Long-term Impacts of the Series of 1970-74 Disasters in Bangladesh*

Shaikh M.S.U. Eskander [a,♣] Edward B. Barbier [b]

[a] Grantham Research Institute on Climate Change and the Environment, London School of Economics, Houghton Street, London WC2A 2AE, UK.

[b] Department of Economics and Finance, University of Wyoming, 1000 E. University Ave, Laramie, WY 82071, USA.

---

*We use childhood exposure to disasters in Bangladesh as natural experiments inducing variations in adulthood outcomes. Based on an overlapping generation model, we hypothesize that children from households with greater disaster-exposure will have lower adulthood health, schooling and consumption outcomes. A unique dataset from Bangladesh identifies that children from the 1970 cyclone and the 1974 famine regions experience significant schooling and consumption adversities, especially among the rural, female-headed and less-educated households. Public programs benefiting the females and the poor, alongside the development of healthcare and schooling infrastructure, can be useful protective measures against the long-term harms of a disaster. (*JEL: *Q54, I31)*

Keywords: Bangladesh, Consumption, Disasters, Health, Schooling.

* We thank Suman Banerjee, Ajay Bhabe, Ben Gilbert, Thorsten Janus, Felix Naschold, Ben Rashford, Sherrill Shaffer and participants at the 84th Southern Economic Association Conference for their useful feedback and suggestions.

♣ Corresponding author. Tel: +44 7856003276.

E-mail addresses: S.M.Eskander@lse.ac.uk (Shaikh M.S.U. Eskander), *ebarbier@uwyo.edu* (Edward B. Barbier).

Long-term Impacts of the Series of 1970-74 Disasters in Bangladesh

Disasters, such as illness or mortality of household members, crop or other income loss due to natural catastrophes, and civil and political conflicts, have both the short- and long-term harmful impacts on the affected households (Maccini and Yang 2009). Households in developing countries are the most frequent victims of such disasters. From 1970 to 2008, over 95 percent of deaths from natural disasters occurred in developing countries; from 2001 to 2006, the losses from natural disasters in low-income countries amounted to 0.3 percent of GDP (IPCC 2012).[1] Widespread poverty often leaves especially the agricultural households with fewer means to invest in protection to reduce risks of disasters, and in insurance to reduce possible losses from such disasters.[2] Consequently, coping strategies, such as cutting back on the consumption of food and nutrients or selling productive assets, adversely affect the human capital development and income-earning potential of children (Duflo 2003; Jensen 2000).

Given these linkages, the existing literature emphasizes the importance of measuring the long-term impacts of a disaster on the children born and raised during such an event, including potentially lower health, schooling and consumption outcomes when they become adults (e.g., Almond, Edlund, and Palme 2009; Banerjee et al. 2010; Maccini and Yang 2009). However, existing studies have not been able to establish an unambiguous relationship for such impacts; rather, results vary, in both direction and magnitude, over disasters and countries. Moreover, most studies focus on developed countries (e.g., Almond, Edlund, and Palme 2009; Banerjee et al. 2010; Cutler, Miller, and Norton 2007; Van Den Berg, Lindeboom, and Portrait 2006), while there are few studies of poor countries such as Bangladesh.[3] Against these backdrops, we investigate the long-term health, schooling and consumption impacts of three of the deadliest

[1] Low-income countries loss less in percentage of GDP than medium-income countries (1 percent) but more than higher-income countries (0.1 percent). These loss figures vary from 1 percent to 8 percent for small exposed countries during 1970-2010. However, such loss values are lower-bound estimates due to difficulties in monetizing many subjective losses (IPCC 2012: pp. 7).

2 In 2012, 47 percent of the population of low-income countries still lived on less than US$1.90 (2011 PPP) a day per capita, and 74 percent lived on less than US$3.10 (2011 PPP) a day per capita (World Bank 2015). Low-income countries are those in which 2014 GNI per capita was $1,045 or less.

3 Literature on developing countries mostly focuses on the impacts of conflicts and civil wars (e.g., Bundervoet, Verwimp, and Akresh 2009; Lee 2014; Verwimp and Van Bavel 2013).

natural and political disasters that took place in Bangladesh from 1970 to 1974: the 1970 cyclone, the 1971 war and the 1974 famine.

Medical evidence indicates that poor environmental conditions during the prenatal and neonatal periods have adverse consequences on an individual's life expectancy, height, cognitive ability, and productivity (Barker 1990; Barker 1995; Barker 1999). This "fetal origin" hypothesis, which is extensively investigated in epidemiology and public health literature, receives considerable empirical attention in economics as well (Almond and Currie, 2011).[4] Evidence from this literature suggests that economic downturns can have mixed impacts. In the Netherlands, individuals born during a recession had lower adult survival rate (Van Den Berg, Lindeboom, and Portrait 2006), and were more susceptible to cancer mortality (Yeung et al., 2014). However, Cutler, Miller, and Norton (2007) could not find any long-term morbidity effects for cohorts born during the Dustbowl era of the 1930s in the United States, although individuals born during the Great Depression in low-income states had substantially lower incomes and higher work disability rates than workers born in those states in 1929 (Thomasson and Fishback 2014). In addition, Banerjee et al. (2010) discovered that a negative change in the productive capacity of French vineyards did not have detectable effects on life expectancy or health outcomes, but did reduce height in adulthood.

Similar to economic recessions, early life exposure to civil wars and conflicts may result in lower health, schooling and labor market outcomes in the long-term (Akresh, Lucchetti, and Thirumurthy 2012; Bundervoet, Verwimp, and Akresh 2009; Kesternich et al. 2014; Lee 2014; Verwimp and Van Bavel 2013). Sotomayor (2013) showed that individuals in the womb or early infancy in the aftermath of the 1928 and 1932 tropical storms in Puerto Rico were more likely to contract hypertension, high cholesterol and diabetes, and were considerably more likely to have no formal schooling. Neelsen and Stratman (2011) found that infants during the 1941-42 famine

4 Broadly, the economics literature investigating the "fetal origin" hypothesis can be categorized in terms of the types of extreme events taking place during the prenatal, neonatal and early childhood. Examples of such extreme events with profound adverse impacts on children in the long-term include civil wars and conflicts (Akresh, Lucchetti, and Thirumurthy 2012; Bundervoet, Verwimp, and Akresh 2009; Kesternich et al. 2014; Lee 2014; Verwimp and Van Bavel 2013), economic cycles (Banerjee et al. 2010; Cutler, Miller, and Norton 2007; Thomasson and Fishback 2014; Van Den Berg, Lindeboom, and Portrait 2006; Yeung et al. 2014), early life exposure to disease (Cutler et al. 2010; Lin and Liu 2014; Venkataramani 2012), tropical storms (Sotomayor 2013), radiation fallout (Almond, Edlund, and Palme 2009) and rainfall (Maccini and Yang 2009).

in Greece had significantly lower schooling and labor market outcomes in their adulthood, with stronger impacts for urban cohorts. Chen and Zhou (2007) indicated that the 1959-61 famine in China caused serious health and economic consequences for the survivors, especially for those in early childhood during the famine. Almond, Edlund, and Palme (2009) showed that the radiation spread due to the 1986 Chernobyl nuclear accident in Ukraine resulted in adverse schooling and income impacts, but no health impacts, in Sweden. Field, Robles, and Torero (2009) revealed that the prenatal iodine supplementation raised educational attainment by half a year of schooling in Tanzania, with larger impacts for girls. In addition, Maccini and Yang (2009) found that the long-term well-being of Indonesian women was highly sensitive to their early-life environmental conditions. Likewise, higher early-life rainfall had positive effects on adult outcomes for women, but not men, which may reflect gender biases in household resource allocation.

The existing literature on the likely long-term effects of a disaster on children suggests that these impacts may occur through the following mechanism. A disaster immediately affects the income of adults, and results in less investment in the health, nutrition and schooling of children, who then have a potentially lower stock of human capital in their adulthood. The long-term impact, therefore, manifests as lower health and schooling, and thus lower earned income in the adulthood of children born and raised during a disaster. To explore this possible mechanism, we develop an overlapping generation (OLG) model demonstrating that a disaster during the childhood lowers the human capital development and the adulthood consumption of that young generation. We hypothesize that children from households with greater exposure to a disaster, measured in terms of birth cohorts and birthplaces, will have lower health, schooling and consumption outcomes. In our empirical application to test this hypothesis, we focus on the long-term health, schooling and consumption impacts of the series of 1970-1974 disasters in Bangladesh: the 1970 cyclone, the 1971 war and the 1974 famine. Using the Bangladesh Household Income and Expenditure Survey (HIES) dataset, we employ a difference-in-difference method empirically to investigate the long-term impacts for regions and cohorts with different degrees of exposure to these disasters.

The immediate impacts of the series of 1970-1974 disasters in Bangladesh are widely researched (Sen 1981; Sommer and Mosley 1972); however, this is the first investigation into their long-term impacts in terms of health, schooling and consumption outcomes. By controlling for the indirect effects of other contemporary disasters, we make an important contribution by identifying direct, indirect and net measures of such long-term effects of a disaster. The underlying analysis may also have important policy suggestions to mitigate such long-term adversities. For example, the results of our analysis identify that government programs aiming at benefiting the rural poor and the females, such as educational and infrastructural development programs, might have remedial influences on the harms of a disaster. In passing, these results also confirm the long-term benifiting effects of public-funded projects such as food-for-education and female secondary school scholarship to increase especially the female education, social safety net and food-for-work programs to support the extreme poor and infrastructural development programs.

The outline of the remainder of the paper is as follows. Section I develops the overlapping generation model of a representative agricultural household. Section II introduces the background of the series of 1970-1974 disasters in Bangladesh. Section III identifies empirical strategies and describes the data and variables. Section IV reports and analyzes the main results. Section V provides the necessary robustness checks. Finally, Section VI draws on policy implications and concludes.

I. Conceptual Framework

We develop an overlapping generation model of an agricultural economy to capture the long-term effects of disaster-exposure. The agricultural economy consists of $M > 0$ homogeneous households, which is represented by a single household. At any point in time, the representative household consists of two overlapping generations: an old generation (denoted $t-1$) and a young generation (denoted t). The old generation uses its given human capital endowment e_{t-1} to earn strictly concave agricultural income $q(e_{t-1}), q' > 0, q'' < 0$. For simplicity, we express production as a function of human capital only.[5] The old generation transfers the unspent money (b_t) to the young generation after its own consumption (c_{t-1}) to solve

$$(1) \qquad \max_{c_{t-1}, b_t} u(c_{t-1}) + \rho v(b_t)$$

subject to the budget constraint

$$(2) \qquad c_{t-1} + b_t = \big(1 - z(\tau a_{t-1})\big) q(e_{t-1}),$$

[5] We define human capital in terms of the measures of individual ability such as education and health status.

where $u(c_{t-1}), u' > 0, u'' < 0$ denotes the utility from its own consumption; $v(b_t), v' > 0, v'' < 0$ the altruistic utility from transferring to the young generation; and $\rho > 0$ the weight on the altruistic utility component. On the right hand side of (2), the old generation's income equals its production level $q(e_{t-1})$ net of the percentage loss $z(\tau a_{t-1})$, $z(0) = 0, z' < 0$ from disaster exposure. If there is no disaster, then $\tau = 0$, and, therefore $z = 0$. If there is a disaster, then $\tau = 1$, but the loss decreases with the household's distance from the center a_{t-1} since $z'(\tau a_{t-1}) < 0$.

The young generation transforms the monetary receipt into human capital, for instance, by investing in the development of health and education. We simplify the human capital investment decision of the young generation by assuming that it increases with the young generation's endowment, that is, $e_t = e_t(b_t)$ with $e_t'(b_t) > 0$. The solution to (1) subject to (2) implies that

(3) $$u'(c_{t-1}) = \rho v'(b_t).$$

The first order condition (3) yields the optimal consumption-transfer tradeoff for the old generation at the equality of corresponding marginal benefits. This optimality condition leads to following propositions (1)–(3).

Proposition 1. *A disaster in time $t-1$ decreases the human capital of the young generation. That is, $e_t'(a_{t-1}) < 0$.*

Proof. We find $b_t'(a_{t-1})$ from (3), using the implicit function theorem. Then, we have $e_t'(a_{t-1}) = e_t'(b_t)b_t'(a_{t-1}) < 0$ since $e_t'(b_t) > 0$ and $b_t'(a_{t-1}) < 0$.

Proposition 2. *A disaster in time $t-1$ decreases the consumption of the young generation. That is, $c_t'(a_{t-1}) < 0$.*

Proof. The young generation's optimality condition is symmetric to (3), and can be expressed as $u'(c_t) = \rho v'\left(\left(1 - z(\tau a_t)\right)q(e_t) - c_t\right)$. Using the implicit function theorem, we have that $c_t'(a_{t-1}) = c_t'(e_t)e_t'(a_{t-1}) < 0$.

Proposition 3. *The adverse effects of a disaster in $t-1$ on the human capital and consumption of the young generation decrease with the human capital of the old generation. That is, $\partial e_t'(a_{t-1})/\partial e_{t-1} < 0$ and $\partial c_t'(a_{t-1})/\partial e_{t-1} < 0$.*

Proof. Assuming $\partial b_t'(a_{t-1})/\partial e_{t-1} \leq 0$, we have $\partial e_t'(a_{t-1})/\partial e_{t-1} = e_t''(b_t) b_t'(a_{t-1})\, \partial b_t/\partial e_{t-1} + e_t'(b_t)\, \partial b_t'(a_{t-1})/\partial e_{t-1} < 0$ since $\partial b_t/\partial e_{t-1} > 0, e_t''(b_t) < 0$ and $b_t'(a_{t-1}) > 0$. Similarly, we have $\partial c_t'(a_{t-1})/\partial e_{t-1} < 0$.

Propositions (1) and (2) indicate that childhood exposure to a disaster will result in lower health, schooling and consumption outcomes in adulthood. Age, together with distance of birthplace from the center of a disaster, determines an individual's exposure to that disaster (Almond, Edlund, and Palme 2009; Banerjee et al. 2010; Maccini and Yang 2009). In general, we hypothesize that children from households with greater exposure to a disaster, measured in terms of birth cohorts and birthplaces, have lower health, schooling and consumption outcomes in their adulthood. Section II.B classifies different regions and cohorts to identify the treatment and control groups as detailed in Table 1, and mapped in Figures 1 and 2. In addition, proposition (3) implies that parental schooling will have a mitigating influence on the variations in adulthood outcomes. While this conceptual framework is generic and applicable to any country, we chose the series of 1970-1974 disasters in Bangladesh to test this hypothesis empirically.

II. Background

Geographic location and land characteristics of Bangladesh make it one of the most disaster-prone countries in the world: 26 percent of the population are affected by cyclones and 70 percent live in flood-prone regions (Cash et al. 2014). Wide-scale flooding has been the recurrent type of disaster striking Bangladesh, and the country remains one of the worst sufferers of cyclonic casualties in the world. However, the series of 1970-1974 disasters, which includes the 1970 cyclone, the 1971 war and the 1974 famine, is exceptional even for Bangladesh due to the extent of severity in terms of number of casualties and monetary losses (see Van Schendel (2009) for details).

A. *Timeline of Disasters*

The series of 1970-1974 disasters started in November, 1970 when "the Great Bhola Cyclone of 1970", "the 1970 cyclone" for short, struck the coastal regions of Bangladesh (then East Pakistan). It formed over the central Bay of Bengal on November 8, 1970, and then intensified while traveling north towards the coasts of Bangladesh and India. It reached the peak with winds of 115 miles per hour on November 11 and made landfall on the coast of Bangladesh the following afternoon. Considered as the deadliest tropical cyclone and one of the deadliest natural disasters in modern times, it resulted in widespread loss of life and property (Sommer and Mosley 1972). The center of the cyclone was Tazumuddin subdivision, Barisal, where the destruction reached the maximum: nearly 47 percent of the total population died, and all the standing rice crops were destroyed. In general, the 1970 cyclone severely affected the coastal regions of Noakhali and Barisal (Sommer and Mosley 1972).[6] Altogether, around 35 percent of the rice crops were destroyed in Barisal (Figure 3), and all the coastal and neighboring districts were severely affected. Total mortality was more than 300,000 people, and nearly four million people were directly affected. The estimated total damage was $86.4 million in 1970 U.S. Dollars, equivalent to $450 million in 2006 (EM-DAT 2010). The mean mortality rate throughout the affected regions was 16.5 percent, and over 0.15 million people relied upon aid for half of their food, even three months after the cyclone (Sommer and Mosley 1972).

However, the insufficiency of the relief efforts by the central government of Pakistan created widespread dissatisfaction among the people of East Pakistan and resulted in the resurgence of Bengali Nationalism. Awami League, the largest political party in East Pakistan, won in the national elections of 1970. The eventual liberation war of Bangladesh in 1971 resulted in the killing of millions of Bengali civilians.[7]

Bangladesh was facing serious challenges in its early-independence days to tackle the increased prices of essential commodities, which were directly hurting the people. The situation became worse when the famine struck the northern regions of Rangpur and Mymensingh in 1974. The 1974 famine was associated with the severe monsoon floods that came during June to September of 1974 on an inflated Brahmaputra River (Sen 1981). A significant amount of crop was damaged, which led to a further escalation of rice prices, a spike in unemployment and reduced purchasing power (Razzaque et al. 1990; Sen 1981). Market failures and price speculation in the food-grains market also played a substantial role in the cause of the famine

[6] Regions, as defined in this paper, correspond to former districts that are formed of several current districts. For example, Noakhali region includes the districts of Noakhali, Feni and Lakshmipur; Chittagong region includes Chittagong and Cox's Bazar; Barisal region includes Barisal, Barguna, Bhola, Jhalkathi, Patuakhali and Pirojpur.

[7] Across different sources, the actual death figures vary between 0.3 and 3 million (Rummel 1997: Table 8.2).

(Ravallion 1985). Altogether, the 1974 famine caused an estimated 0.45–1.5 million deaths through starvation and diseases such as cholera and diarrhea (Alamgir 1980).

B. Disaster Regions and Cohorts

Based on historical evidence on the immediate effects of the series of 1970-74 disasters (e.g., Sen 1981; Sommer and Mosley 1972), we classify Bangladesh into regional groups as detailed in Table 1 and mapped in Figures 1 and 2. We exclude highly urban Dhaka and Chittagong and the population-scarce Chittagong Hill Tracts (CHT). In addition, we do not include regions severely affected by one disaster when estimating the impacts of another disaster in order to separate their corresponding impacts. Given that the 1971 war severely affected all the regions of Bangladesh, we do not classify any war regions for our econometric estimations.

Classification of cyclone regions is straightforward, as detailed in Table 1 and mapped in Figure 1. We include severely cyclone-affected coastal districts of Barisal and Noakhali in the treatment regions (CR2). We classify as a separate group (CR1) those regions mildly affected by the 1970 cyclone, such as Faridpur and Khulna. Finally, our control regions CR0 include Jessore and Rajshahi, which experienced similar historic crop losses as Barisal and Noakhali but were unaffected by the 1970 cyclone (Figure 3).

Similarly, Table 1 and Figure 2 outline the classification of famine regions, FR0-FR2. Regions severely affected by the 1974 famine (FR2) include the Rangpur and Mymensingh districts. Neighboring Bogra and Sylhet districts are the mildly affected FR1 regions. Finally, Jessore and Rajshahi districts are the control regions FR0, which experienced similar historic crop losses as the treatment regions, but were unaffected by the 1974 famine (Figure 4).

Based on the literature (e.g., Barker 1990; Duflo 2003; Jensen 2000; Neelsen and Stratman 2011), we include newborns during a disaster as well as newborns one year before and after the disaster in the disaster-affected cohorts. In particular, newborns during 1969-71, 1970-72 and 1973-75, respectively, are the cohorts affected by the 1970 cyclone, 1971 war and 1974 famine.

III. Identification and Data

We exploit the variations in timing and geography (Table 1, and Figures 1 and 2) of a disaster. We estimate two econometric specifications, described below, for the series of 1970-74 disasters in Bangladesh. The first equation estimating the variations in outcome variable y is

$$(4) \qquad y_i = \sum_{j=1}^{2} \beta_j * (R_{jk} * C_k) + x_i'\delta + \tau_{yob} + \Delta_{pob} + H_{yos} + \epsilon_i,$$

if an individual i comes from an agricultural household. Indices, $j = 0,1,2$ and k refer to regional groups and disasters, both in their chronological orders (Table 1). In particular, R_{jk} and C_k denote the disaster regions and cohorts, respectively. We expect greater exposure to a disaster to result in greater long-term impacts. Therefore, we interact R_{jk} and C_k which yields the parameter of interest $\beta_j, j = 1,2\ \forall k$; and we expect $\hat{\beta}_2 < \hat{\beta}_1 < 0\ \forall k$. The vector of controls, x', includes household- and regional-level variables (Table 2). In addition, τ_{yob}, Δ_{pob} and H_{yos}, respectively, represent the vectors of birth year, birth place (subdivision) and survey year indicators.

Parameters $\hat{\beta}_j$ estimate the direct effects of disaster k on the cohort C_k from region j. However, longer-durations of disasters, or consecutive disasters spanning over few years such as in our case of 1970-74 series of disasters in Bangladesh, may result into confounding effects; and, therefore, may bias the estimation by influencing the selection into fertility (Almond 2006). To address this issue, our estimation of net effects of disasters requires separating the cross or indirect influences of other contemporary disasters on the effects of a disaster. The second estimating equation, controlling for the indirect effects to estimate the net effects of a disaster, is

$$(5) \quad y_i = \sum_{j=1}^{2} \beta_j * (R_{jk} * C_k) + \sum_{k \neq l} \sum_{j=1}^{2} \gamma_{jl} * (R_{jk} * C_l) + x'\delta + \tau_{yob} + \Delta_{pob} + H_{yos} + \epsilon_i,$$

if an individual i comes from an agricultural household. Interaction between R_{jk} and C_l controls for the indirect effects of disaster l on disaster $k\ \forall k \neq l$.

Within a cohort, long-term effects of disaster exposure should be common to all households and individuals born in the same locality (e.g., Almond, Edlund, and Palme 2009; Maccini and Yang 2009). Therefore, variations in children's adulthood outcomes resulting from the variations in their time and place of birth should be absorbed by τ_{yob} and Δ_{pob}. In particular, τ_{yob} controls for all other year-specific influences on children's adulthood outcomes; whereas, Δ_{pob} controls for persistent effects of disaster exposure on the regions and households where the children are born. Finally, since data comes from three different survey years, we include a vector of survey year indicators, H_{yos}, to control for any variations in adulthood outcomes specific to survey year.

Since HIES does not report the place of birth, we assume that the respondents are born in their corresponding place of current residence. We limit our estimating samples to the agricultural households, who are historically less-likely to migrate (Population Census of Bangladesh, various issues), to reduce the possibility of differences between the places of current residence and birth. However, limiting the estimating sample only to agricultural households creates the sample selection bias (Heckman 1979). We use Heckman selection models to correct this problem, whenever appropriate. We use agricultural landholding, i.e., decimals of agricultural land owned by the household, to select the agricultural sample.

Parameters $\beta_j, j = 1,2$ allow for differential effects of regions on disaster cohorts and we hypothesize that $\hat{\beta}_2 < \hat{\beta}_1 < 0\ \forall k$. That is, we expect that newborns in the severely affected regions will experience greater adverse impacts of the disaster in their adulthood. These parameters measure the extent of regional variations in outcomes, controlling for all the permanent differences between treatment and control regions. We assume that

$$(6) \qquad cov\left(\epsilon_i, R_{jk} * C_k | C_k, R_{jk} * C_l, x', \Delta_{pob}, H_{yos}\right) = 0, \forall j = 1,2\ and\ k.$$

That is, our identifying assumption is the independence between the disturbances and the measure of exposure to a disaster, conditional on permanent differences between the districts of birth and other control variables. However, $\epsilon_i = \eta_{id} + u_i$, where u_i is the white noise error term, but η_{id} may be correlated across i within d. We cluster the standard errors at the union level to overcome this problem.[8]

Outcome and household-level control variables come from the Household Income and Expenditure Survey (HIES), which is the principal source of household-level socio-economic data in Bangladesh. Major components of HIES include, among others, the data on household expenditure, income, consumption, education, and health. We use HIES datasets from the survey years 2000, 2005 and 2010, with corresponding sample sizes of 7,440, 10,080 and 11,240, respectively. We restrict the summary statistics of the variables, as detailed in Table 2, to disaster regions and birth cohorts as identified in Table 1.

[8] A "union" is the lowest administrative tire in Bangladesh, usually formed of 2 or more villages.

HIES contains data on the incidence and duration of (chronic) illness. Surveyed individuals self-report whether they suffer from any chronic illness in the previous year. Common examples of such illnesses include injuries, disabilities, chronic heart disease, breathing problem, chronic dysentery, ulcers, blood pressure, arthritis, rheumatism, eczema, diabetes, cancer, leprosy, paralysis and hysteria. We define the first health outcome variable, *Health Status*, as 1 if an individual does not suffer from any such illness (i.e., good health), and 0 if the individual suffers (i.e., ill health). In addition to this discrete indicator, HIES reports the duration of illness. We extract the second health outcome variable, *Ln(Healthy Lifetime)*, as the logged value of one plus an individual's total life-years without any chronic illness.[9]

We use two indicators of schooling outcomes, schooling status and years of schooling. "Schooling Status" refers to 1 if an individual completes at least the 5th grade (i.e., educated) and 0 if not (i.e., uneducated). In addition, we extract the continuous schooling outcome variable, *Ln(Years of Schooling)*, as the logged value of one plus an individual's total years of schooling.

Two indicators of consumption and income outcomes are solvency status and per-capita consumption expenditure. We define "*Solvency Status*" as 1 if a household spends on or above the national average per-capita expenditure (i.e., solvent or non-poor) and 0 if otherwise (i.e., insolvent or poor). In addition, the continuous measure of expenditure, *Ln(expenditure)*, is the logged value of one plus per-capita consumption expenditure of a household.[10]

x' is a vector of controls for current household characteristics, and labor market conditions during the birth year to control for selection into fertility (Almond, Edlund, and Palme 2009). Measures of household characteristics are age, gender, location and parental schooling. We define "*gender*" as 1 if the household head is a male and 0 if otherwise, "*location*" as 1 if the household lives in a rural area and 0 if otherwise, and "*parental schooling*" as 1 if at least one of the parents completes at least 5th grade (i.e., educated parents) and 0 if otherwise (i.e., uneducated parents. In addition, we use *dependency on agriculture* (i.e., percentage of labor force employed in agriculture during the birth year) as a measure of regional labor market

9 Such log-transformations of outcome variables greatly reduce the variances and skewness and kurtosis statistics, and, therefore, justify the use of lognormal models (e.g., Cameron and Trivedi 2010).

10 We use consumption expenditure instead of income since the self-reported income data may be a biased measure of income status. Instead, surveyors verify and collect itemized expenditures on food and nonfood consumptions.

conditions during the birth year. Data on regional controls come from various issues of the Statistical Yearbook of Bangladesh and the Population Census of Bangladesh.

IV. Estimation Results

We report and discuss the regression results in this section. Our main discussion uses the estimates of net effects based on (5). In addition, we compare the direct and net effects through the comparison of results based on (4) and (5), and thus discuss the indirect effects of disaster (IV.D). Finally, Section IV.E discusses the influences of policy variables on the long-term effect of disasters. All regression results are appended, where we report $\hat{\beta}_j, \hat{\gamma}_{jl}$ and the components of $\hat{\delta}$ related to policy variables location, gender and parental schooling. In all three cases, we restrict our estimating samples to years 1964-1980.

A. The 1970 Cyclone

We start with estimating the long-term health, schooling and consumption effects of the 1970 cyclone, using the definition of cyclone cohorts (CC) and regions (CR0–CR2) in Table 1. Due to missing values, we have 2,013–3,116 valid observations in the regressions reported in Table 3.

Results in Table 3 confirm that $\hat{\beta}_2 < 0$ for the 1970 cyclone. That is, 1969-71 cohorts from cyclone-affected CR2 regions have lower health, schooling and consumption outcomes. However, $\hat{\beta}_1 \nless 0$ indicates that the neighboring CR1 regions do not experience any adversities of the 1970 cyclone. All the estimated effects are statistically insignificant for CR1 regions, whereas they are statistically significant for cyclone-affected regions except for “Health Status”. Moreover, we find that parental schooling has significant positive effects on schooling outcomes, which provides some support to Proposition 3.

Variations in health and schooling outcomes are insignificant for neighboring regions; however, cyclone-affected regions experience some health and schooling adversities arising from the exposure to the 1970 cyclone. In particular, when compared to those from the control regions, 1969-71 cohorts from cyclone-affected regions have 39.6 percent lower healthy-lifetime, 21.9-percentage points lower probability of schooling and 63.8 percent lower years of schooling. These results support the Proposition 1.

In terms of consumption outcomes, we find that the 1969-71 cohorts from the cyclone-affected regions have 10.7-percentage points probability of spending lower than the national average; whereas, they spend 28.8 percent lower than the control regions. These results support the Proposition 2, although the neighboring regions do not experience any significant difference in consumption outcomes.

Together, we identify significant long-term health, schooling and consumption adversities for the severely cyclone-affected regions, which are consistent with a set of related literature (e.g., Sotomayor 2013). These results standout albeit few social and natural remedies. First, the surprising phenomenon of in-migration of extended family members to provide mental and financial supports to the survivors of the 1970 cyclone potentially lowers the long-term adversities (Sommer and Mosley 1972). Second, production of rice went back to the normal levels in Barisal and Noakhali immediately after the 1970 cyclone (Figure 3). Together, in-migration and regular harvests might have some further unobserved mitigating influences on the variations in health, schooling and consumption outcomes emerging from the 1970 cyclone.

B. The 1971 Liberation War

The 1971 war affected all the regions of Bangladesh, and, therefore, we limit our investigation of its long-term effects to a cohort analysis using the definition of war cohorts (WC) in Table 1. Apart from excluding Dhaka, Chittagong and CHT regions, we also exclude severely cyclone- and famine-affected regions, which leave us with 1,183–1,720 valid observations (Table 4).

We do not identify any significant health, schooling or consumption adversities arising from the exposure to the 1971 war; rather, our estimates of net effects show that the 1970-72 cohorts experience 7.1- and 11-percentage points higher probabilities of healthiness and schooling and 16.9 percent higher years of schooling.

Apart from the fact that Bangladesh had a regular harvest in 1971 (Figures 3 and 4), adverse effects of the 1970 cyclone and the 1974 famine potentially explain the absence of adversities arising from the 1971 war. Since the war took place between two deadly natural disasters, indirect effects of cyclone and famine undermine the otherwise potential adversities of the 1971 war. Our estimates show that the 1970 cyclone has significant indirect effects on schooling and consumption outcomes, whereas the 1974 famine affects the consumption outcomes.

While a set of literature provides evidence of long-term adversities of civil wars and conflicts,[11] our insignificant results for the long-term effects of the 1971 war are consistent with the findings of other studies. For example, relatively high mortality might undermine the long-term effects of a disaster since usually the disaster-survivors are the fittest among the victims (e.g., Rasmussen 2001). The German invasion of Leningrad, which caused the death of one-third of 2.5 million residents, resulted in limited long-term health effects (e.g., Stanner et al. 1997; Sparén et al. 2004). Similarly, the Finnish famine of 1866-68 killed around 8 percent of the population, but did not inflict any long-term mortality effects on the survivors in utero during the famine (Kannisto, Christensen, and Vaupel 1997).

C. The 1974 Famine

For our investigation into the long-term effects of the 1974 famine, we use the definitions of famine cohorts (FC) and regions (FR0–FR2) in Table 1. There are 2,013–3,116 valid observations used in the regressions reported in Table 5.

We do not identify any significant health adversities from the exposure to the 1974 famine. However, when compared to those from the control regions, 1973-75 cohorts from both the affected and neighboring regions experience significantly lower schooling and consumption outcomes. In particular, our estimates of net effects show that the 1973-75 cohorts from the affected regions have 14.1- and 7.0-percentage points lower probabilities of schooling and solvency, respectively, and 34.7 and 13.0 percent lower years of schooling and expenditure, respectively. Similarly, 1973-75 cohorts from the neighboring regions have 14.6- and 9.9-percentage points lower probabilities of schooling and solvency, respectively, and 39.1 and 21.1 percent lower years of schooling and expenditure, respectively.

Together, except for health outcomes, our results show that $\hat{\beta}_1, \hat{\beta}_2 < 0$ and thus support the Propositions 1 and 2. In addition, parental schooling has significant positive effects on schooling outcomes, which provides some support to Proposition 3. However, we have $\hat{\beta}_1 < \hat{\beta}_2 < 0$. That

[11] For example, Lee (2014) found that the South Korean individuals in utero during the worst time of the 1950-53 Korean War have significantly lower educational attainment, labor market performance, and other socioeconomic outcomes in 1990 and in 2000. Similarly, Akresh, Lucchetti, and Thirumurthy (2012) found that the Eritrean children exposed to the 1998-2000 Ethiopia-Eritrea war experience some negative health impacts such as lower height-for-age Z-scores. Bundervoet, Verwimp, and Akresh (2009) found similar health adversities attributed to exposure to the civil war in Burundi.

is, although 1973-75 cohorts from both the famine-affected and neighboring regions have significantly lower schooling and consumption outcomes, these adversities are stronger for the neighboring regions.

Several factors may explain these effects. The government of Bangladesh provided some food support to the victims of the famine, which may have affected the long-term outcomes. Moreover, most of the recipients of public food supports from Dinajpur were originally from the neighboring district of Rangpur (Sen 1981), indicating a large out-migration of famine-affected people. This may have made the neighboring regions of Bogra and Pabna more susceptible to the famine and potentially explains the stronger and more significant variations in schooling and consumption outcomes for these two regions.

In general, the related literature supports our evidence from the 1974 famine in Bangladesh. For example, both the 1959-61 Chinese famine and 1941-42 Greek famine affect the younger children more adversely. Chen and Zhou (2007) found significant long-term negative effects of China's 1959–1961 famine on the health and economic status of the survivors, especially for those in early childhood during the famine. Neelsen and Stratmann (2011) identified significant long-term education and labor market effects of early-life exposure to the 1941-42 Greek famine. In addition, Razzaque et al. (1990) found higher infant mortality among the in utero children and infants during the 1974 famine in Bangladesh.[12]

D. *Indirect Effects of Disasters*

Regressions based on (4) and (5), respectively, estimate the direct and net effects of each disaster under consideration. Both specifications yield similar results; however, estimated net adversities are stronger and more significant for all three disasters. Specification (5) additionally controls for the indirect effects of other contemporary disasters on the effects of a disaster. In passing, we identify the indirect effects of those disasters, estimated as $\hat{\gamma}_{jl}$. These estimated indirect effects suggest that their influences on the net effects of the 1970 cyclone are significant.

Table 3 shows that the 1971 war and the 1974 famine yield some indirect effects on the variations in long-term outcomes of the 1969-71 cohorts from the neighboring and cyclone-affected regions. The war cohorts 1970-72 from the neighboring regions have 13.4-percentage

[12] However, Razzaque et al. (1990) used the Matlab Demographic Surveillance System (DSS) dataset, whose geographic coverage falls outside the definition of famine regions in this paper.

points higher probability of healthiness and 11.4-percentage points lower probability of solvency, whereas those from the cyclone-affected regions have 24.9 percent higher per-capita expenditure. On the other hand, the famine cohorts 1973-75 from the neighboring regions have significantly lower schooling and consumption outcomes and those from the cyclone-affected regions have lower probability of solvency.

Since we extend our estimating samples to the years 1964-80, both the cyclone and famine cohorts become relevant in estimating the cohort effects of the 1971 war. Moreover, the cyclone cohorts 1969-71 overlap with the war cohorts 1970-72. Therefore, controlling for the cyclone and famine cohorts is important for the correct estimation of the long-term effects of the 1971 war (Table 4). We identify that the cyclone cohorts 1969-71 have significantly lower schooling and consumption outcomes, whereas the famine cohorts 1973-75 have significantly lower expenditure.

Finally, in case of the 1974 famine, the cyclone cohorts 1969-71 from the neighboring regions have significantly lower schooling and consumption outcomes, although no such variations exist for the famine-affected regions (Table 5). However, we identify contrasting indirect effects of the war cohorts 1970-72 on the neighboring and famine-affected cohorts: schooling and consumption outcomes are significantly higher for the neighboring, but lower for the famine-affected, regions.

E. Policy Variables

The vector of controls, x_i', includes the location, gender and parental schooling status. Regression results in Tables 3–5 confirm the influences of location, gender and parental schooling status on the variations in long-term health, schooling and consumption outcomes.

First, location, defined as 1 if rural and 0 if urban, is an indirect but robust measure of the availability of amenities in a locality. Although such a definition of location is mostly statistical, as an "urban" household often operates its agricultural lands in an adjacent "rural" area, most health and schooling facilities are available in better quantity and quality in urban areas than the rural areas. Tables 3–5 show that rural households have lower schooling and consumption outcomes for all three disasters, whereas they also have lower health status in case of the 1971 war. Moreover, results in Table 7 confirm that the disaster-affected rural households apparently suffer more, except for solvency status. Such additional adversities experienced by rural households shed light on the importance of infrastructural development as an adaptation policy.

Absence of sufficient healthcare and schooling facilities deprives the disaster-hit rural people from meeting their basic needs, and on course affects the long-term welfare of their children. On the contrary, urban areas are less susceptible to the effects of a disaster mostly due to better availability of facilities and better connectivity with the capital city of Dhaka from where all the post-disaster management and rehabilitation programs are usually run.

Next, 79 percent of the households are male-headed (Table 2), and males significantly outperform females in health and schooling outcomes (Tables 3–5). Moreover, disaster-affected male-headed households apparently suffer less in the long-term, except for some exceptions (Table 6). In a male-dominated conservative society such as Bangladesh, females become household heads only in absence of their husbands or an adult son. Such households, being economically vulnerable, are often unable to adopt an alternative coping strategy rather than cutting back on their basic food and nutrient consumptions. In addition, female children are often least prioritized in intra-household budget allocations, especially during any budget contraction (Chen, Huq, and d'Souza 1981).[13] Such increased adversities experienced by females and female-headed households necessitate public interventions to target the wellbeing of the female children and female-headed households, who are often the most vulnerable in the aftermath of a disaster.

Finally, although only 6 percent of the household heads have educated parents, i.e., at least one of the parents completing at least 5th grade, our results identify that households with educated parents have significantly higher probability and years of schooling. However, health outcomes are unaffected; and, quite surprisingly, parental schooling, indeed, lowers the probability of solvency.[14] These results reinforce the importance of inrastructure: although the educated parents educate their children, parental schooling may not always contribute to the

[13] For example, intra-household allocations of food, nutrients and healthcare services are biased against the female children, especially during economic hardships, in rural India and Bangladesh (Sen and Sengupta 1983; Behrman 1988; Chen, Huq, and d'Souza 1981). Such discriminations are often influenced by gendered differences in labor market returns (Sen and Sengupta 1983) as well as socioeconomic status of the parents (Behrman 1988).

[14] Nevertheless, literature identifies parental education as an important component of any integrated approach to mitigating the long-term adversities of extreme events, especially in developing and less-developed countries. For example, among the Tigrai-Ethiopian families exposed to famines and civil wars during 1973-1991, Kiros and Hogan (2001) found significant variations in child mortality by parental education; and, therefore, concluded parental education as an important policy intervention in reducing the harms of famines and wars.

development of income-earning capabilities of children from agricultural households, who are mostly from rural areas where income-generating options are often limited.

V. Robustness Check

We also perform some robustness checks of our main regression results from Section IV. For this purpose, we consider an alternative specification (V.A), disaggregation of treatment regions (V.B), and limiting estimation into rural agricultural households (V.C).

A. Alternative Measure of Geographic Exposure

Instead of categorical disaster regions, our alternative specification considers a continuous measure of geographic exposure to a disaster. We consider the beeline distance of the birthplace from the center of a disaster as a measure of one's exposure to that disaster. The center of the 1970 cyclone was Tazumuddin subdivision, Barisal, where the destruction reached the maximum (Sommer and Mosley 1972). On the other hand, the central point of the famine regions was Fulchhari subdivision, Rangpur. Although it was not where the famine started, this is a landmark where the River Teesta meets Brahmaputra, and the flood of June, 1974 was most severe.

Our alternative strategy uses logged distance from the center of a disaster as a continuous measure of exposure to that disaster. The alternative equation estimating the variations in y is

(7) $$y_i = \beta * (D_i * C_k) + \sum_{k \neq l} \sum_{j=1}^{2} \gamma_l * (D_i * C_l) + x'\delta + \tau_{yob} + \Delta_{pob} + H_{yos} + \epsilon_i,$$

if an individual i comes from an agricultural household. D_i denotes the logged distance (plus one) of birthplaces from the center of a disaster. Similar to (5), we interact D_i with C_k. Parameter of interest is β, and we expect $\hat{\beta} > 0\ \forall k$. Likewise, interaction between D_i and C_l controls for the indirect effects of disaster l on disaster $k\ \forall k \neq l$. As before, x' includes household- and regional-level controls, whereas τ_{yob}, Δ_{pob} and H_{yos}, respectively, represent the vectors of birth year, birth place and survey year indicators. Once again, our identifying assumption is the independence between the disturbances and the measure of exposure to a disaster, conditional on permanent differences between the districts of birth and other control variables. Moreover, we use agricultural landholding to select the agriculture sample. Tables 8 and 9 report the regression results based on (7) for the 1971 cyclone and 1974 famine, respectively.

Our alternative regression results confirm that $\hat{\beta} > 0$, and, therefore, support our main results in Tables 3 and 5. Once again, we do not identify significant health adversities, however, individuals born closer to the center of either the 1971 cyclone or the 1974 famine have significantly lower schooling and consumption outcomes in their adulthood.

B. Disaggregated Disaster Regions

Although we choose the severely disaster-affected regions based on related literature, there might be further variations in outcomes within the CR2 and FR2 regions. For example, the 1970 cyclone severely affected both the Barisal and Noakhali regions. However, its epicenter was in Barisal, which resulted in this region being the most severely affected in terms of immediate losses in lives and properties. Similarly, Rangpur region was the primary victim of the 1974 famine, and some authors including Sen (1981) have pointed out that many famine-victims receiving food-assistance from neighboring districts were originally the migrants from Rangpur. Considering these facts, we breakdown disaster-affected regions, as categorized in Table 1, into two categories: primary victims (Barisal and Rangpur, respectively, for the cyclone and famine) and secondary victims (Noakhali and Mymensingh, respectively, for the cyclone and famine). We then employ specification (5) to obtain our parameters of interests (Table 10).

Overall, the estimated coefficients using disaggregated disaster-affected regions are similar to our main results in Tables 3 and 5. Variations in health outcomes are insignificant. However, schooling and consumption variations are profound for both the disasters, with such adversities being stronger and more significant for Noakhali than Barisal in the case of the 1970 cyclone and for Mymensingh than Rangpur in the case of the 1974 famine. That is, primary disaster-affected regions bear lower long-term effects of a disaster than the secondary disaster-affected regions.

One possible explanation for this outcome is that since most of the post-disaster assistance programs aim at helping the primary disaster-affected regions, people who survive a disaster from those regions recover better than the secondary disaster-affected regions. Moreover, extended families may also provide significant assistance to victims, which appear to have happened after the 1970 cyclone in Barisal. Survivors of the cyclone in the region did not out-migrate; rather, extended family members travelled and migrated to the region to help their affected family members (Sommer and Mosley 1972).

C. Rural Agricultural Samples

We also estimate equation (5) for rural agricultural households only. We report the results in Tables 11–13 for the 1970 cyclone, the 1971 war and the 1974 famine, respectively.

Consistent with the coefficient estimates of location variable in Table 3, rural agricultural households suffer more from cyclone exposure than households from urban areas. We identify stronger and more significant variations in long-term health, schooling and consumption outcomes due to exposure to the 1970 cyclone for the rural agricultural households (Table 11). In addition to schooling and consumption adversities, the rural agricultural households from cyclone-affected regions have lower health outcomes as well. However, except for solvency status, those from the neighboring regions do not suffer in the long-term.

Similar to the results in Table 4, we do not find any long-term adverse effects of the 1971 war. Rather, rural agricultural households from 1970-72 cohorts have significantly greater schooling outcomes (Table 12). However, these are less significant than our main estimates, and thus are consistent with apparently negative coefficient estimates of location variable, in Table 4.

Finally, estimates for the 1974 famine are also consistent with our main results in Table 5. As before, we do not identify any adverse health effects, however, rural agricultural households from both the neighboring and famine-affected regions have significantly lower schooling and consumption outcomes, with these adversities being stronger for the neighboring regions (Table 13). Furthermore, consistent with the coefficient estimates of location variable, a comparison between the coefficient estimates in Tables 5 and 13 reveals that the rural agricultural households suffer more than their urban counterparts.

VI. Conclusion

We investigate the long-term effects of three of the deadliest natural and political disasters that took place in Bangladesh from 1970 to 1974: the 1970 cyclone, the 1971 war, and the 1974 famine. In addition to the immediate losses in lives and properties, exposure to these disasters has consequences across generations. We identify some regional variations in health, schooling and consumption outcomes resulting from the series of 1970-74 disasters. In addition, we estimate the net effects through separating the indirect effects of other contemporary disasters on the long-term impacts of each disaster.

We identify household- and regional-level controls such as location, gender and parental schooling to provide potential pathways of protective measures. In addition to the overall adversities the disaster-affected regions experience, rural, female-headed households and households with uneducated parents are more vulnerable to the exposure to any disaster. Such additional variations in outcomes increase the importance of infrastructural development as an integral part of the protective measures and adaptation strategies. Especially in rural areas, development of facilities to meet basic health and schooling needs is necessary to lower the long-lasting impacts of a disaster on children. Such an expansion of primary schooling and basic healthcare facilities occurred in Bangladesh immediately after independence, which led to rapid development of healthcare and schooling infrastructure during the post-1971 era. In particular, the government of Bangladesh nationalized primary schooling in 1974, which was eventually made free and compulsory for all. As this intervention would have affected the schooling of all the treatment cohorts we analyzed, it could have influenced the long-run impacts of the disaster in terms of schooling outcomes.

Together with gendered variations in outcomes, our finding that parental schooling mitigates the harms of a disaster promotes the importance of educating the females. In fact, our results justify the programs undertaken by the government of Bangladesh encouraging smaller family size through family planning programs and educating females through female secondary school stipend program. Such programs increase the income-earning abilities of especially the female-headed and rural households. In addition, the female secondary school stipend program may encourage households to send and keep their girls at school rather than forego their education in response to income losses sustained during a disaster.

In sum, we identify parental schooling as well as infrastructural development to have remedial influences on the adversities of a disaster.[15] Relatively educated parents are more aware that defensive measures adopted during and after a disaster can reduce any resulting losses (Haque et al. 2012).[16] In addition, specific types of infrastructure, such as schools and hospitals, may counteract the potential long-term effects of a disaster (Banerjee et al. 2010; Cutler, Deaton, and Lleras-Muney 2006). Over the past 50 years, mortality and morbidity from natural disasters have fallen substantially in the coastal areas of Bangladesh, partly because of improvements in disaster management in the form of the construction of thousands of cyclone shelters (Cash et al.

[15] For example, Duflo (2001) identified that the construction of primary schools led to an increase in education and earning in Indonesia. Bohlmark and Lindahl (2015) showed that the 1992 Swedish voucher reform, which enabled private schools receiving public funds, significantly improved the educational outcomes of the benefited students.

[16] Examples of such defensive measures include early warning systems, cyclone shelters, evacuation plans, coastal embankments, reforestation schemes and increased awareness and communication.

2014; Haque et al. 2012).[17] We suggest that such infrastructural development in the aftermath of a disaster may help reduce the potential long-term impacts on children.

Since natural disasters are frequent in Bangladesh, our results have relevant public policy implications for any future disaster such as floods and cyclones or any civil conflicts. Such natural and political disasters will affect the human capital development and adulthood income-earning potential of the children. Our empirical findings for Bangladesh may be relevant for any developing country with frequent exposure to natural and political disasters.

[17] For example, only around 4 thousand people died from the 2007 cyclone, whereas the corresponding figure from the 1970 cyclone was more than 0.3 million.

Appendices

TABLE 1 – TIMELINE OF MAJOR DISASTERS IN BANGLADESH, 1970-74

Year	Disaster	Severity	Disaster Regions	Disaster Cohorts
1970	The Great Bhola Cyclone	More than 0.30 million people died in southern Bangladesh	2. Barisal and Noakhali 1. Faridpur and Khulna 0. Jessore and Rajshahi	1. 1969-71 0. 1961-68 and 1972-80
1971	The Liberation War of Bangladesh	Up to 3 million people died[18]	2. Entire Bangladesh	1. 1970-72 0. 1961-69 and 1973-80
1974	The Bangladesh Famine	Up to 1.5 million people died in northern Bangladesh	2. Rangpur and Mymensingh 1. Bogra and Pabna 0. Jessore and Rajshahi	1. 1973-75 0. 1961-72 and 1976-80

Notes: Timeline is adapted from Van Schendel (2009). Disaster regions refer to 2 if severely-affected regions, 1 if neighboring regions, and 0 if unaffected control regions. Disasters cohorts stand for 1 if affected cohorts and 0 if treatment cohorts.

[18] See Table 8.2 in Rummel 1997.

TABLE 2 – SUMMARY STATISTICS

Variables	Mean	Standard Deviation	Minimum	Maximum
Health Status – Good (%)	0.793	0.405	0	1
Ln(Healthy Life-years)	2.830	1.447	0	3.829
Primary Schooling Status (%)	0.335	0.472	0	1
Ln(Years of Schooling)	0.785	1.017	0	2.833
Solvency Status	0.184	0.388	0	1
Ln(Per-capita Expenditure)	6.970	0.557	4.453	9.838
Location (Rural)	0.851	0.356	0	1
Gender – Male (%)	0.791	0.407	0	1
Parental Primary Schooling Status (%)	0.060	0.238	0	1
Age of the household Head	34.960	5.537	19	45
Birth-year ALF (%)	82.219	6.973	56.390	91.400

Notes: Summary statistics consider birth cohorts 1964-80 and exclude Chittagong, CHT and Dhaka regions, so that the number of valid observations is 3,400. Section III provides the detail description and construction of variables.

TABLE 3 – EFFECTS OF THE 1970 CYCLONE: MAIN RESULTS.

	Health Status		Ln(Healthy Lifetime)		Schooling Status ^{S}		Ln(Years of Schooling) ^{S}		Solvency Status ^{S}		Ln(Expenditure) ^{S}	
CC*CR1	0.012	-0.040	-0.040	-0.143	0.068	-0.018	0.057	0.054	-0.002	0.021	0.046	0.046
	(0.070)	(0.103)	(0.156)	(0.221)	(0.111)	(0.110)	(0.183)	(0.210)	(0.126)	(0.158)	(0.082)	(0.085)
CC*CR2	-0.129	-0.191	-0.323*	-0.396*	-0.219***	-0.219***	-0.604***	-0.638***	-0.076	-0.107***	-0.195***	-0.288***
	(0.083)	(0.117)	(0.185)	(0.227)	(0.039)	(0.053)	(0.158)	(0.203)	(0.047)	(0.028)	(0.075)	(0.074)
WC*CR1		0.134**		0.299		0.040		-0.268		-0.114***		-0.132
		(0.057)		(0.249)		(0.121)		(0.231)		(0.037)		(0.095)
WC*CR2		-0.032		-0.092		-0.090		-0.130		0.122		0.249**
		(0.119)		(0.315)		(0.127)		(0.227)		(0.168)		(0.104)
FC*CR1		0.085		0.193		-0.217***		-0.617***		-0.136***		-0.327***
		(0.075)		(0.229)		(0.048)		(0.220)		(0.012)		(0.076)
FC*CR2		-0.224		-0.518		-0.107		-0.374		-0.095**		0.022
		(0.139)		(0.371)		(0.098)		(0.248)		(0.040)		(0.089)
Location	-0.044	-0.045	-0.091	-0.093	-0.862***	-0.868***	-3.025***	-3.148***	-0.960***	-0.964***	-1.564***	-1.674***
	(0.028)	(0.028)	(0.091)	(0.091)	(0.020)	(0.021)	(0.337)	(0.363)	(0.009)	(0.009)	(0.141)	(0.154)
Gender	0.116**	0.112**	0.286*	0.277*	0.214***	0.220***	0.552***	0.576***	-0.023	-0.013	0.057	0.075
	(0.050)	(0.050)	(0.148)	(0.148)	(0.031)	(0.031)	(0.095)	(0.098)	(0.042)	(0.040)	(0.053)	(0.053)
Parental Schooling	0.033	0.034	0.064	0.070	0.090*	0.089*	0.247***	0.243***	-0.049*	-0.049*	-0.041	-0.044
	(0.034)	(0.033)	(0.114)	(0.114)	(0.048)	(0.048)	(0.084)	(0.084)	(0.027)	(0.027)	(0.030)	(0.030)
Observations	2,400	2,400	3,116	3,116	2,628	2,628	2,927	2,927	2,013	2,013	2,933	2,933
R^2/Pseudo-R^2	0.121	0.123	0.202	0.203	0.151	0.154	0.247	0.251	0.223	0.229	0.470	0.475

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only the parameters of interest, according to (4) and (5). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Outcome variables follow the definitions in Section III. Cyclone regions (i.e., CR1 and CR2) and cohorts (i.e., CC) follow the definitions from Table 1. Superscript "^{S}" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 4 – IMPACTS OF THE 1971 WAR: MAIN RESULTS

	Health Status		Ln(Healthy Lifetime)		Schooling Status ^{S}		Ln(Years of Schooling) ^{S}		Solvency Status ^{S}		Ln(Expenditure) ^{S}	
WC	0.043	0.071*	0.137	0.214	0.013	0.110**	0.059	0.220**	0.015	0.023	0.014	0.051
	(0.032)	(0.039)	(0.096)	(0.135)	(0.038)	(0.053)	(0.066)	(0.090)	(0.032)	(0.041)	(0.032)	(0.040)
CC		0.003		0.002		-0.196***		-0.392***		-0.094***		-0.187***
		(0.037)		(0.113)		(0.039)		(0.084)		(0.028)		(0.035)
FC		0.066		0.173		-0.072		-0.132		-0.100***		-0.151***
		(0.053)		(0.167)		(0.059)		(0.120)		(0.031)		(0.052)
Location	-0.079**	-0.079**	-0.182	-0.181	-0.881***	-0.902***	-3.111***	-3.495***	-0.972***	-0.977***	-1.492***	-1.682***
	(0.035)	(0.035)	(0.111)	(0.111)	(0.022)	(0.022)	(0.339)	(0.370)	(0.010)	(0.009)	(0.184)	(0.199)
Gender	0.189**	0.192**	0.464**	0.468**	0.237***	0.258***	0.616***	0.674***	-0.046	-0.036	0.043	0.068
	(0.076)	(0.077)	(0.220)	(0.221)	(0.035)	(0.031)	(0.116)	(0.118)	(0.061)	(0.059)	(0.080)	(0.078)
Parental Schooling	-0.038	-0.038	-0.130	-0.127	0.099	0.107	0.284***	0.292***	-0.049	-0.049	-0.024	-0.021
	(0.050)	(0.051)	(0.153)	(0.155)	(0.065)	(0.068)	(0.109)	(0.110)	(0.034)	(0.034)	(0.045)	(0.044)
Observations	1,346	1,346	1,720	1,720	1,475	1,475	1,610	1,610	1,183	1,183	1,615	1,615
R^2/Pseudo-R^2	0.120	0.121	0.194	0.195	0.164	0.176	0.253	0.266	0.217	0.228	0.417	0.431

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only the parameters of interest, according to (4) and (5). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Outcome variables follow the definitions in Section III. Cohorts (i.e., CC, WC and FC) follow the definitions from Table 1. Superscript "^{S}" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 5 – IMPACTS OF THE 1974 FAMINE: MAIN RESULTS

	Health Status		Ln(Healthy Lifetime)		Schooling Status ^{S}		Ln(Years of Schooling) ^{S}		Solvency Status ^{S}		Ln(Expenditure) ^{S}	
FC1*FR1	-0.139	-0.140	-0.309	-0.308	-0.126	-0.146*	-0.355**	-0.391**	-0.099*	-0.116***	-0.176**	-0.211***
	(0.118)	(0.114)	(0.242)	(0.233)	(0.079)	(0.076)	(0.177)	(0.185)	(0.059)	(0.031)	(0.078)	(0.081)
FC1*FR2	0.012	0.028	0.085	0.131	-0.108*	-0.141**	-0.273**	-0.347**	-0.070*	-0.078**	-0.101*	-0.130**
	(0.060)	(0.059)	(0.181)	(0.185)	(0.057)	(0.056)	(0.126)	(0.139)	(0.039)	(0.037)	(0.056)	(0.062)
CC1*FR1		0.004		0.048		-0.205***		-0.497***		-0.145***		-0.329***
		(0.088)		(0.243)		(0.069)		(0.181)		(0.008)		(0.081)
CC1*FR2		0.044		0.137		0.064		0.134		0.122		0.056
		(0.048)		(0.168)		(0.072)		(0.117)		(0.075)		(0.045)
WC1*FR1		-0.014		-0.078		0.372**		0.644***		0.721***		0.347***
		(0.115)		(0.317)		(0.150)		(0.197)		(0.130)		(0.103)
WC1*FR2		-0.011		-0.015		-0.180***		-0.415***		-0.111***		-0.165***
		(0.066)		(0.192)		(0.052)		(0.145)		(0.023)		(0.059)
Location	-0.044	-0.043	-0.088	-0.085	-0.857***	-0.869***	-2.926***	-3.178***	-0.956***	-0.966***	-1.544***	-1.663***
	(0.028)	(0.028)	(0.091)	(0.091)	(0.019)	(0.021)	(0.326)	(0.369)	(0.010)	(0.008)	(0.138)	(0.154)
Gender	0.117**	0.117**	0.293**	0.294**	0.213***	0.225***	0.549***	0.588***	-0.033	-0.011	0.058	0.076
	(0.050)	(0.050)	(0.148)	(0.148)	(0.031)	(0.031)	(0.096)	(0.099)	(0.043)	(0.040)	(0.054)	(0.054)
Parental Schooling	0.034	0.034	0.063	0.065	0.090*	0.087*	0.244***	0.237***	-0.048*	-0.049*	-0.042	-0.046
	(0.033)	(0.033)	(0.114)	(0.114)	(0.047)	(0.048)	(0.084)	(0.084)	(0.028)	(0.027)	(0.030)	(0.030)
Observations	2,400	2,400	3,116	3,116	2,628	2,628	2,927	2,927	2,013	2,013	2,933	2,933
R^2/Pseudo-R^2	0.121	0.121	0.202	0.202	0.147	0.152	0.242	0.248	0.217	0.236	0.469	0.476

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only the parameters of interest, according to (4) and (5). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Outcome variables follow the definitions in Section III. Famine regions (i.e., FR1 and FR2) and cohorts (i.e., FC) follow the definitions from Table 1. Superscript "^{S}" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 6 – GENDERED VARIATIONS IN THE IMPACTS OF DISASTERS

	Health Status	Ln(Healthy Lifetime)	Schooling Status [S]	Ln(Years of Schooling) [S]	Solvency Status [S]	Ln(Expenditure) [S]
1970 Cyclone						
Male*CC*CR1	0.243***	1.289	0.733***	-0.010	0.879***	0.149
	(0.008)	(0.845)	(0.007)	(0.285)	(0.007)	(0.161)
Male*CC*CR2	0.073	-0.047	-0.042	0.312	-0.172***	-0.026
	(0.265)	(0.630)	(0.418)	(0.697)	(0.016)	(0.362)
1971 War						
Male*WC	0.058	0.183	0.094	0.212	-0.056	-0.004
	(0.153)	(0.673)	(0.216)	(0.275)	(0.112)	(0.197)
1974 Famine						
Male*FC*FR1	0.216***	2.733***	0.717***	-0.258	0.877***	0.536***
	(0.007)	(0.339)	(0.007)	(0.232)	(0.007)	(0.103)
Male*FC*FR2	-0.145	-0.307	-0.129	-0.107	0.075	-0.080
	(0.153)	(0.467)	(0.156)	(0.313)	(0.188)	(0.375)

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. Superscript "S" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 7 – LOCATIONAL VARIATIONS IN THE IMPACTS OF DISASTERS

	Health Status	Ln(Healthy Lifetime)	Schooling Status ^{S}	Ln(Years of Schooling) ^{S}	Solvency Status ^{S}	Ln(Expenditure) ^{S}
1970 Cyclone						
Rural*CC*CR1	0.112	0.336	0.019	0.243	-0.164***	-0.436
	(0.100)	(0.499)	(0.301)	(0.582)	(0.008)	(0.369)
Rural*CC*CR2	-0.826***	-1.161***	-0.291***	-0.696	0.890***	-0.091
	(0.006)	(0.447)	(0.045)	(0.489)	(0.007)	(0.190)
1971 War						
Rural*WC	0.013	0.068	0.020	-0.144	-0.142***	-0.146
	(0.084)	(0.238)	(0.104)	(0.184)	(0.035)	(0.106)
1974 Famine						
Rural*FC*FR1	0.101	0.334	-0.255***	-0.467	0.878***	0.117
	(0.136)	(0.711)	(0.082)	(0.532)	(0.007)	(0.184)
Rural*FC*FR2	0.091	0.192	0.043	0.178	0.899***	0.110
	(0.154)	(0.738)	(0.237)	(0.346)	(0.006)	(0.147)

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. Superscript "^{S}" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 8 – IMPACTS OF 1970 CYCLONE: ALTERNATIVE SPECIFICATION

VARIABLES	Health Status	Ln(Healthy Lifetime)	Schooling Status S	Ln(Years of Schooling) S	Solvency Status S	Ln(Expenditure) S
CC*Ln(Distance)	0.030	0.097	0.152**	0.314***	0.091*	0.158***
	(0.049)	(0.130)	(0.060)	(0.106)	(0.048)	(0.035)
WC*Ln(Distance)	-0.008	-0.001	-0.178**	-0.304**	-0.117*	-0.245***
	(0.056)	(0.155)	(0.075)	(0.126)	(0.060)	(0.050)
FC*Ln(Distance)	0.086	0.232	-0.026	-0.036	0.021	-0.060
	(0.054)	(0.161)	(0.060)	(0.114)	(0.050)	(0.040)
Location	-0.046	-0.094	-0.871***	-3.193***	-0.965***	-1.680***
	(0.028)	(0.091)	(0.019)	(0.345)	(0.008)	(0.150)
Gender	0.116**	0.288*	0.223***	0.578***	-0.014	0.072
	(0.050)	(0.148)	(0.030)	(0.097)	(0.040)	(0.054)
Parental Schooling	0.035	0.068	0.089*	0.240***	-0.048*	-0.045
	(0.033)	(0.114)	(0.048)	(0.084)	(0.027)	(0.030)
Observations	2,400	3,115	2,628	2,927	2,013	2,933
R^2/Pseudo-R^2	0.121	0.201	0.154	0.251	0.231	0.476

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only the parameters of interest, according to (7). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Outcome variables follow the definitions in Section III. Ln(Distance) corresponds to the logged distance (plus one) of birthplace from the cyclone epicenter. Superscript "S" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 9 – IMPACTS OF THE 1974 FAMINE: ALTERNATIVE SPECIFICATION

VARIABLES	Health Status	Ln(Healthy Lifetime)	Schooling Status [S]	Ln(Years of Schooling) [S]	Solvency Status [S]	Ln(Expenditure) [S]
FC*Ln(Distance)	-0.031	-0.080	0.097**	0.187**	0.107***	0.124***
	(0.047)	(0.128)	(0.049)	(0.076)	(0.040)	(0.032)
CC*Ln(Distance)	-0.007	-0.039	-0.088*	-0.170**	-0.017	-0.028
	(0.033)	(0.099)	(0.045)	(0.073)	(0.034)	(0.028)
WC*Ln(Distance)	-0.000	-0.011	0.164***	0.304***	0.134***	0.190***
	(0.039)	(0.121)	(0.057)	(0.095)	(0.042)	(0.046)
Location	-0.045	-0.090	-0.871***	-3.212***	-0.965***	-1.680***
	(0.028)	(0.091)	(0.019)	(0.347)	(0.008)	(0.150)
Gender	0.116**	0.288*	0.225***	0.587***	-0.012	0.075
	(0.050)	(0.148)	(0.030)	(0.097)	(0.040)	(0.054)
Parental Schooling	0.034	0.064	0.088*	0.239***	-0.051*	-0.047
	(0.033)	(0.114)	(0.048)	(0.084)	(0.027)	(0.030)
Observations	2,400	3,115	2,628	2,927	2,013	2,933
R^2/Pseudo-R^2	0.120	0.200	0.154	0.251	0.230	0.475

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only the parameters of interest, according to (7). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Outcome variables follow the definitions in Section III. Ln(Distance) corresponds to the logged distance (plus one) of birthplace from the center of the famine. Superscript "S" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 10 – EFFECTS OF DISASTERS, DISAGGREGATED REGIONS

	Health Status	Ln(Healthy Lifetime)	Schooling Status ^{S}	Ln(Years of Schooling) ^{S}	Solvency Status ^{S}	Ln(Expenditure) ^{S}
1970 Cyclone						
CC*CR1	-0.041	-0.147	-0.018	0.053	0.021	0.046
	(0.103)	(0.221)	(0.110)	(0.210)	(0.157)	(0.085)
CC*Noakhali	-0.173	-0.338	-0.257***	-0.866*	-0.118***	-0.460***
	(0.189)	(0.409)	(0.057)	(0.445)	(0.033)	(0.130)
CC*Barisal	-0.164	-0.343	-0.192***	-0.521**	-0.105***	-0.229***
	(0.149)	(0.261)	(0.070)	(0.211)	(0.031)	(0.083)
1974 Famine						
FC*FR1	-0.140	-0.309	-0.147*	-0.392**	-0.116***	-0.212***
	(0.114)	(0.233)	(0.075)	(0.185)	(0.031)	(0.081)
FC*Mymensingh	0.019	0.099	-0.236***	-0.715***	-0.116***	-0.235***
	(0.071)	(0.230)	(0.040)	(0.188)	(0.021)	(0.088)
FC*Rangpur	0.036	0.169	0.083	0.175	0.018	0.025
	(0.094)	(0.267)	(0.129)	(0.178)	(0.097)	(0.064)

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only $\hat{\beta}$ using disaggreagted disaster-affected regions, according to (5). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Superscript "^{S}" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 11 – IMPACTS OF THE 1970 CYCLONE, RURAL AGRICULTURAL SAMPLES

	Health Status	Ln(Healthy Lifetime)	Schooling Status [S]	Ln(Years of Schooling) [S]	Solvency Status [S]	Ln(Expenditure) [S]
CC*CR1	0.010	-0.051	-0.023	0.088	-0.114***	0.007
	(0.105)	(0.240)	(0.123)	(0.224)	(0.037)	(0.078)
CC*CR2	-0.219*	-0.441*	-0.252***	-0.782***	-0.121***	-0.347***
	(0.128)	(0.238)	(0.041)	(0.219)	(0.025)	(0.078)
WC*CR1	0.126*	0.254	0.071	-0.254	-0.064	-0.114
	(0.071)	(0.274)	(0.138)	(0.253)	(0.087)	(0.099)
WC*CR2	-0.049	-0.165	-0.097	-0.066	0.185	0.286**
	(0.128)	(0.318)	(0.143)	(0.254)	(0.240)	(0.117)
FC*CR1	0.083	0.193	-0.219***	-0.611***	-0.144***	-0.351***
	(0.090)	(0.262)	(0.053)	(0.221)	(0.009)	(0.078)
FC*CR2	-0.268*	-0.593	-0.097	-0.357	-0.127***	0.035
	(0.157)	(0.415)	(0.116)	(0.257)	(0.021)	(0.100)
Gender	0.091*	0.212	0.208***	0.553***	0.008	0.083
	(0.053)	(0.157)	(0.038)	(0.113)	(0.043)	(0.060)
Parental Schooling	0.042	0.097	0.089	0.240***	-0.084***	-0.058*
	(0.037)	(0.128)	(0.055)	(0.093)	(0.027)	(0.033)
Observations	2,063	2,741	2,275	2,570	1,674	2,575
R^2/Pseudo-R^2	0.123	0.207	0.165	0.265	0.249	0.483

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only the parameters of interest, according to (4) and (5). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Outcome variables follow the definitions in Section III. Cyclone regions (i.e., CR1 and CR2) and cohorts (i.e., CC) follow the definitions from Table 1. Superscript "S" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 12 – IMPACTS OF THE 1971 WAR, RURAL AGRICULTURAL SAMPLES

	Health Status	Ln(Healthy Lifetime)	Schooling Status [S]	Ln(Years of Schooling) [S]	Solvency Status [S]	Ln(Expenditure) [S]
WC	0.068	0.206	0.122**	0.186*	0.015	0.036
	(0.045)	(0.147)	(0.060)	(0.095)	(0.047)	(0.043)
CC	-0.003	-0.007	-0.219***	-0.415***	-0.124***	-0.208***
	(0.042)	(0.124)	(0.047)	(0.092)	(0.026)	(0.037)
FC	0.039	0.108	-0.100	-0.206	-0.115***	-0.176***
	(0.065)	(0.183)	(0.064)	(0.126)	(0.033)	(0.058)
Gender	0.156*	0.355	0.275***	0.681***	0.003	0.085
	(0.084)	(0.232)	(0.030)	(0.137)	(0.058)	(0.086)
Parental Schooling	-0.054	-0.172	0.126	0.295**	-0.064*	-0.032
	(0.058)	(0.176)	(0.085)	(0.123)	(0.037)	(0.049)
Observations	1,132	1,492	1,251	1,393	969	1,397
R^2/Pseudo-R^2	0.113	0.199	0.209	0.300	0.269	0.465

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only the parameters of interest, according to (4) and (5). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Outcome variables follow the definitions in Section III. Cohorts (i.e., CC, WC and FC) follow the definitions from Table 1. Superscript "[S]" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

TABLE 13 – IMPACTS OF THE 1974 FAMINE, RURAL AGRICULTURAL SAMPLES

	Health Status	Ln(Healthy Lifetime)	Schooling Status ^{S}	Ln(Years of Schooling) ^{S}	Solvency Status ^{S}	Ln(Expenditure) ^{S}
FC1*FR1	-0.096	-0.219	-0.188***	-0.454**	-0.119***	-0.210**
	(0.110)	(0.233)	(0.067)	(0.183)	(0.035)	(0.085)
FC1*FR2	0.057	0.198	-0.144**	-0.372**	-0.094***	-0.143**
	(0.057)	(0.193)	(0.060)	(0.149)	(0.034)	(0.065)
CC1*FR1	-0.015	0.021	-0.242***	-0.623***	-0.153***	-0.364***
	(0.101)	(0.256)	(0.054)	(0.196)	(0.008)	(0.087)
CC1*FR2	0.067	0.212	0.057	0.126	0.149*	0.056
	(0.047)	(0.173)	(0.077)	(0.123)	(0.085)	(0.048)
WC1*FR1	-0.000	-0.049	0.446***	0.776***	0.790***	0.371***
	(0.113)	(0.320)	(0.144)	(0.202)	(0.092)	(0.108)
WC1*FR2	-0.017	-0.012	-0.193***	-0.447***	-0.125***	-0.155**
	(0.072)	(0.204)	(0.054)	(0.157)	(0.020)	(0.064)
Gender	0.098*	0.232	0.216***	0.575***	0.010	0.087
	(0.054)	(0.157)	(0.037)	(0.114)	(0.043)	(0.061)
Parental Schooling	0.041	0.094	0.089	0.232**	-0.082***	-0.061*
	(0.037)	(0.128)	(0.055)	(0.093)	(0.026)	(0.033)
Observations	2,063	2,741	2,275	2,570	1,674	2,575
R^2/Pseudo-R^2	0.120	0.206	0.162	0.263	0.253	0.483

Notes: Standard errors clustered at the union level are shown in parentheses. ***,** and * represent statistical significance at 1, 5 and 10 percent levels, respectively. We report only the parameters of interest, according to (4) and (5). We report marginal effects from probit regressions for binary dependent variables (i.e., Health, Schooling and Solvency Statuses), and coefficients from ordinary least squares regressions for continuous dependent variables (i.e., Ln(Healthy lifetime), Ln(Years of Schooling) and Ln(Expenditure)). Outcome variables follow the definitions in Section III. Famine regions (i.e., FR1 and FR2) and cohorts (i.e., FC) follow the definitions from Table 1. Superscript "^{S}" indicates that the estimated inverse mills ratio is significant and a Heckman selection model is used. Otherwise, we run probit/ols regressions on the agricultural sample.

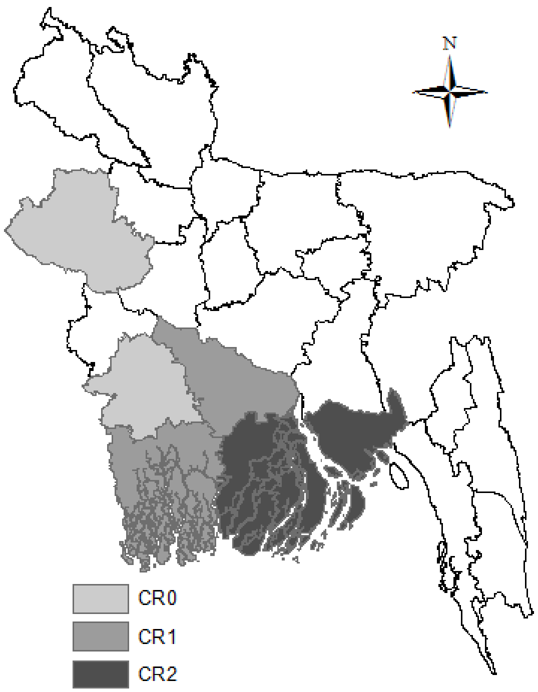

FIGURE 1. CYCLONE REGIONS

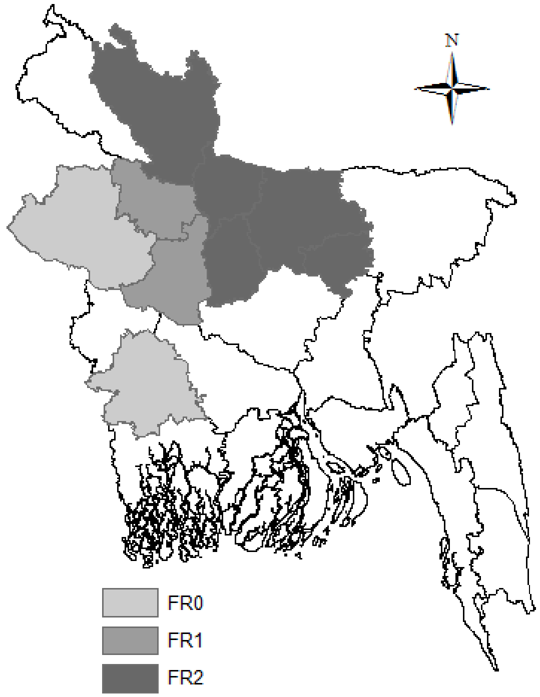

FIGURE 2. FAMINE REGIONS

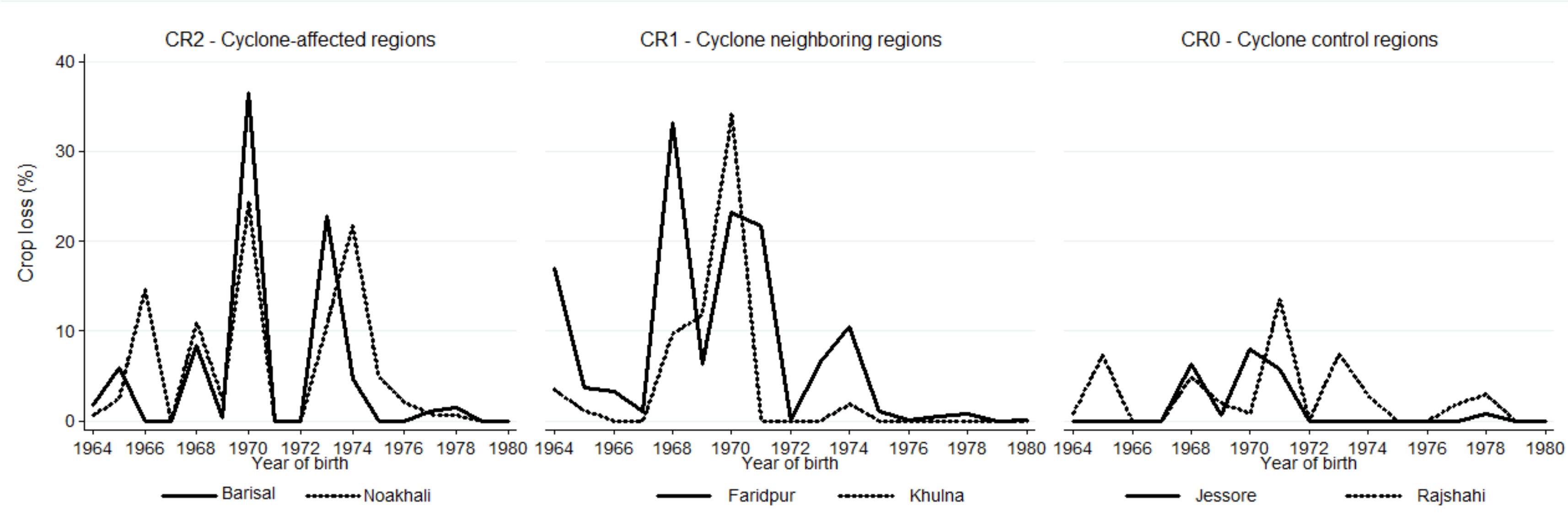

FIGURE 3. PERCENTAGE LOSS OF RICE CROPS BY CYCLONE REGIONS, 1964-1980

Source: Data comes from various issues of Statistical Yearbook of Bangladesh, compiled by authors.

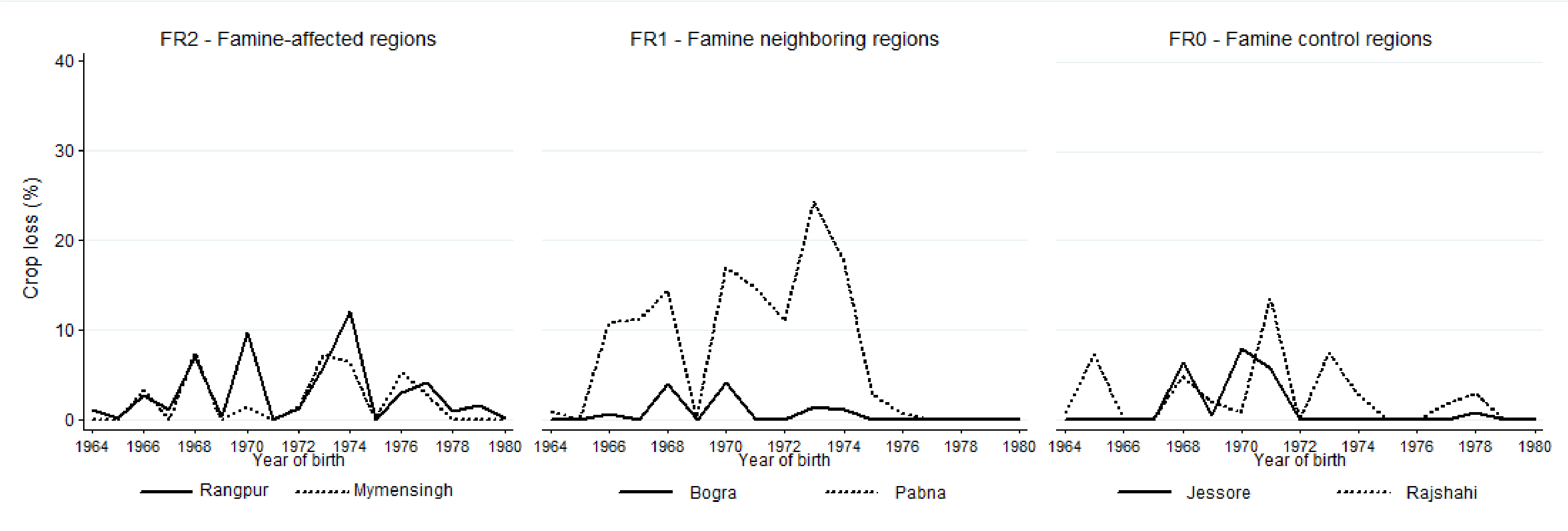

FIGURE 4. PERCENTAGE LOSS OF RICE CROPS BY FAMINE REGIONS, 1964-1980
Source: Data comes from various issues of Statistical Yearbook of Bangladesh, compiled by authors.

References

Akresh, Richard, Leonardo Lucchetti, and Harsha Thirumurthy. 2012. "Wars and child health: Evidence from the Eritrean–Ethiopian conflict." *Journal of Development Economics* 99.2: 330-340.

Alamgir, Mohiuddin. 1980. *Famine in South Asia. Political economy of mass starvation*, Oelgeschlager, Gunn & Hain, Publishers, Inc.

Almond, Douglas, and Janet Currie. 2011. "Killing me softly: The fetal origins hypothesis." *The Journal of Economic Perspectives* 153-172.

Almond, Douglas, Lena Edlund, and Mårten Palme. 2009. "Chernobyl's Subclinical Legacy: Prenatal Exposure to Radioactive Fallout and School Outcomes in Sweden." *The Quarterly Journal of Economics* 124.4: 1729-1772.

Almond, Douglas. 2006. "Is the 1918 Influenza pandemic over? Long-term effects of in utero Influenza exposure in the post-1940 US population." *Journal of Political Economy* 114.4: 672-712.

Banerjee, Abhijit, Esther Duflo, Gilles Postel-Vinay, and Tim Watts. 2010. "Long-run health impacts of income shocks: wine and phylloxera in nineteenth-century France." *The Review of Economics and Statistics* 92.4: 714-728.

Bangladesh Bureau of Statistics. various years. "*Statistical Yearbook of Bangladesh."* Dhaka: Ministry of Planning, Government of Bangladesh.

Bangladesh Bureau of Statistics. 2000. "*Household Income and Expenditure Survey (HIES) 2000*." Dhaka: Ministry of Planning, Government of Bangladesh.

Bangladesh Bureau of Statistics. 2005. "*Household Income and Expenditure Survey (HIES) 2005*." Dhaka: Ministry of Planning, Government of Bangladesh.

Bangladesh Bureau of Statistics. various years. "*Population censuses: preliminary report*." Dhaka: Ministry of Planning, Government of Bangladesh.

Bangladesh Bureau of Statistics. 2010. "*Household Income and Expenditure Survey (HIES) 2010*." Dhaka: Ministry of Planning, Government of Bangladesh.

Barker, David J. 1990. "The fetal and infant origins of adult disease." *BMJ: British Medical Journal* 301.6761: 1111.

Barker, David J. 1995. "Fetal origins of coronary heart disease." *BMJ: British Medical Journa*, 311.6998: 171.

Barker, David J. 1999. "Fetal origins of cardiovascular disease." *Annals of Medicine* 31: 3-6.

Behrman, Jere R. 1988. "Intrahousehold allocation of nutrients in rural India: Are boys favored? Do parents exhibit inequality aversion?." *Oxford Economic Papers* 32-54.

Böhlmark, Anders, and Mikael Lindahl. 2015. "Independent Schools and Long-run Educational Outcomes: Evidence from Sweden's Large-scale Voucher Reform." *Economica* 82(327): 508-551.

Bundervoet, Tom, Philip Verwimp, and Richard Akresh. 2009. "Health and civil war in rural Burundi." *Journal of Human Resources* 44.2: 536-563.

Cameron, A. Colin, and Pravin K. Trivedi. 2010. *Microeconometrics Using Stata*, 3rd edition, Stata Press books.

Cash, Richard A., Shantana R. Halder, Mushtuq Husain, Md Sirajul Islam, Fuad H. Mallick, Maria A. May, Mahmudur Rahman, and M. Aminur Rahman. 2014. "Reducing the health effect of natural hazards in Bangladesh." *The Lancet* 382.9910: 2094-2103.

Chen, Lincoln C., Emdadul Huq, and Stan d'Souza. 1981. "Sex bias in the family allocation of food and health care in rural Bangladesh." *Population and Development Review* 55-70.

Chen, Yuyu, and Li-An Zhou. 2007. "The long-term health and economic consequences of the 1959–1961 famine in China." *Journal of Health Economics* 26.4: 659-681.

Cutler, David M., Grant Miller, and Douglas M. Norton. 2007. "Evidence on early-life income and late-life health from America's Dust Bowl era." *Proceedings of the National Academy of Sciences* 104.33: 13244-13249.

Cutler, David, Angus Deaton, and Adriana Lleras-Muney. 2006. "The Determinants of Mortality." *Journal of Economic Perspectives* 20:3: 97–120.

Cutler, David, Winnie Fung, Michael Kremer, Monica Singhal, and Tom Vogl. 2010. "Early-life malaria exposure and adult outcomes: Evidence from malaria eradication in India." *American Economic Journal: Applied Economics* 72-94.

Duflo, Esther. 2003. "Grandmothers and Granddaughters: Old-Age Pensions and Intrahousehold Allocation in South Africa." *The World Bank Economic Review* 17.1: 1-25.

Duflo, Esther. 2001. "Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment." *The American Economic Review* 91.4: 795.

EM-DAT, C.R.E.D. 2010. "the OFDA/CRED International Disaster Database." *Université Catholique*.

Field, Erica, Omar Robles, and Maximo Torero. 2009. "Iodine deficiency and schooling attainment in Tanzania." *American Economic Journal: Applied Economics* 140-169.

Haque, Ubydul, Masahiro Hashizume, Korine N. Kolivras, Hans J. Overgaard, Bivash Das, and Taro Yamamoto. 2012. "Reduced death rates from cyclones in Bangladesh: what more needs to be done?." *Bulletin of the World Health Organization* 90.2: 150-156.

Heckman, James J. 1979. "Sample selection bias as a specification error." *Econometrica: Journal of the Econometric Society* 153-161.

IPCC. 2012. Summary for Policymakers. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA 1-19.

Jensen, Robert. 2000. "Agricultural volatility and investments in children." *American Economic Review* 399-404.

Kannisto, Väinö, Kaare Christensen, and James W. Vaupel. 1997. "No Increased Mortality in Later Life for Cohorts Born during Famine." *American Journal of Epidemiology* 145: 987–94.

Kesternich, Iris, Bettina Siflinger, James P. Smith, and Joachim K. Winter. 2014. "The effects of World War II on economic and health outcomes across Europe." *Review of Economics and Statistics* 96.1: 103-118.

Kiros, Gebre-Egziabher, and Dennis P. Hogan. 2001. "War, famine and excess child mortality in Africa: the role of parental education." *International Journal of Epidemiology* 30.3: 447-455.

Lee, Chulhee. 2014. "In utero exposure to the Korean War and its long-term effects on socioeconomic and health outcomes." *Journal of Health Economics* 33: 76-93.

Lin, Ming-Jen, and Elaine M. Liu. 2014. "Does in utero Exposure to Illness Matter? The 1918 Influenza Epidemic in Taiwan as a Natural Experiment." *Journal of Health Economics* 37: 152-163.

Maccini, Sharon, and Dean Yang. 2009. "Under the weather: Health, schooling, and economic consequences of early-life rainfall." *The American Economic Review* 1006-1026.

Neelsen, Sven, and Thomas Stratmann. 2011. "Effects of prenatal and early life malnutrition: Evidence from the Greek famine." *Journal of Health Economics* 30.3: 479-488.

Rasmussen, Kathleen M. 2001. "The "Fetal Origins" Hypothesis: Challenges and Opportunities for Maternal and Child Nutrition." *Annual Review of Nutrition* 21: 73–95.

Ravallion, Martin. 1985. "The performance of rice markets in Bangladesh during the 1974 famine." *The Economic Journal* 15-29.

Razzaque, Abdur, Nurul Alam, Lokky Wai, and Andrew Foster. 1990. "Sustained effects of the 1974–5 famine on infant and child mortality in a rural area of Bangladesh." *Population Studies* 44.1: 145-154.

Rummel, Rudolph J. 1997. "Statistics of Democide: Genocide and Mass Murder Since 1900." Charlottesville, Virginia: Center for National Security Law, School of Law, University of Virginia.

Sen, Amartya. 1981. "Ingredients of famine analysis: availability and entitlements." *The Quarterly Journal of Economics* 433-464.

Sen, Amartya, and Sunil Sengupta. 1983. "Malnutrition of rural children and the sex bias." *Economic and Political Weekly* 855-864.

Sommer, Alfred, and Wiley H. Mosley. 1972. "East Bengal cyclone of November, 1970: epidemiological approach to disaster assessment." *The Lancet* 299.7759: 1030-1036.

Sotomayor, Orlando. 2013. "Fetal and infant origins of diabetes and ill health: Evidence from Puerto Rico's 1928 and 1932 hurricanes." *Economics & Human Biology* 11.3: 281-293.

Sparén, Pär, Denny Vågerö, Dmitri B. Shestov, Svetlana Plavinskaja, Nina Parfenova, Valeri Hoptiar, Dominique Paturot, and Maria Rosaria Galanti. 2004. "Long term mortality after severe starvation during the siege of Leningrad: prospective cohort study." *British Medical Journal* 328.7430: 11.

Stanner, Sara A., K. Bulmer, C. Andres, Olga E. Lantseva, V. Borodina, V. V. Poteen, and John S. Yudkin. 1997. "Does malnutrition in utero determine diabetes and coronary heart disease in adulthood? Results from the Leningrad siege study, a cross sectional study." *British Medical Journal* 315.7119: 1342-1348.

Thomasson, Melissa A., and Price V. Fishback. 2014. "Hard Times in the Land of Plenty: The Effect on Income and Disability Later in Life for People Born During the Great Depression." *Explorations in Economic History* 54: 64-78.

Van Den Berg, Gerard J., Maarten Lindeboom, and France Portrait. 2006. "Economic conditions early in life and individual mortality." *The American Economic Review* 290-302.

Van Schendel, Willem. 2009. *A history of Bangladesh*. Cambridge: Cambridge University Press.

Venkataramani, Atheendar S. 2012. "Early life exposure to malaria and cognition in adulthood: Evidence from Mexico." *Journal of Health Economics* 31.5: 767-780.

Verwimp, Philip, and Jan Van Bavel. 2013. "Schooling, violent conflict, and gender in Burundi." *The World Bank Economic Review* lht010.

Vogl, Tom S. 2014. "Height, skills, and labor market outcomes in Mexico." *Journal of Development Economics* 107: 84-96.

World Bank. 2015. *World Development Indicators*. Washington, DC: The World Bank.

Yeung, Gary YC., Gerard J. Van den Berg, Maarten Lindeboom, and France RM Portrait. 2014. "The impact of early-life economic conditions on cause-specific mortality during adulthood." *Journal of Population Economics* 27.3: 895-919.