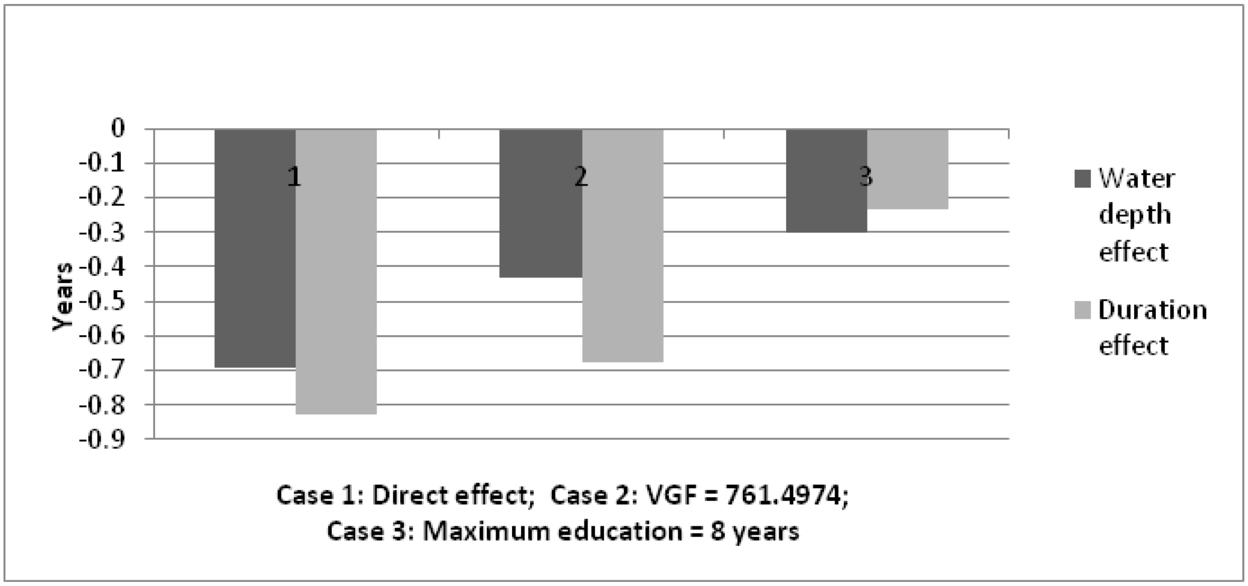
In Figure 5, we simulate the flood impacts by assuming the sample mean of VGF receipt (in 1998-1999) and a maximum education of eight years. The simulations use the estimates in Columns 5 and 6. We find that public assistance only marginally mitigates the flood impact (Case 2), but human capital (measured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

Table 8 shows our results using the data from Ethiopia and Malawi. Columns 1 through 3 summarize our 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) decreases school progression in the absence of drought, but increases school progression when drought hits the area.[15] However, this result might have been caused by endogenous allocation of such a program to, for example, drought-prone areas (or households). We test this possibility in Table 9. Alternatively,

[15] In this analysis, we do not control for endogeneity of program allocation except by differencing the 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.

adult members may tend to work in the programs, meaning that the demand for child labor in the household's own production or domestic work may increase.

Figure 5. Public assistance and ex-ante actions in Bangladesh



Interestingly, we do not find any significant effect of household assets once we include the public assistance variables. Therefore, in Ethiopia, we conclude that public assistance is more important than private ex-ante actions for disaster mitigation.

The results for Malawi are summarized in Columns 4 through 6 in Table 8. In contrast to the Ethiopian case, our results indicate that receipt of food aid plays only a small role in mitigating disaster impacts in Malawi. Instead, total asset value and maximum education significantly mitigate drought impacts in this country.

Table 8. Dynamic effects of drought on schooling progression in Ethiopia and Malawi: Pre-flood assets and ex-post public assistance

Dependent: Change in grade

	(1)	(2)	(3)	(4)	(5)	(6)
		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 × maximum education			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 fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
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

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

Next we check the robustness of our results by restricting our sample to areas that were very severely exposed to the 1998 flood in Bangladesh, or high-risk disaster areas in Ethiopia and Malawi (Table 9). High-risk areas are defined as areas having estimated probabilities of drought > 0.4 and 0.5, respectively, in Ethiopia and Malawi (see Table 1). Our results, which are summarized in Columns 1 to 4, support the above-described findings, and also prove that the effects of public assistance are greater than those shown in Table 8, indicating that the role of public assistance is larger in areas severely exposed to the flood.

Columns 5 and 6 show our results for 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 to be larger than the direct negative effect, implying that there seems to be bias from the endogenous allocation of public work programs. However, this does not rule out a substitution effect among children.

Interestingly, we obtain similar results for Malawi. The direct effect of food aid is negative, while food aid mitigates the adverse impacts of drought. However, the relatively small sample size in this data set prevents us from reaching a clear conclusion in this case.

Table 9. Robustness: High-risk and severely exposed areas
Dependent: Change in grade

	(1)	(2)	(3)	(4)	(5)	(6)
	Bangladeshi flood				Ethiopian drought	Malawian drought
Disaster variable	Depth	Days	Repair	Out of home		
Sample	Very 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 × VGF	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 × maximum education	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 × household 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 fixed effects	Yes	Yes	Yes	Yes		
Region fixed effects					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

Notes: Numbers in parentheses are absolute t-values obtained using robust standard errors with union clusters. Age and female (or male) dummies are included in all specification. GR, VGF, and NGO are the sum of transfers received from these sources in 1998-1999. The severely exposed sample is used in the Bangladeshi analysis. In the Ethiopian and Malawian data sets, the high-risk samples are defined as areas having drought probabilities > 0.40 and 0.50, respectively (see Table 1).

Risks and Asset Portfolio

In this section, we examine how natural hazard risks affect a 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, and the likelihood of receiving public assistance. Here, we compute disaster risk using actual realizations of disasters that took place between the initial and final survey rounds. In the case of Bangladesh, we compute the probability of floods during 1998–2004. For Ethiopia and Malawi, we compute the risk for drought during 1999–2004 and 2000–2004, respectively. The 1998 flood in Bangladesh was a single severe incident 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 is 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 the 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. In contrast, transactions in land markets are relatively uncommon, owing to the imperfection (or lack of) land markets in the studied 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 (as discussed 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.

Table 10 summarizes our estimation results from the three countries. The probability of drought or flood is estimated from the incidences during the period from the initial to final survey rounds, and we take the average of the estimates within a given 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 holdings (here proxied by land size). The future disaster risk estimates are interacted with landholding.

Columns 1 through 4 show our results for the Bangladesh data set. 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. We see a threshold probability above which the flood probability increases the 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 a threshold probability (0.189 in Column 7 and 0.159 in Column 8).

In Malawi, we see evidence for threshold probabilities above which the probability of drought significantly increases the maximum years of education (thresholds of 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, especially since the threshold probabilities are relatively small. The environment of no disaster risk seems to encourage investments in human capital and livestock. However, as the disaster risk increases, precautionary motives to invest in assets with the expectation of future disaster will offset the 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 across a reasonable range of future disaster probabilities.

Interestingly, the above findings are consistent with our earlier findings on the risk-mitigating effects of household education. In Bangladesh (Tables 3b and 4) and Malawi (Table 6), we see that maximum education significantly mitigates the negative impact of flood and drought, respectively, on schooling investment. For Ethiopia (Table 5) we do not find a significant effect for 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.

Table 10. Asset portfolio prior to disaster

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Bangladesh				Ethiopia				Malawi			
	Maximum education	Maximum education	Cattle	Cattle	Maximum education	Maximum education	Cattle	Cattle	Maximum education	Maximum education	Cattle	Cattle
Disaster probability	28.54		20,650.8		1.183		-17,157.4		-19.10		100,788.7	
	(1.76)		(0.58)		(0.07)		(3.38)		(3.28)		(1.10)	
Squared probability	-172.55		-26,499.9		-11.20		45,430.8		40.08		-183,276.6	
	(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	1,026.9	1,361.1	-0.079	205,023	8,953.3	7,492.4
	(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	-7,060.6	-12,979.2	1.781	-1.323	-70,400.7	-55,855.5
	(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	3,061.12	2,408.45	-7.730	-17.39	25,910.3	40,762.7	-1.471	5.382	139,949.3	112,502
	(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	1,361	1,361	1,376	1,376	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

Notes: Numbers in parentheses are t-values obtained 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, the regions are redefined: regions 7, 8, and 9 in SNPPR are grouped as one.

6. CONCLUSION

This paper uses panel data from Bangladesh, Ethiopia, and Malawi to examine the impacts of natural disasters on schooling investments, emphasizing the roles of ex-ante actions and ex-post responses. We find that the importance of ex-ante actions depends on the disaster risks and the likelihood of public assistance.

Our empirical results show that there is an interesting heterogeneity in asset portfolios as well as in ex-ante and ex-post responses. In Bangladesh and Malawi, a higher future disaster probability increases the likelihood of an agent holding more human capital relative to land. However, in Ethiopia, investments in human capital are not systematically related to 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 observe an interesting nonlinearity, namely that the effect of future disaster risk on asset holding becomes positive when the disaster probability goes above a (relatively small) threshold. There seem to be two offsetting effects of disaster risk: future risk discourages investment by making returns uncertain, but it encourages investments toward mitigating disaster impacts. In disaster-prone areas, the latter effect offsets the former.

Our results confirm that both ex-ante private and ex-post public responses, working mostly through emergency assistance programs in the latter case, help mitigate disaster impacts. However, 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 in mitigating the shocks on child schooling. In contrast, Malawi relies on private ex-ante actions, while the utility of public assistance is, by and large, insignificant. The Bangladesh example shows active roles for both ex-ante and ex-post actions. Interestingly, these observations are consistent with our findings on the relationship between ex-ante actions and disaster risk.

These results 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 the ineffectiveness of this country's public assistance scheme? Is the importance of ex-post public assistance in Ethiopia correlated with better program effectiveness (in terms of emergency assistance targeting) and/or the greater difficulties faced by poor Ethiopian households in undertaking ex-ante risk-mitigating actions? Finally, in Bangladesh, do different types of households benefit differently from ex-post and ex-ante actions, with wealthier households better able to undertake ex-ante actions, while poorer households benefit more from well-targeted emergency assistance?

All in all, our results show that among the studied ex-ante actions, the accumulation of human capital within the household prior to disasters helps mitigate the negative effects of disasters in both the short and long runs. Our results suggest that disaster-prone countries should strengthen their efforts to increase investment in human capital in order to mitigate disaster impacts (that is, income variance), rather than relying too heavily on emergency assistance once disaster strikes.

REFERENCES

Binswanger, H. P., and M. R. Rosenzweig. 1986. Behavioural and material determinants of production relations in agriculture. *Journal of Development Studies* 22 (3): 503–539.

Coady, D., M. E. Grosh, and J. Hoddinott. 2004. *Targeting of transfers in developing countries: Review of lessons and experience*. Washington, D.C.: World Bank.

Coate, S., and M. Ravallion. 1993. Reciprocity without commitment: Characterization and performance of informal insurance arrangements. *Journal of Development Economics* 40 (1): 1–24.

Crespo Cuaresma, J., J. Hlouskova, and M. Obersteiner. 2008. Natural disasters as creative destruction? Evidence from developing countries. *Economic Inquiry* 46 (2): 214–226.

Deaton, A. 1991. Saving and liquidity constraints. *Econometrica* 59 (5): 1221–1248.

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.

Dercon, S. 2002. Income risk, coping strategies and safety nets. *World Bank Research Observer* 17 (2): 141-166.

Dercon, S., and L. Christiaensen. 2007. *Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia*. Policy Research Working Paper 4257. Washington, D.C.: World Bank.

Ferreira, F., and N. Schady. 2008. Aggregate economic shocks, child schooling and child health. Manuscript. World Bank, Washington. D.C.

Gine, X., R. Townsend, and J. Vickery. 2007. Rational expectations: Evidence from planting decisions in semi-arid India. Manuscript. World Bank, Washington, D.C.

Jacoby, H. G., and E. Skoufias. 1997. Risk, financial markets, and human capital in a developing country. *Review of Economic Studies* 64 (3): 311–335.

Kimball, M. S. 1990. Precautionary saving in the small and in the large. *Econometrica* 58 (1): 53–73.

Ligon, E. 1998. Risk sharing and information in village economies. *Review of Economic Studies* 65 (4): 847-864.

Ligon, E., J. P. Thomas, and T. Worrall. 1997. *Informal insurance arrangements in village economies*. CUDARE Working Paper 825. Berkeley, Calif.: Department of Agricultural and Resource Economics, University of California.

Morduch, J. 1999. Between the state and the market: Can informal insurance patch the safety net? *World Bank Research Observer* 14 (2): 187–207.

Noy, I. 2008. The macroeconomic consequences of disasters. *Journal of Development Economics* 88 (2): 221–231.

Owens, T., J. Hoddinott, and B. Kinsey. 2003. Ex-ante actions and ex-post public responses to drought shocks: Evidence and simulations from Zimbabwe. *World Development* 31 (7): 1239–1255.

Porter, C. C. 2008. Gone with the wind?: Hurricane risk, fertility, and education. Manuscript. University of Washington, Seattle, Wash.

Quisumbing, A. 2005a. Targeting and fairness of emergency food assistance: The 1998 floods in Bangladesh. Manuscript. International Food Policy Research Institute, Washington, D.C.

________. 2005b. A drop in the bucket? The impact of food assistance after the 1998 floods in Bangladesh. Manuscript. International Food Policy Research Institute, Washington, D.C.

Rosenzweig, M. R. 1988. Risk, implicit contracts and the family in rural areas of low-income countries. *Economic Journal* 98 (393): 1148-1170.

Rosenzweig, M. R., and O. Stark. 1989. Consumption smoothing, migration, and marriage: Evidence from rural India. *Journal of Political Economy* 97 (4): 905-926.

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 (2): 223-244.

Skidmore, M., and H. Toya. 2002. Do natural disasters promote long-run growth? *Economic Inquiry* 40 (4): 664–687.

Skoufias, E. 2003. Economic crises and natural disasters: Coping strategies and policy implications. *World Development* 31 (7): 1087-1102.

Tol, R., and F. Leek. 1999. Economic analysis of natural disasters. In *Climate change and risk,* ed. T. E. Downing, A. J. Olsthoorn, and R. S. T. Tol. London: Routledge.

Townsend, M. 1994. Risk and insurance in village India. *Econometrica* 62 (3): 539-591.

Yamauchi, F., Y. Yohannes, and A. Quisumbing. 2009. *Natural disasters, self-insurance, and human capital investment: Evidence from Bangladesh, Ethiopia, and Malawi*. IFPRI Discussion Paper. Washington, D.C.: International Food Policy Research Institute. Forthcoming.

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2033 K Street, NW
Washington, DC 20006-1002 USA
Tel.: +1-202-862-5600
Fax: +1-202-467-4439
Email: ifpri@cgiar.org

IFPRI ADDIS ABABA

P. O. Box 5689
Addis Ababa, Ethiopia
Tel.: +251 11 6463215
Fax: +251 11 6462927
Email: ifpri-addisababa@cgiar.org

IFPRI NEW DELHI

CG Block, NASC Complex, PUSA
New Delhi 110-012 India
Tel.: 91 11 2584-6565
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