Lack of Food Access and Double Catastrophe in Early Life: Lessons from the 1974–1975 Bangladesh Famine

Shabnam, Nourin and Guven, Cahit and Ulubasoglu, Mehmet

Curtin University, Deakin University, Deakin University

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Lack of Food Access and Double Catastrophe in Early Life: Lessons from the 1974–1975 Bangladesh Famine[#]

Nourin Shabnam[a*], Cahit Guven[b**], and Mehmet A. Ulubasoglu[b***]

[a]Curtin University, Australia

[b]Deakin University, Australia

Abstract

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JEL classification: I15, I25, J13, J24.

Keywords: The 1974–1975 Bangladesh Famine; Food Access; Early Life Malnutrition; Education Outcomes; Double Catastrophe.

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[*] Email: nourin.shabnam@curtin.edu.au
[**] Email: cahit.guven@deakin.edu.au
[***] Corresponding author: 70 Elgar Road, Burwood Victoria 3125, Australia. Tel: (+61 3) 9244 6592. Fax: (+61 3) 9244 6583. Email: mehmet.ulubasoglu@deakin.edu.au

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Abstract

We study the education outcomes of the 1974–1975 Bangladesh famine on early-life survivors using the 1991 Bangladesh microcensus data. We find that famine adversely affected the survivor children in areas that experienced higher rice prices relative to labour wage. In addition, children living in wealthy households in famine-stricken areas had better education outcomes than children with no famine exposure at all. We also find that, surprisingly, exposure to double catastrophe (i.e., concurrent famine and flood) in early life had weaker effects than exposure to single catastrophe. We show that disaster-alleviation mechanisms worked better in districts affected by double disasters.

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1. Introduction

One frequent explanation for the large observed cross-country variations in economic performance is disparities in human capital between countries (Mankiw et al., 1992; Barro & Lee 1996; Kalaitzidakis et al., 2001). A corpus of studies suggests that health is a key factor in human capital formation (Bleakley, 2010, Madsen, 2018), with early-childhood malnutrition being one of the principal drivers (Ampaabeng & Tan, 2013). Several studies also document strong relationships between early-life conditions and later-life outcomes, such as life expectancy (Doblhammer et al., 2011). In particular, adverse effects appear to be acute for individuals that experienced a malnutrition episode in utero or in their first two years of life (Bryce et al., 2008).

Investigations into the impact of early-life malnutrition on later-life outcomes confront the problem of establishing a causal relationship because exposure to any shock is often not random (Chen & Zhou, 2007). To address this drawback, a recent strand of literature exploits nationwide famines, using them as a natural experiment as famines provide exogenous variation in exposure to malnutrition (Neelsen & Stratmann, 2011). The first approach in this literature utilises only the cohort variation, known as the treatment–control approach. Using this approach, researchers compare birth cohorts that experienced the shock just before or just after birth. This approach is commonly used when the duration of the famine is very short because the short duration allows less chance of selection bias that might arise from the impacts of famine on fertility (Song, 2009; Gørgens et al., 2012). However, estimates from this approach could be questionable because cohorts might experience several other shocks over their lifetime. To tackle this issue, researchers use the cohort variation together with the regional variation pertaining to the intensity of famine exposure. In this setting, a growing body of literature uses famine-related mortality at the regional level as a famine severity measure. This is done in combination with cohort fixed effects to control for any shock that each birth cohort might experience later in life.[1]

The primary objective of the present paper is to investigate the effects of early-life malnutrition on survivor children's education outcomes using the 1974–1975 Bangladesh famine as natural experiment. We depart from the existing literature that examines the long-term outcomes of famine-led malnutrition in two major respects. First, we study the early childhood effects of famine by exploiting two famine severity indicators that are tightly linked to the genesis of the famine, which is food access: the rice-exchange rate of labour (i.e., price of rice relative to the wage of a unit amount of labour) and rice production in the famine year. This approach differs from many studies that utilise famine-related mortality to measure famine severity. It must be noted that mortality only measures the outcome of an extreme form of malnutrition while other levels of malnutrition can also afflict famine victims, especially children. In addition, measuring famine-driven mortality in a famine environment is notoriously difficult (Ravallion 1997). Second, given that the 1974–1975 Bangladesh famine coincided with deadly floods in some districts, we explore the novel question of whether and how double catastrophe in early life, compared to a single catastrophe, affects later-life outcomes. To the best of our knowledge, the question of 'double catastrophes' has hitherto not been investigated in the literature. Our objective is not only to examine the later-life outcomes of single vs double catastrophe, but how disaster response and recovery mechanisms may have worked differently in the two different disaster scenarios.

[1] In this connection, the Chinese famine of 1959–1961 has received substantial attention in the literature for its long-term effects (e.g., Chen & Zhou, 2007; Huang & Zhou, 2013; Kim, Deng, Fleisher & Li, 2014; Kim, Fleisher & Sun, 2017). Findings suggest that the Chinese famine had significant negative effects on survivors' education, height, cognitive skill, labour supply and earnings in adulthood. Neelsen and Stratmann (2011) examined the 1941–1942 Greek famine and documented its adverse effects on education and labour market performance for its survivors. For the effects Netherlands hunger famine in 1944–1945, see Scholte et al. (2015). See Ampaabeng & Tan (2013) for the Ghanaian famine. See Barker (1986) for foetal origins hypothesis.

In most cases, 'food availability decline' (FAD) is believed to be the principal trigger of famines. However, in his Nobel-winning work, Sen (1981) posited the 'entitlement approach', arguing that disproportionate access to available food supply due to hoarding and more generally, weak distribution mechanisms is the major cause of famine in Bangladesh. In other words, people lost their entitlement to food despite greater food production, because food prices began to rise sharply because of hoarding and speculation about future price increases (see also Ravallion 1985; Dyson, 1991; Lin and Yang, 2000; Hernández-Julián et al., 2014). While we cannot directly test the food availability and food entitlement explanations because of the lack of proper hoarding data, our famine severity indicators, the rice-exchange rate of labour and total rice production, capture different aspects of food access during famine, which we shed light on. In particular, the former measures the food access based on a key relative price set in the rice and labour markets and the latter is based on the physical supply of rice available in the local economy. Both indicators exhibit strong geographic variation.

Using the 1991 Bangladesh micro census dataset that includes 10.58 million individual observations and represents random 10% sample of the country's population, our results document that the famine-affected cohorts have significantly lower levels of literacy and are more likely to be primary school dropouts later in life. Our estimates show that an estimated total of 1,713,840 children born during 1972–75 were adversely affected by the famine by either remaining illiterate or dropping out of primary school. More specifically, famine adversely affected the education outcomes of the survivor children later in life in areas that experienced increased rice prices relative to the wage of a unit amount of labour. We also find, seemingly paradoxically, that increased rice production in a district reduces the likelihood of literacy and increases the probability of dropping out of primary school. This finding could be indicating the hoarding and distribution problems experienced during famine. To probe further into this result, we utilise two income/wealth indicators available in the census dataset and are good measures of affluence in the Bangladesh context—whether the children live in brick-wall houses and whether they live in concrete-roof houses. We find that the adverse effects of famine are significantly lower for children who live in a brick-wall or concrete-roof house. Surprisingly, those children even had better education outcomes compared to children *with no famine exposure at all.* These results suggest that children living in wealthy households during the time of famine were advantaged. This advantage could be interpreted as an additional evidence for greater food access by the wealthy population and lack of food entitlement for the broader population.[2]

Turning to our second contribution, the 1974–75 Bangladesh famine coincided with deadly floods in some districts. This raises the novel question of whether and how double catastrophe in early life affects later-life outcomes compared to a single catastrophe. The significant geographic differences in famine severity and floods in Bangladesh generate spatial variation to disentangle the effects of these two disasters. We measure flood severity using three novel indicators at the district level: height of flood inundation (in ft), flood duration (in months), and flood-affected area as a percentage of the total area of a district. Our findings indicate that famine is a more dominant adverse factor than flood in explaining education outcomes. Moreover, and surprisingly, the adverse effects of early-life malnutrition are stronger in 'only famine-affected' districts than those in the 'flood- and famine-affected' districts. This result shows that a child that experienced two disasters (i.e., famine and flood) had less severe later-life consequences than a child who faced only one catastrophe (i.e., famine). We provide

[2] This finding partly accords with one of the early studies by Lin and Yang (2000), who find that both food availability and urban biased ration system explain the Great China Famine 1959-1961. In a more recent study by Meng, Qian and Yared (2015), weak distributional mechanisms due to central planning were found to be one of the major causes of the Great China Famine. Both studies investigate the problem using macro-level (i.e., province and county) mortality and grain production data, while we utilise person-level census data and study the problem in the context of the "foetal origins" hypothesis. See also Gooch (2017) the additional institutional reasons behind the Great China Famine.

evidence that this outcome could be explained by greater number of *langarkhanas*[3] in the double-disaster areas than in the single-disaster areas. That is, alleviation mechanisms for disasters were stronger in districts shocked by the two catastrophes than those experiencing only one disaster, suggesting that the government provided more resources to areas where the disaster exposure was the greatest.

The remainder of the paper is organized as follows. Section 2 provides an overview of the 1974–1975 Bangladesh famine. Section 3 explains the data and measurement of variables, Section 4 describes the empirical approach, and Section 5 discusses empirical results. Section 6 examines the impact of double-catastrophe vs single catastrophe, and Section 7 concludes.

2. The 1974–1975 Bengal Famine: An Overview

Just three years after the liberation war in 1971, Bangladesh experienced a fatal famine that was one of the worst famines in recent history around the globe.[4] The famine struck in June 1974 and started to wane by the end of that year; it officially ended in July 1975 (Kagy, 2012). Importantly, the most severe period was between July 1974 and October 1974 (Alamgir, 1980; Hernández-Julián et al., 2014). Within this short duration, the famine arguably led to the death of around one and a half million people (Alamgir, 1980; Schendel, 2009). The famine occurred in all districts of Bangladesh but was worse in some districts, particularly those affected by concurrent floods, that is, the spatial famine intensity was associated with flood exposure (Sen, 1981). Map 1 shows the snapshot of the flooded districts in Bangladesh. The three most famine-

[3] *Langarkhana* was a type of gruel kitchen that distributed free cooked meals of a modest size to people who were exposed to either flood or starvation. In 1974, the Bangladesh Government opened roughly 6,000 *gruel kitchens* and fed almost four million people (Muqtada, 1981).

[4] Other famines around the world in the 20th century include those in the Soviet Union, Ethiopia, Sudan, Mozambique, Nigeria, Niger, Angola, Zaire, Uganda, Somalia, and Liberia. Many of these happened since 1980 (Ravallion 1997).

affected districts were Mymensingh, Rangpur, and Sylhet according to the first famine survey by the Bangladesh Institute of Development Studies (BIDS) in 1974.[5]

In the first few years after independence, Bangladesh was listed as one of the poorest nations in the world. In 1974, nearly 90% of its total population lived in rural areas and the economy was agriculture based. Although the agriculture sector contributed 60% of the national gross domestic product and supplied employment opportunities to almost 80% of the population, a key idiosyncrasy is that majority of individuals did not own land. In addition, life expectancy was 47 and 49 years for males and females, respectively. Approximately 15% of all children died under the age of five, and more than 50% of households consumed less than the minimum calorie requirements. Moreover, the nation of 75 million people had just experienced a protracted civil war and the state machinery was corrupt and incompetent (Quddus & Becker, 2000). It is noteworthy that from March 1974, the price of rice started to upturn sharply (Hernández-Julián et al., 2014). Figure 1 presents the average price of rice in Bangladesh for the period of July 1972 to June 1976.

With the above-mentioned fragile socioeconomic conditions, even the slightest shock could lead to starvation across the nation. Heavy rainfall and a series of troubling floods along the Brahmaputra River started in June 1974 and destroyed a major part of the *aus* (the principal rice crop harvested in July–August). Flood also washed away the seedlings of the *aman* (the second most principal rice crop), as its transplanted period was between July and September. Flood also affected a part of *boro* (another principal rice crop), since its harvesting period was April–June. Another important issue was that the import of food grains from abroad was approximately 28% lower in 1974 than in the preceding year (Alamgir, 1980). Like many other developing countries, Bangladesh had been receiving regular food aid from the United States.

[5] This survey was conducted in November 1974 on 19 greater districts and the most affected districts were identified in terms of maximum depth of flood inundation, six feet and above, the maximum periods of flood and number of persons seeking relief during the famine (Alamgir, 1980).

However, this food aid was severely threatened in 1974 when the United States withheld 2.2 million tons of food aid and the then-United States ambassador to Bangladesh made it clear that the United States would probably not continue to commit food aid to Bangladesh because of its export of jute to Cuba. These combined issues led to a food crisis in Bangladesh and provides some background for the FAD approach.

Despite these events, the quantity of rice production in Bangladesh did not decline nor did the quantity of food grain. The total production of rice in 1974 was roughly 13% more than it had been in 1973, and the amount food grain to feed the population in 1974 was 12.36 million tons, almost 7% more than it had been in 1973 (Alamgir & Salimullah, 1977; Alamgir, 1980; and Sen, 1981).[6, 7] Further, there was a substantial increase in rice production in the three most affected districts—Mymensing, Rangpur, and Sylhet (22%, 17%, and 10%, respectively)—between 1973 and 1974 (Alamgir & Salimullah, 1977; Alamgir, 1980).

Taking into consideration the increased rice production and food grain supply, a shortfall in food availability, commonly known as the FAD approach, cannot alone explain the 1974–1975 famine in Bangladesh. Thus, Sen (1981) put forward a compelling argument that the increased price of rice and reduced purchasing power of the people resulted in the famine, commonly known as the "entitlement approach." Sen argued that the price of rice was escalating and rice-purchasing power of the daily wage declined during the famine.

An additional support for increasing rice prices comes from Ravallion (1985). Using monthly time series of rice prices during 1972-75, Ravallion (1985) finds that newspapers reports of future crop damage resulted in high rice prices in Bangladesh during famine. Rice markets worked poorly and were unable reflect the future scarcities because of the assumptions

[6] The data for food production in 1974 included the *aman crop* harvested in the preceding year, i.e., November 1973–January 1974, when there were no floods (Sen, 1981).

[7] A chart of chronology of the events for the 1974–1975 Bangladesh famine is presented in Appendix Table 1.

made by speculators, which resulted in excessive hoarding of rice. In particular, Ravallion thinks that hoarders may have had over-optimisting expectations about rice prices during famine or they may have expected quantity rationing in the future. By both accounts, markets failed to deliver their primary function through equilibrating excess demand with price adjustments (p. 28).

Although the reasons for the uncontrolled increase in rice price were difficult to fully articulate, the key contributing factors were distributional, including inflation and speculation about future price increases (Sen 1981; Dyson, 1991; Hernández-Julián et al., 2014). Floods and the cessation of food aid from the United States created a rumour of famine, which led to hoarding of the available food by some people and the escalation of rice prices in the market. Meanwhile, other people lost their entitlements to food as they lost their employment and income because of floods. Exploring the available data on the decline in the rice-exchange rate of labour between June and October 1974 at the district-level, we find that greatest decline was in the three districts that experienced the most severe famine. That is, the greater the decrease in rice-exchange rate in a district, the greater the severity of famine of that district. In addition, this famine mostly affected the wage labourers and landless labourers. Importantly, the 'crude death rate' among landless families was three times higher than families with three or more acres of land (Chowdhury & Chen, 1977; Currey & Hugo, 2012).

3. Data

The main data used in this study are from the Bangladesh Population and Housing Censuses available on the Integrated Public Use Microdata Series (IPUMS) website (Minnesota Population Center, 2014). The IPUMS dataset provides person-level data from the 1991 Bangladesh census round, including 10.58 million person-observations representing a 10 percent sample of the Bangladesh population.[8] This census, conducted on 2 March 1991, includes some basic demographic and socioeconomic information for everyone in the household.

The 1991 census wave does not include information on place of birth. This might be a challenge for our estimations because the individuals included in our regression sample might have migrated across regions. In particular, the specification without controlling for birthplace information might bias the literacy effects of famine upwardly. However, data on inter-district net migration for the years 1974–1981, published by the Bangladesh Bureau of Statistics (1984) and reported by Nabi (1992), allows us check whether migration is likely to affect our results. In addition, the 1991 census dataset does not contain the birth year information of its sample. We compute this information using the available age variable in the dataset as $Year\ of\ Birth = Census\ Year - Age - 1$.[9]

3.1 Dependent Variables

In examining the effects of famine on education, we use literacy as one of our main outcomes of interest. A person is considered literature if s/he read and write. Our measure is specified as 100 for literate persons and 0 otherwise. We choose literacy as an education indicator for two

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[8] The IPUMS also include the two latest census rounds, the 2001 Bangladesh census and the 2011 Bangladesh census waves containing micro data. However, we do not use these two rounds because quantifying the education outcomes such as literacy and primary school dropout may have been affected by recent nation-wide interventions.

[9] The reliability of age information in the census data depends on many factors—for instance, whether the respondent knows their actual date of birth and whether the respondent takes the time to remember their age. Moreover, it is not unlikely in Bangladesh that people report themselves to be younger than they actually are. We subtract "1" to identify the year of birth for a few reasons. For example, the 1991 census in Bangladesh was conducted on 2 March 1991. If a person is born in April 1970, they are more likely to casually report their age as 20 years on the census day in spite of their actual age i.e., almost 21 years. Likewise, if a person is born in December 1970, they may choose to report their age as 20 years as well. One issue may arise if this person is born in the first quarter of 1970, if there birthday is just before the census survey and they report their actual age as 21 years. In this case, our formula erroneously calculates their year of birth as 1969 instead of 1970. Also, even if individuals remembered their birthday correctly, our approach of subtracting 1 from the census year is likely to provide the appropriate year of birth for the majority cohort born in March 03–December 31 in a given year. However, we exercise caution in our empirical specification by using an "age correction" dummy in case this subtraction is not accurate.

main reasons. First, it helps to understand the level of human capital by gauging the economic value of an individual's skill set. More precisely, literacy facilitates better employment prospects and a better socioeconomic status for individuals and the economy as a whole (Desai, 2012). Extant literature tells us that there is a nexus between malnutrition in early-life and literacy of adult survivors (Neelsen & Stratmann, 2011). Second, the data on literacy for 10.58 million individuals are available in the 1991 census dataset and enable us to do a rigorous and systematic analysis of the long-term effects of famine on famine survivors. We also choose 'being primary school dropout' as the second outcome variable. This is defined as 100 if a person dropped out of primary school and 0 otherwise. This is based on extant literature and anecdotal evidence that shows early-childhood malnutrition is connected with the discontinuation of a child's schooling (Leiva et al., 2001; Alderman et al., 2006; Molina, 2012).

3.2 Key Independent Variables: Measuring Food Access

We use two indicators with spatial variation as a proxy for food access, which in turn measures the severity of the famine.

The rice-exchange rate of labour. This is the price of rice relative to the wage of a unit amount of labour. Our regressions use the percentage change in this measure between June and October 1974 for each district in Bangladesh. The data on this variable are compiled by the BIDS (1974), reported in Alamgir & Salimullah, (1977) and calculated by Sen (1981). Map 2 shows the inter-district variation of the change in rice-exchange rate of labour.[10] To elabourate on the economics behind this variable, it is not difficult to imagine that labour here is the unskilled agricultural labour. According to Ravallion (1997), arguably this measure is the single most important relative price determining the probability of starvation during the famine. It can

[10] We acknowledge that our measure used for food availability (total rice production by greater district) does not consider intra-regional rice trade flows, which may be a limitation in the determination of rice prices (see Ravallion 1985).

measure the high and unstable prices during famine, which can reflect hoarding and speculative behaviour, which in turn depends on miscalculations by hoarders or misreporting by newspapers related to the future scarcity of food. Therefore, rice purchasing power of agricultural wage in each area is a reasonable measure of food access for households. Ravallion (1997) also provides evidence that this relative price is correlated with the mortality rate during famine but argues that measuring mortality in a famine environment is notoriously difficult[11] while this relative price is easier to measure, and therefore, is much more reliable.

The change in rice production (%) represents the percentage change in rice production between 1973 and 1974 for each district in Bangladesh. The data on this variable are compiled by the BIDS (1974), reported in Alamgir & Salimullah, (1977) and Sen (1981). Map 3 shows the inter-district variation of the change in rice production in percentage as a famine severity measure. It must be acknowledged that food availability itself may not need to be the primary cause of famine. There were famines in history where there was little crop failure or cases with large crop failure but no famine in consequence. However, crop failure in the famine year in Bangladesh due to disasters is a well-documented fact.

Notably, these two famine severity measures capture two important aspects of food access: rice purchasing power of a unit amount of labour and physical availability of rice in the local economy. They are reported at the greater district level. There were 19 greater districts/regions in Bangladesh in 1974. To obtain district-level famine severity measures, we first identify the regions that each district belonged to and then assign the severity measures for greater districts to 64 current districts. See below the implications of this regarding standard errors.

[11] Deaths occur during famine not only because of starvation, but also due to the disease environment, health management and health care, and suicides. There are also non-linearities associated with mortality and high grain prices (income loss) and consumption during famine, which are difficult to quantify. For example, Ravallion (1987, ch. 2) shows that mortality was an increasing concave function of foodgrain price during two severe famines in South India in 1877 and Bangladesh 1974-75.

3.3 Descriptive Statistics

Table 1 presents the descriptive statistics for the key variables. Our benchmark regression sample includes 2,475,054 people, of whom 802,663 were born between 1972 and 1975 (i.e., treatment group), 1,672,391 were born between 1976 and 1979 and between 1968 and 1971 (i.e., comparison group). The average age of the regression sample is about 16 years. Fifty percent of the sample is male and 78% of the sample lives in rural areas. On average, 45% and 62% of the sample are literate and primary school dropouts, respectively, with a sizeable variation in both literacy and primary school dropout as shown by the standard deviation of almost 50 and 49, respectively. Finally, the average change in the rice-exchange rate of labour and the average change in rice production are approximately 42% and 14%, respectively.

4. Econometric Approach

To empirically quantify the education effects of famine on the early-life survivors, we estimate the following model using ordinary least squares where robust standard errors are clustered at the district level[12]:

$$\begin{aligned} Y_{ijt} &= \lambda_0 + \lambda_1 \left(TreatmentDummy_{it} \times FamineSeverity\ Index1_j\right) \\ &+ \lambda_2 \left(TreatmentDummy_{it} \times FamineSeverity\ Index2_j\right) + \lambda_3 \left(TreatmentDummy_{it} \times AgeCorrectionDummy_{it}\right) \\ &+ Male_i + Religion_i + Rural_i + yob_i + {yob_i}^2 + \alpha_j + \gamma_t \\ &+ \varepsilon_{ijt} \qquad (1) \end{aligned}$$

[12] Note that, with the 19 greater-district clusters, the number of groups is not sufficiently large to address the Moulton problem. However, clustering the standard errors at the 19 greater-district level instead of 64 districts makes little change to our key results. We present these results in Appendix.

where Y_{ijt} is the education indicators described above, employed in alternative regressions for individual i, born in district j in year t. $TreatmentDummy_{it}$ indicates whether individual i was born during famine. Our benchmark treatment group is the cohort born between 1972 and 1975 and the control group includes the cohorts born in the four years before 1972 and in the four years after 1975. The benchmark treatment group is equal to 1 if a person was born in 1972–1975 and is equal to 0 if born in 1976–1979 or 1968–1971. We also exploit two alternative treatment dummies for robustness checks, see section 4.1 below. $FamineSeverity\ Index1_j$ represents our first food access measure, the change in rice-exchange rate of labour (%), and $FamineSeverity\ Index2_j$ is our second food access measure, the change in rice production (%), each for district j.[13] The key variable of interest is the interaction variable between $Treatment\ Dummy_{it}$ and $FamineSeverity\ Index1_j$, and $FamineSeverity\ Index2_j$ which aim to capture the effects of food access. Turning to control variables, age reporting is a common problem in developing countries and is mostly linked with lower cognitive ability (Baten et al., 2014). Also called the "age-heaping" problem, this issue does not seem to be severe in our case because we find that the total size of birth cohorts reporting ages ending in 0 and 5 in our sample is not substantially larger as compared with their preceding and successive years.[14] However, this does not rule out a possible age reporting issue around the census date, 2 March 1991, for which we subtracted "1" from reported age to compute the birth year more accurately (see footnote 13). Nonetheless, as a caution, we interact the treatment dummy with *age-correction dummy* that takes 1 for the birth cohorts whose ages end with '0' or '5', in case this subtraction is not accurate. $Male_i$ represents gender as indicated

[13] We also estimate the specification where only one food access measure is included in the model and present the results in Appendix. This specification delivers hardly any different results than Equation (1).

[14] This is possibly because individuals in our sample are young. We notice that the older birth cohorts in the census, such as those are above 40 years of age, present an acute age heaping problem in Bangladesh as observed in the 1991 census (the age distribution table is available upon request).

by 1 if the individual is male and 0 otherwise. $Religion_i$ takes 1 if the individual i is non-Muslim and 0 otherwise. The $Rural_i$ dummy stands for rural residence as indicated by 1 and 0 otherwise. Further, yob_i is the year of birth of individual i. We also include the squared year of birth (i.e., $yob_i{}^2$) to address the nonlinearities in outcome trends (Almond & Mazumder, 2005; Neelsen & Stratmann 2011). α_j, that is, the district fixed-effects, is used to control the time-invariant factors that vary across districts. The inclusion of γ_t, that is, cohort fixed-effects, ensures that possible common shocks that each cohort might have experienced in their later lives (e.g., school expansion programs and change in education policies) differentially are controlled for in terms of their effects on the outcomes of interest Y. We present the estimates of λ_1 and λ_2 .

In other set of regressions, we estimate Model (1) using the control group born only after the famine. In other words, we drop the cohort born before famine from the control group in case there is the possibility that children above two years of age were also affected by famine.

To probe further into food access, we also use a three-way interaction term among the treatment dummy, change in rice production, and one of the two wealth indicators. The wealth indicators available in the census include whether individuals live in a brick-wall house, and whether they live in a concrete-roof house. The key objective of the three-way interaction is to identify whether the effects of famine vary with socioeconomic status within the districts.[15] Those households that live in a brick-wall house or concrete-roof house are more likely to be able to access the available rice given their higher income and wealth status. The aforementioned wealth indicators are appropriate measures of affluence in Bangladesh context.

[15] See section 5.1 for a discussion on the version of Equation (2) where wealth is interacted with the change in rice-exchange rate of labour (%) rather than rice production.

In our benchmark regression sample, 12% lived in brick-wall house, while 6% lived in concrete-roof house as of 1991.[16] We estimate the following model:

$$Y_{ijt} = \eta_0 + \eta_1 \text{ InWl}_{it} + \eta_2\big(Treatment\ Dummy_{it} \times FamineSeverity\ Index2_j\big)$$
$$+ \eta_3 \left(Treatment\ Dummy_{it} \times InWl_{it}\right)$$
$$+ \eta_4 \left(InWl_{it} \times FamineSeverity\ Index2_j\right)$$
$$+ \eta_5\big(Treatment\ Dummy_{it} \times FamineSeverity\ Index2_j \times InWl_{it}\big)$$

$$+\eta_6 \left(Treatment\ Dummy_{it} \times AgeCorrectionDummy_{it}\right) + Male_i + Religion_i + Rural_i$$
$$+ yob_i + yob_i^{\ 2} + \alpha_j + \gamma_t + \varepsilon_{ijt} \qquad (2)$$

where InWl_{it} stands for one of the two wealth variables. We present the estimates of η_4 and η_5.

4.1 Definition of Treatment and Control Groups

To quantify the long-term consequences of the 1974–1975 Bangladesh famine among child survivors, we consider the birth cohorts born during the famine and the birth cohorts born within the four years either side of the famine period as our regression sample. In particular, we construct three treatment groups. Supported by most of the literature, the Bangladesh famine began in June 1974 and ended in July 1975, with the harshest period being from July 1974 to October 1974 (Alamgir, 1980; Hernández-Julián et al., 2014). Following Walker et al. (2007), Bryce et al. (2008), Victoria et al. (2008), and Neelsen and Stratmann (2011), it is plausible to assume the ensuing consequences of early-life undernourishment experienced in the first three years of life. Unlike the census rounds from other countries like Greece, however, the 1991

[16] We also considered whether agriculture is the main source of income for the household in place of the two wealth indicators. 42% of the individuals in the sample belonged to a household whose main source of income is agriculture. We estimated the three-way interaction terms involving agriculture as the source of income are to be insignificant. One explanation for this finding is that an individual who derives income from agriculture may only be a worker on the land, and hence, may not have control over the output/produce, while a wealthy person is likely to be a land owner, and hence, may control the output/produce. The results are available upon request.

Bangladesh census does not have month of birth information. Thus, we consider the identified effects in our regressions as 'early childhood effects'. The 1972–1975 birth cohort was between 15 and 18 years of age in the 1991 census round. This treatment group, *Treatment 1*, is our benchmark group. To shed light on possible early childhood groups, the 1972 birth cohort was exposed to famine in their second year, the 1973 birth cohort experienced the famine in their first and second years, the 1974 birth cohort experienced famine in utero and in the first year, and the 1975 birth cohort that experienced the famine as a foetus. Finally, we confine the birth cohorts to four years before and after the famine period as our comparison group because these cohorts were not exposed to famine in their first two years of life or in utero. Our comparison group is the 1968–1971 birth cohort and the 1976–1979 birth cohorts.

To check the robustness of the estimated measures, our second treatment group, *Treatment 2*, includes the 1972–1976 birth cohort. We add the 1976 birth cohort to the first treatment group because although the famine was over in July 1975, persons born in early 1976 were exposed to famine in utero in 1975. In this case, our new control group includes the birth cohort born between 1967 and 1971 and 1977–1981, that is, the birth cohort born five years before and after the above mentioned new treatment group.

Our third treatment group, *Treatment 3*, consists of the 1972–1974 birth cohort as treatment group and the 1976–1978, 1968–1969, and 1971 birth cohorts as control group. In particular, we exclude the 1971 and 1976 birth cohorts from our regression sample as another way of addressing the potential "age-reporting" problem in our dataset; individuals born in these two particular years were aged ending in '0' and '5', that is, they were 20 and 15 years old, respectively, in 1991.

4.2 Potential Biases

Inter-district Migration: Despite several measures, selection biases may still prevail in our estimation in several ways. Persons in districts with a greater severity of famine might migrate to regions that are less famine stricken, as migration is not restricted in Bangladesh. Moreover, the 1991 census wave does not identify where someone was born, or where they lived during the famine. In a country that has such high migration rates, it may not be plausible to assume that where someone currently resides is where they have always lived. With this point in mind, we analyse the inter-district net migration data for between 1974 and 1981 (Map 4). Specifically, we run regressions of inter-district net migration rate,[17] the two food access measures, and the three flood severity measures. Table 2 reports that there is no significant relationship between famine and flood severity measures and net migration.[18] While we do not make a blanket conclusion that migration does not affect our results, we take comfort that at least it is not statistically related to our famine (i.e., food access) and flood severity measures.

Comparability of Treatment and Control Groups: An important concern with the treatment-control design is to ensure the comparability between the two groups. We take several measures to be able to meaningfully compare the birth cohorts born before, during, and after famine. First, using cohort fixed effects ensures that we control for later-life shocks that are common to all cohorts across Bangladesh. This means, for example, school expansion programs, changes in education policies, extended resources (e.g., teacher availability and quality), and other demographic and economic shocks common to all cohorts are controlled for. However, it is possible that cohorts living in different districts could have faced uncommon shocks, reducing

[17] Inter-regional migration in Bangladesh is mostly from rural to urban areas, so we can assume that net migration is dominated by out-migration from rural areas.

[18] The results do not change appreciably when we remove two major cities, Dhaka and Chittagong, from the sample.

comparability between the treatment and control cohorts in different districts. This problem is likely to arise due to differential famine severity faced by different district where different levels of famine severity might be correlated with different levels of future investment in education. To control for this possibility, we control for district-specific cohort trends (Appendix Table 5 panel A) and find that our estimates are robust to this issue.

Parental Controls: Our estimated results could be biased due to selection bias caused by parental characteristics. Nevertheless, when we control for parental characteristics (literacy and income sources of both parents in the regressions (Appendix Table 5 panel B), the results remain similar.

Infant/Child Mortality Bias: Neelsen and Stratmann (2011) find that cohorts with stronger genetic endowments are more likely to survive famine shocks. Using data from a small rural sample in Bangladesh, Razzaque et al. (1990) find that infant and child mortality were higher in areas affected during 1974-75 famine up to the 24-month period after famine. To our knowledge, no data on district-level infant mortality rates during the famine exist in Bangladesh to allow us to investigate the problem in our context. Therefore, we acknowledge that the ‘survival of the fittest’ effect (along with the fact that genetic endowments can affect the socioeconomic outcomes) could downwardly bias the literacy effects of famine.

Fertility Bias. People could respond to famine by differential fertility. If poorer people have fewer children during famine, this could also bias our literacy estimates downwards. In the absence of district-level data on births and deaths during famine, we estimate regressions to understand whether our food access indicators can predict sample size differences between the treatment and control group in the census data (Appendix Table 6). The results showed that famine effects are unlikely to be driven entirely by cohort size differences.

5. Empirical Results

Table 3 presents the estimated coefficients using interaction variables between treatment dummies and two severity measures. These measures include the change in rice-exchange rate of labour (%) between June and October 1974 and the change in rice production (%) between 1973 and 1974. Panel A presents the coefficients of interaction terms for our benchmark model (i.e., Model 1) for two outcomes—literacy and primary school dropout—exploiting two food access measures. Appendix Table 7 presents the results from the model where only one food access measure is adopted. The results are hardly any different than those in Table 3, implying that our food access measures are sufficiently independent and are not collinear.

In panel A of Table 3, the estimated coefficients of the interaction term between *Treatment 1*— that is equal to 1 if a person was born between 1972 and 1975 and equal to 0 if born between 1976 and 1979 or between 1968 and 1971—and the change in the rice-exchange rate of labour are −0.057 for literacy as outcome and 0.064 for primary school dropout as outcome (columns 1 and 4). This means that if the percentile change in the rice-exchange rate of labour in a district decreased by 1% from June to October 1974, the individuals of that district are 0.057% less likely to be literate and 0.064% more likely to have dropped out from primary school. These results are statistically significant at the 1% level. To gain a better understanding of the economic significance of these results, we translate these coefficients in terms of the population of Bangladesh in 1991. Given that 10% of the population born between 1968 and 1979 is 2,475,054, a coefficient of 0.057% would mean that for each one-standard-deviation increase in the percentage of rice-exchange rate of labour, an estimated 70,721 (=24,750,540 x 0.324 x 0.00057 x 15.472) children born during 1972–75 remained illiterate later in life in Bangladesh. Considering change in rice production, for each one-standard-deviation increase in this measure (i.e., increase in rice availability), an estimated 40,726 (=24,750,540 x 0.324 x 0.00039 x 13.022) children remained illiterate. This is a surprising result in that it implies that greater rice availability reduces the probability of literacy later in life. Considering that three standard deviations from the mean roughly covers 99% of the districts in normal distributions, our estimates suggest that more than 668,682 (6 x (70,721 + 40,726)) children remained illiterate because of lack of food access.[19]

Likewise, Panel B shows that a significant and positive number of children born during the famine dropped out of primary schooling later in life in Bangladesh. Our estimates with both famine severity measures (0.104 and 0.116) are significant at the 1% level. They suggest that, for an additional one standard deviation in rice-exchange of labour, an estimated 90,600 (=17,080,200 x 0.324 x 0.00104 x 15.472) children born during 1972–75 dropped out of school later in life. Similarly, for each one-standard-deviation increase in change in rice production, an estimated 83,593 (=17,080,200 x 0.324 x 0.00116 x 13.022) children dropped out of school. Again, this result is surprising at face value. Considering three standard deviations from the means of both severity measures, an estimated 1,045,158 children born during 1972–1975 dropped out of primary school later in life. The combined estimated effect of remaining illiterate and dropping out of primary school is 1,713,840 (=668,682 + 1,045,158) children.

Although the results obtained by exploiting the change in rice production across districts in Panel A and Panel B are statistically significant, the results are not consistent with our expectation that an increase in food production in a district is unlikely to reduce the literacy rates and accelerate primary school dropout rates of that district. We shed some empirical light on this explanation with three-way interactions in section 5.1 below.

We also conduct the same estimations exploiting *Treatment 2* and *Treatment 3* interacting them with the two famine severity measures in columns 2 and 3 and columns 5 and 6, respectively. We find qualitatively similar results for the three sets of treatment dummies.

[19] This exercise assumes that the effects from the two food access measures can be added. This assumption seems reasonable because Appendix Table A7 shows that our food access measures are sufficiently independent.

Taken together, the effects of famine are pronounced in districts where individuals lost entitlement to food access.

Previous studies (Islam et al., 2016; Islam et al., 2017) document that early-life exposure to shocks may extend beyond two years of age. Thus, inclusion of the pre-famine birth cohort in the control group could be problematic because they were also somewhat exposed to famine. Therefore, we estimate Model 1 using only those born after famine as the control group in order to examine the robustness of the basic results. The difference-in-differences estimates shown in Panel B in Table 3 remain strongly significant, confirming that our benchmark results are not driven by control group definition. As expected, the results presented in Panel B have higher coefficient magnitudes, possibly because the cohorts born before include famine-affected children (though to a lower degree than those born during famine), and removing them from the control group increases the coefficient.

Finally, Appendix Table A8 presents the results of the estimation where standard errors are clustered at the 19 greater-district levels. Our main results survive this robustness check.

5.1 The Role of Affluence in Famine Effects

We estimate Model (2) to understand whether wealth can provide further insights into our results. Our basic motivation here is that higher wealth means greater access to food, and this might even lead to speculative behaviour. Here, we exploit only the change in rice production (%) across districts. The results of the three-way interactions between the treatment dummies, the change in rice production (%), and wealth indicators are reported in Table 4, where the wealth indicator in Panel A is living in a brick-wall house, and in Panel B, living in a concrete-roof house. As indicated before, these indicators could be considered as proxy for affluence, greater access to (or control over) food due to possible associated land ownership.

In each regression, two coefficients are of interest: the two-way interaction between the treatment indicators and the change in rice production (%), and the three-way interaction between the treatment indicators, the change in rice production (%), and wealth indicators. The two-way interaction between the treatment indicators and the change in rice production is expected to be negative. The three-way interaction would then demonstrate whether higher wealth alleviated the adverse famine effect owing to lower rice availability and even provided an advantage for better education later in life. For this three-way interaction, we expect a positive sign for literacy because the famine-affected person living in a brick-wall house has a comparatively better chance of being literate and a negative sign for being a dropout because a child from an affluent family has lower chance of dropping out of school than someone in the associated comparison group.

As anticipated, the estimates of the three-way interactions concerning the three treatment indicators, the change in rice production (%), and living in a brick-wall house, are positive for the literacy outcome and negative for the primary school dropout outcome (columns 1 to 6). All three-way interaction estimates are statistically very significant at 1% to 5% levels. The three-way interaction coefficients for literacy outcome ranges between 0.094 and 0.17, suggesting that the probability of being literate of a famine-affected person with two other distinct features is 0.09% to 0.17% higher than a person in the comparison group. Crucially, the coefficients of the two-way interactions between treatment dummies and change in rice availability are lower (in absolute terms) than the three-way interaction coefficients. This suggests that potential higher access to resources provided an advantage for better education for a child born during famine later in life, *compared to a child with no famine exposure*. For example, in column (1), the two-way interaction coefficient is -0.049 while the three-way interaction coefficient is 0.094. This effect is sustained with other treatment dummies (columns 2 to 3). While not a direct evidence, this surprising finding could be interpreted as a support for the argument that wealthier households would have more access to (or control over) food, which may have been hoarded, such that their children had a better later-life education outcome than a survivor with no malnutrition exposure.

We estimate similar regressions for being a primary school dropout. The three-way interactions suggest that the probability of being a dropout of a famine-affected person from a district with more production of rice and living in a brick-wall house is lower compared with the counterfactual person (column 4). The coefficients exploiting *Treatment 2* and *Treatment 3* also provide us consistent results in this regard (columns 5 and 6).

Panel B replicates the regressions in Panel A but replaces the wealth indicator of living in a brick-wall house with living in a concrete-roof house. Results obtained from all the two-way and three-way interactions are qualitatively and statistically very consistent. For example, we find a positive and significant effect on literacy for the three-way interactions in the range of 0.089 to 0.159 for those who live in a concrete-roof house (columns 1 to 3), a result that is replicated qualitatively and statistically for primary school dropout (columns 4 to 6).

In Appendix Table A9, we also adopt a version of Equation (2) where wealth is interacted with the change in rice-exchange rate of labour (%) instead of rice production. We do not identify any significant (triple) interaction effect with the former, suggesting that the famine effects did not vary with socioeconomic status within the districts where the relative price of rice was higher with respect to labour. Our regressions identify only rice availability (not relative price) in triple interaction.

6. Double Catastrophe in Early-Life

The coefficients of our benchmark model in Model (1) could be biased by one of the deadliest floods in 1974 in Bangladesh that occurred concurrently with the 1974–1975 famine (Alamgir, 1980; Hernández-Julián et al., 2014). Hence, whether the effects of malnutrition in 1974 on the early childhood birth cohorts are engendered from the first disaster (i.e., famine), or whether they are biased by the second disaster (i.e., flood), are valid concerns.[20]

Extant literature has mostly investigated the impact of catastrophic shocks on early-life survivors focusing only on a single shock (Del Ninno & Lundberg 2005; Almond et al., 2007; Chen & Zhou, 2007; Meng & Qian, 2009; Goudet et al., 2011; Ampaabeng & Tan, 2013; Neelsen & Stratmann, 2011; Huang et al., 2013; Fan & Quian, 2015).[21] The double catastrophe provides unique opportunity to understand and disentangle the effects of two concurrent disasters on later-life outcomes. Crucially, the duration of severe famine (i.e., July 1974 to October 1974) coincided with the duration of heavy floods, yet the spatial intensity of both floods and famine in 1974–1975 varied greatly across districts in Bangladesh (Alamgir, 1980; Hernández-Julián et al., 2014). While the famine affected all of the districts in Bangladesh, the floods only affected a subset of districts (Alamgir & Salimullah, 1977; Sen, 1981). Thus, the spatial variation in both flood and famine severity, together with the variation in education outcomes across the cohorts, provide crucial information to quantify and compare the effects of these two concurrent exogenous shocks.

In this query, we augment our Model (1) with the district variation in three flood severity measures: height of flood inundation (ft), flood duration (months), and flood-affected areas (as a percentage of the total area of the district). Maps 5, 6 and 7 show the inter-district variation of flood intensity in terms of the maximum depth of flood inundation, period of flood inundation and the proportion of flood-affected areas as a percentage of the total area of the district, respectively.[22]

[20] Floods are one of the deadliest disasters around the globe. They account for the loss of almost 53,000 human lives in the past decade (EM-DAT, 2011). Several studies using floods in developing countries investigate their early-life malnutrition effects (Del Ninno & Lundberg, 2005; Goudet et al., 2011; Alderman et al., 2012). Floods are the most common type of annual catastrophe in Bangladesh (Mustafi & Azad, 2003; Rayhan, 2010).

[21] Alderman (1996) finds that the effects of successive shocks are stronger than a single shock on households' consumption smoothing.

[22] Considering the maximum depth of flood inundation, 13 districts experienced no flood, but famine was present in those districts. In terms of the duration of the flood, 10 districts were not affected by flood, but they were affected

6.1 The Concurrent Flood and Famine in 1974–1975 in Bangladesh

Flood is a frequent natural catastrophic event in Bangladesh (Mustafi & Azad, 2003; Rayhan, 2010). It occurs every year because of monsoonal rain falling in upstream rivers. Evidence suggests that approximately 60% of the land in Bangladesh is flood-prone, and 25% is overwhelmed by monsoon floodwater between June and October every year (Siddique, 2000).

The 1974 flood was the first major flood to occur after Bangladesh's independence. Despite regular floods in Bangladesh, the 1974 flood was unprecedented for several reasons. First, unlike most floods, which inundate large parts of land for several days or weeks between July and August every year, the 1974 flood began in June and lasted until October (Siddique, 2000; Mustafi & Azad, 2003). Second, the 1974 flood is the fifth largest flood between 1954 and 2004, in terms of flood-affected areas as a percentage of the total area of the country from the year (Hofer & Messerli, 2002). The flood covered more than 52,000 km^2 of land, that is, 36.84% of the country (Hofer & Messerli, 2002). Third, the scale of the flood was huge; nearly 2,000 people died (Alamgir & Salimullah, 1977), more than one million were injured and millions remained homeless between June and October 1974 (Davis, 2010). Further, the 1974 flood resulted in a considerable drop in production. It destroyed a major part of the *aus* rice crop (i.e., the principal rice crop), the seedlings of the *aman* (i.e., the second most important rice crop) and a part of the *boro* (i.e., another important rice crop). It is worth noting that the harvesting periods of *aman* and *boro* are July–August and April–June, respectively, and the transplanted period of *aman* is July–September (Alamgir, 1980; Sen, 1981; Dyson, 1991).[23]

According to Hofer and Messerli (2002), the 1974 flood hit the country in three phases. At the end of June, it attacked the districts situated in the north-western (i.e., Rangpur and

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by famine. Finally, in relation to the proportion of flood-affected areas as a percentage of the total area of the district, seven districts were affected by the famine only. The list of the flood-affected and flood-non-affected districts under each category of flood severity measure is presented in Appendix Tables 3 and 4.

[23] The major contemporaneous consequences of the 1974 flood in Bangladesh are presented in Appendix Table 2.

Pabna), north-eastern (i.e., Sylhet) and central-eastern (i.e., Mymensingh and Comilla) areas of Bangladesh. At the beginning of August, it reached the most severe phase and affected almost all districts. The final phase was regionally concentrated to the north western part of Bangladesh (i.e., Rangpur). Based on the available data for flood severity measures across districts, the maximum depth of flood inundation was recorded as 15 ft in Mymensingh followed by 13 ft in Sylhet and Chittagong; it persisted for the longest period in Pabna, followed by Dhaka, Rangpur and Mymensingh, for 5 months. In terms of the proportion of flood-affected areas as a percentage of the total area of the district, the highest value was recorded in Comilla (88.51%), followed by Dhaka and Tangail (Alamgir & Salimullah, 1977).

6.2. Data on 1974 Flood Severity Measures

The data on flood severity variables, maximum depth of flood inundation (ft), period of flood inundation (months) and the proportion of flood-affected areas as a percentage of the total area of the district, were accessed from the Government of Bangladesh, Water Development Board, Annual Report on Flood in Bangladesh 1974 and April 1975 that were compiled by Alamgir & Salimullah (1977). Importantly, the data were reported at the greater-district level, as there were 19 greater regions in Bangladesh in 1974. To obtain district-level flood severity measures, we specify to which region each of the current 64 districts belonged. This conversion approach results in flood severity measures for 64 districts.

6.3. Model Specification

Our first approach to investigate the role of double catastrophe in early life on education outcomes is to augment Model 1, where we additionally control for the interaction between treatment indicator and flood intensity across districts as follows:

$$
\begin{aligned}
&Y_{ijt} \\
&= \lambda_0 + \lambda_1 \left(Treatment\ 1_{it} \times FamineSeverity\ Index_j\right) \\
&+ \lambda_2 \left(Treatment\ 1_{it} \times FloodSeverity\ Index_j\right) + \lambda_3 \left(TreatmentDummy_{it} \times AgeCorrectionDummy_{it}\right) \\
&+ Male_i + Religion_i + Rural_i + yob_i + {yob_i}^2 + \alpha_j + \gamma_t \\
&+ \mathcal{E}_{ijt} \qquad (3)
\end{aligned}
$$

where $FloodSeverity\ Index_j$ denotes, in alternative regressions, the maximum depth of flood inundation (ft), the period of flood inundation (months), and the proportion of flood-affected areas as a percentage of the total area of the district. We only utilise *Treatment 1* and report the coefficients and *t*-statistics of λ_1 and λ_2 in Table 5. This approach would indicate whether our results related to famine are driven by floods or whether they still exert independent effects.

Importantly, we also estimate Model 1 by splitting the sample into two groups—'both flood and famine affected' and 'only famine affected'—to identify the dominant factor resulting in early-life malnutrition that led to adult education outcomes. As will be seen, this analysis yields quite surprising results.

6. 4. Long-Term Effects of the Double Catastrophe in Early Life: Estimation Results

The estimation results of Model 3 are reported in Table 5. Crucially, we verify that the effects of famine remain similar after controlling for the effects of floods in 1974. The coefficients of the two-way interaction terms for famine effects (using both famine measures) are roughly similar to those reported in Table 3, indicating that famine effect is relatively independent from floods. The table also reports the coefficients of the two-way interaction between *Treatment 1* and the flood severity measures. We find that the coefficients of the interaction between treatment dummy and the flood severity measures are comparatively weakly significant. Of the flood severity measures, period of inundation (months) is negative and significant at 5%, suggesting that the districts where inundation was longer by one month reduces likelihood of literacy in that district by 0.34%. The maximum depth of inundation is negative with a t-statistic 1.49, where the estimate suggests that an additional unit of flood height (ft) reduces the probability of literacy by 0.07%. The flood severity measure of share of flooded districts has no explanatory power on literacy. We also find almost similar results for the 'primary school dropout' outcome, with the interactions between treatment dummy and maximum depth of inundation and the period of inundation being significant around 10% and expected positive signs.

6.5. Single vs Double Catastrophe: 'Only Famine' vs 'Flood & Famine' Districts

Given that the flood and the famine in Bangladesh occurred at the same time and that famine affected all of the districts in Bangladesh but flood did not, it is plausible to expect that the long-term effects of early-life malnutrition on the 1972–1975 cohort differs between the sample from both the flood- and famine-affected districts and the sample from districts affected by the famine only. To investigate that, we estimate separate regressions for each education outcome by splitting our sample into two groups concerning both the flood and famine severity measures. The first subsample includes the individuals in 'flood- and famine-affected' districts, and the second subsample includes the individuals in the 'only famine-affected' districts. Here, we exploit only the rice exchange-rate of labour. Recall that, our results above suggest that food entitlement is strongly supported by the data, so we exploit the rice-exchange rate of labour as the famine severity measure for this analysis.

Table 6 presents the results. In our estimation, we initially expect the effects to be stronger for the sample of 'flood- and famine-affected' individuals than the 'only famine-affected' individuals, as the former group was shocked by the double catastrophe. However, surprisingly, our findings indicate that the chance of being literate is reduced by around 0.05%

in the sample of 'flood- and famine-affected' individuals, while it is reduced by a much larger rate, 0.16%, for 'only famine-affected' group (columns 1 and 2); these results are statistically significant at the 1% level. Further, the probability of an increase in primary school dropout rate is almost 0.06% higher for the sample of 'flood- and famine-affected' individuals and 0.14% for the 'only famine-affected' individuals. The results in columns 3 and 4 and columns 5 and 6 do not suggest any meaningful differences using the other two flood severity measures.

Overall, the results in Table 6 are contrary to our initial expectation mentioned above. This is not only because the effects are larger in the sample of 'only famine-affected' individuals compared with 'flood- and famine-affected' individuals, but also because, in many cases, the effects are at least twice as strong.

6.6. Are Distributional Mechanisms At Work? Gruel Kitchens

One plausible and measurable explanation for the above surprising finding is related to disaster alleviation mechanisms.[24] It is likely that interventions to counter the effects of famine, such as *langarkhanas* (gruel kitchens), could differ in 'flood- and famine-affected' vs. 'only famine-affected' districts. To examine this conjecture, we check the data on the number of *gruel kitchens* (per million people) across districts in 1974 and found that there were fewer, and sometimes none, in 'only-famine affected' districts (Figure 2 and Map 8).

To formally test if the number of *gruel kitchens* (per million people) differed in 'flood- and famine-affected' and 'only famine-affected' districts, we estimate some regressions.[25] We present the results in Table 7. Column 1 presents the coefficients of the rice-exchange rate of

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[24] Another plausible explanation might be that a major part of the "only famine affected" sample is from the hilly and rugged districts, for example Rangamati, Khagrachari, and Bandarban. Anecdotal evidence suggests that these geographically disadvantaged districts are also poor (Hossain, 2013).

[25] We source the data on the number of *gruel kitchens* per million people across the districts from Alamgir & Salimullah (1977). Importantly, these data were also obtained at the greater district level, and we employ the same conversion approach as we did to obtain three flood severity measures for 64 districts.

labour as a district-level famine severity measure. Columns 2–4 present the coefficients of three flood severity dummies: flood dummy 1, flood dummy 2, and flood dummy 3.[26] The coefficients presented in columns 1–4 are positive and significant.

Crucially, we also estimate a two-way interaction model with the interaction between famine severity and flood dummy, pointing to the existence of two catastrophes in a district. In column 5, the coefficient of the interaction term is positive and statistically significant at 1%, indicating that the 'famine-affected districts' that were also inundated by flood, had more *gruel kitchens*. In particular, in the districts that were affected by double shocks (i.e., both famine and flood), government might have established more *gruel kitchens* as a disaster-effect-smoothing mechanism. We also conduct the same exercise using flood dummy 2 and flood dummy 3 (columns 6 and 7) and our results are similar to those in column 5. These results suggest that that the alleviation mechanisms worked better in double-catastrophe districts, such that the probability of being literate and not dropping out of primary school was s higher in those districts compared to single-catastrophe (i.e., 'only famine-affected') districts as of 1991.

7. Conclusions

This paper presents causal evidence on the long-term consequences of early-life malnutrition arising from the 1974–1975 Bangladesh famine, one of the world's most fatal famines. Utilizing the 1991 microcensus dataset that contains 10.58 million person-observations, we exploit the variation between individuals exposed to famine-led malnutrition in their early childhood and

[26] Flood dummies are generated by using the three flood severity measures. They take 1 if the respective flood severity measure is strictly positive and 0 if not. An alternative approach is to use the continuous measure of flood severity across districts. However, since this section is mainly focused on affirming whether the effects of malnutrition in 1974 on the birth cohorts are engendered from famine, or whether they are biased by flood, the use of continuous measures of flood severity might not be a direct approach. Hence, the binary model is preferred. Crucially, experimenting with the treatment dummy interacting with continuous measure of the flood severity across districts does not pick up any statistically significant effects, suggesting that it is not the severity but the presence of floods that led to the establishment of *gruel kitchens* in districts.

a counterfactual group with no such malnutrition experience, and then to identify whether both groups differ in educational outcomes later in life.

Famines are typically thought to arise from severe food shortages. Sen (1981), in his account of the 1974–1975 famine in Bangladesh that ultimately won him the Nobel Prize, claimed that the disproportionate access to food in the time of food shortage, which was induced by weak institutions leading to entitlement issues, was a more crucial factor in famine than the concomitant decrease in food supply. With this compelling explanation in mind, we use two food access measures with spatial variation: the rice-exchange rate of labour and total rice production in each district. Our approach departs from most of the studies which use famine-related mortality to measure famine severity and is more tightly linked to the genesis of the famine.

Our key finding is that greater rice-exchange rate of labour (i.e., higher rice prices relative to the wage of a unit amount of labour) reduces the probability of literacy and increases the likelihood of dropping out of primary school later in life. Paradoxically, higher rice production decreases (increases) the probability of literacy (dropping out of primary school). Probing further into this finding, our investigation shows that children born to wealthier households during famine scored even better education outcomes than children with no famine exposure, potentially pointing to the greater food access of wealthier households. This advantage could point to the existence of hoarding in wealthy families, and lack of food entitlement for the broader population.

In a second unique contribution, the paper goes on to study a novel question of the effects of a double catastrophe – concurrent famine and flood experienced in early life. To the best of our knowledge, no study has hitherto analysed the effects of two such concurrent shocks faced by early-life survivors. The spatial variations in the distribution of famine and flood presence (i.e., famine occurred in all districts but floods occurred only in some districts) enable a unique natural experimental design to study this question. We use three different flood severity measures at the district level: height of flood inundation (ft), flood duration (months), and flood-affected areas (as a percentage of the total area of the district). Our findings suggest that although floods had adverse education outcomes for survivors, famine was a stronger cause of early-life malnutrition. We also find that, surprisingly, the effects were stronger in the sample of 'only famine-affected' districts as compared to the sample of 'both flood- and famine-affected' districts. We show that the early-life survivors located in double-catastrophe areas were thus advantaged because the government accumulated resources in areas where natural disaster exposure was the greatest.

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Table 1: Descriptive Statistics - Means

	Full Sample (1)	Experienced Both Famine and Flood (2)	Did not Experience Any Disasters (3)
Treatment dummy	0.324		
	(0.468)		
Age	16.316	16.558	16.200
	(3.557)	(1.240)	(4.236)
Birth year	1973.684	1973.442	1973.800
	(3.557)	(1.240)	(4.236)
Literacy	45.118	43.492	48.505
	(49.761)	(49.575)	(49.978)
Primary school dropout	61.750	63.939	57.190
	(48.600)	(48.018)	(49.480)
Male	0.504	0.513	0.499
	(0.500)	(0.500)	(0.500)
Rural	0.779	0.781	0.778
	(0.415)	(0.414)	(0.415)
Famine severity measures:			
The change in rice-exchange rate of labour (%)	41.777	41.797	41.768
	(15.472)	(15.428)	(15.493)
The change in rice production (%)	14.086	14.128	14.000
	(13.022)	(13.001)	(13.006)
Flood severity measures:			
Maximum depth of flood inundation (ft)	8.510	8.529	8.501
	(4.395)	(4.383)	(4.401)
Period of flood inundation (months)	2.747	2.748	2.745
	(1.320)	(1.321)	(1.318)
Number of Observations	2475054	802663	1672391

Notes: Column 1 includes individuals who were born between 1968 and 1979 and reside in Bangladesh in 1991. Column 2 includes individuals born in 1972–1975, who experienced both flood and famine in their first 24 months of life or remaining in utero. Column 3 includes individuals born during 1968–1971 and 1976–1979 who experienced neither flood nor famine in their critical age.

Table 2: The Relationship between Famine, Flood, and Migration

	Outcome: Net Migration Rate				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
The change in rice-exchange rate of labour	0.018				
	(0.65)				
The change in rice production (%)		0.066			
		(0.86)			
Maximum depth of flood inundation (ft)			-0.105		
			(0.48)		
Period of flood inundation (months)				-0.028	
				(0.72)	
Proportion of flood-affected areas as a % of the total area of the district					0.833
					(1.32)
Number of Observations	64	64	64	64	64
R^2	0.007	0.083	0.020	0.015	0.065

Notes: OLS regressions. Absolute t-statistics are in parentheses. *p<0.10, ** p<0.05, *** p<0.010. Standard errors clustered at the greater-district level.

Table 3: Long-Term Effects of 1974-75 Famine on Education Outcomes of Early-Life Survivors

Outcome→	Literacy			Primary School Dropout		
	1972-75 Cohort (1)	1972-76 Cohort (2)	1972-74 Cohort (3)	1972-75 Cohort (4)	1972-76 Cohort (5)	1972-74 Cohort (6)
Panel A: Control Group Includes People Born Before And After Famine						
Coefficients on ↓						
Treatment Dummy× The change in rice-exchange rate of labour	-0.057***	-0.088***	-0.087***	0.064***	0.091***	0.095***
	(5.966)	(5.882)	(6.550)	(5.434)	(4.691)	(5.537)
Treatment Dummy ×The change in rice production (%)	-0.039***	-0.051**	-0.054***	0.041**	0.057*	0.058**
	(2.916)	(2.372)	(2.858)	(2.394)	(1.821)	(2.168)
Number of Observations	2475054	3220132	2653520	2475054	3220132	2653520
R^2	0.078	0.110	0.087	0.075	0.132	0.094
Panel B: Control Group Includes People Born After Famine						
Coefficients on ↓						
Treatment Dummy × The change in rice-exchange rate of labour	-0.104***	-0.140***	-0.142***	0.113***	0.143***	0.153***
	(7.060)	(6.666)	(7.742)	(5.804)	(4.854)	(5.953)
Treatment Dummy × The change in rice production (%)	-0.116***	-0.105***	-0.106***	0.121***	0.116**	0.114**
	(4.110)	(2.992)	(3.326)	(3.404)	(2.212)	(2.449)
Number of Observations	1708020	2366218	1883963	1708020	2366218	1883963
R^2	0.066	0.115	0.084	0.067	0.149	0.098

Notes: Estimation of Model (1) using OLS. Each specification estimates separate regressions exploiting two severity measures interacted with treatment dummies. Coefficients on interaction variables are presented. Controls: rural, male, birth year, birth year squared, religious, treatment dummy interacted with age-heaping dummy, district fixed-effects and cohort fixed-effects. Treatment dummy 1 is equal to 1 if a person was born in 1972–1975, and is equal to 0 if born in 1976–1979 or in 1968–1971. Treatment dummy 2 is equal to 1 if a person was born in 1972–1976, and is equal to 0 if born in 1977–1981 or in 1967–1971. Treatment dummy 3 is equal to 1 if a person was born in 1972–1974, but is equal to 0 if born in 1976–1978 or 1968–1969 and 1971. Robust standard errors are clustered at the district level. Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

Table 4: Long-Term Effects of the 1974-75 Famine: The Role of Wealth Indicators

Outcome →	Literacy			Primary School Dropout		
	1972-75 Cohort (1)	1972-76 Cohort (2)	1972-74 Cohort (3)	1972-75 Cohort (4)	1972-76 Cohort (5)	1972-74 Cohort (6)
Panel A: Interactions with Brick-Wall House						
Living in a brick-wall house× The change in rice production (%)	0.134**	0.067	0.089*	-0.116***	-0.053	-0.068*
	(2.449)	(1.486)	(1.925)	(2.755)	(1.473)	(1.801)
Treatment Dummy × The change in rice production (%)	-0.049***	-0.070***	-0.070***	0.051***	0.076**	0.075***
	(4.150)	(3.136)	(3.784)	(3.167)	(2.378)	(2.801)
Treatment Dummy × Living in a brick-wall house	-2.487**	-2.745	-2.665*	1.446*	-2.265*	-0.512
	(2.530)	(1.566)	(1.930)	(1.770)	(1.998)	(0.558)
Treatment Dummy × The change in rice production (%) × living in a brick-wall house	0.094**	0.170**	0.150**	-0.101***	-0.166***	-0.157***
	(2.208)	(2.373)	(2.470)	(2.831)	(3.356)	(3.756)
Number of Observations	2465749	3209195	2643664	2465749	3209195	2643664
R^2	0.113	0.141	0.120	0.114	0.165	0.130
Panel B: Interactions with Concrete-Roof House						
Living in a concrete-roof house× The change in rice production (%)	0.196**	0.131**	0.155**	-0.175***	-0.102**	-0.124**
	(2.379)	(2.382)	(2.371)	(2.783)	(2.201)	(2.317)
Treatment Dummy × The change in rice production (%)	-0.044***	-0.061***	-0.063***	0.046***	0.066**	0.066**
	(3.618)	(2.821)	(3.394)	(2.831)	(2.144)	(2.529)
Treatment Dummy × Living in a concrete-roof house	-2.637***	-3.940**	-3.218**	1.704*	-1.162	0.039
	(2.693)	(2.316)	(2.408)	(1.925)	(0.927)	(0.039)
Treatment Dummy × The change in rice production (%) × living in a concrete-roof house	0.089**	0.159**	0.137**	-0.093**	-0.163***	-0.148***
	(2.017)	(2.177)	(2.154)	(2.461)	(3.124)	(3.245)
Number of Observations	2465749	3209195	2643664	2465749	3209195	2643664
R^2	0.096	0.126	0.104	0.096	0.150	0.113

Notes: Coefficients on interaction variables are presented. Controls: rural, male, birth year, birth year squared, religious, treatment dummy interacted with age-heaping dummy, district fixed-effects and cohort fixed-effects. Treatment dummy 1 is equal to 1 if a person was born in 1972–1975, and is equal to 0 if born in 1976–1979 or in 1968–1971. Treatment dummy 2 is equal to 1 if a person was born in 1972–1976, and is equal to 0 if born in 1977–1981 or in 1967–1971. Treatment dummy 3 is equal to 1 if a person was born in 1972–1974, but is equal to 0 if born in 1976–1978 or 1968–1969 and 1971. Robust standard errors are clustered at the district level. Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

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Table 5: Double Catastrophe in Early Life: Long-Term Effects of Concurrent Famine and Floods (1972-75 Birth Cohort)

Outcome→	Literacy			Primary School Dropout		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment dummy × The change in rice-exchange rate of labour (%)	-0.0554***	-0.0486***	-0.0457***	0.0644***	0.0527***	0.0565***
	(5.35)	(4.14)	(3.81)	(5.57)	(3.78)	(4.20)
Treatment dummy × The change in rice production (%)	-0.0435***	-0.0449***	-0.0401***	0.0410**	0.0488***	0.0416**
	(3.42)	(3.49)	(3.22)	(2.21)	(2.84)	(2.52)
Treatment dummy × Maximum depth of flood inundation (ft)		-0.0659			0.0892*	
		(1.49)			(1.72)	
Treatment dummy × Period of flood inundation (months)			-0.337**			0.230
			(2.07)			(1.62)
Treatment dummy × Proportion of flood-affected areas as % of the total area of the district	-0.00539			0.000222		
	(0.72)			(0.03)		
Number of Observations	2475054	2475054	2475054	2475054	2475054	2475054
R^2	0.078	0.078	0.078	0.075	0.075	0.075

Notes: Coefficients on interaction variables are presented. Controls: rural, male, birth year, birth year squared, religious, treatment dummy interacted with age-heaping dummy, district fixed-effects and cohort fixed-effects. Treatment dummy is equal to 1 if a person was born in 1972–1975, and is equal to 0 if born in 1976–1979 or in 1968–1971. Robust standard errors are clustered at the district level. Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

Table 6: Double Catastrophe in Early Life: Split-Sample Approach

Flood Severity Measure→	Maximum Depth of Flood Inundation (ft)		Period of Flood Inundation (months)		Proportion of Flood-Affected Areas	
	(1)	(2)	(3)	(4)	(5)	(6)
	Experienced Both Flood & Famine	Experienced Only Famine	Experienced Both Flood & Famine	Experienced Only Famine	Experienced Both Flood & Famine	Experienced Only Famine
Panel A: Outcome: Literacy						
Treatment dummy × The change in rice-exchange rate of labour (%)	-0.052***	-0.159***	-0.052***	-0.125***	-0.054***	-0.124*
	(5.392)	(4.212)	(5.368)	(3.261)	(5.810)	(2.308)
Number of Observations	2137141	337913	2259129	215925	2333820	141234
R^2	0.079	0.079	0.079	0.065	0.080	0.063
Panel B: Outcome: Primary School Dropout						
Treatment dummy × The change in rice-exchange rate of labour (%)	0.060***	0.143***	0.060***	0.144***	0.062***	0.154**
	(4.898)	(3.574)	(4.918)	(3.319)	(5.184)	(2.602)
Number of Observations	2137141	337913	2259129	215925	2333820	141234
R^2	0.075	0.077	0.075	0.068	0.076	0.066

Notes: Coefficients on interaction variables are presented. Controls: rural, male, birth year, birth year squared, religious, treatment dummy interacted with age-heaping dummy, district fixed-effects and cohort fixed-effects. Treatment dummy is equal to 1 if a person was born in 1972–1975, and is equal to 0 if born in 1976–1979 or in 1968–1971. Robust standard errors are clustered at the district level. Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

Table 7: Disaster Severity and Disaster Relief

Independent Variable↓	Outcome: Number of Gruel Kitchens (Langarkhanas) (per million people)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
The change in rice-exchange rate of labour	0.533**				-2.179***	-2.330***	-2.686***
	(3.35)				(6.97)	(19.47)	(1.07)
Flood dummy 1		46.603***			-53.093***		
		(6.64)			(4.49)		
Flood dummy 2			49.756***			-54.730***	
			(6.02)			(7.11)	
Flood dummy 3				54.022***			-75.606***
				(5.06)			(12.51)
The change in rice-exchange rate of labour × flood dummy 1					2.709***		
					(8.31)		
The change in rice-exchange rate of labour × flood dummy 2						2.883***	
						(18.14)	
The change in rice-exchange rate of labour × flood dummy 3							3.310***
							(26.66)
Number of Observations	64	64	64	64	64	64	64
R^2	0.107	0.481	0.446	0.389	0.985	0.673	0.637

Notes: OLS regressions at the district level. Rice- exchange rate of labour is a famine severity measure across districts. Flood dummy 1 is equal to 1 if a district had a strictly positive depth of flood inundation and 0 otherwise. Flood dummy 2 is equal to 1 if a district had a strictly positive period of flood inundation and 0 otherwise. Flood dummy 3 is equal to 1 if a district had a strictly positive proportion of flood-affected areas as a percentage of total area of the district and 0 otherwise. Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

Appendix

Appendix Table 1: Chronology of Events: The 1974–1975 Famine

Dates	Major Events
26 March-15 December in 1971	Liberation War
Flood in July-October 1974	Heavy rainfall and a series of troubling floods destroyed a major part of the *aus*, washed away the seedlings of the *aman* , and affected a part of *boro*
Between 1973 and 1974	Import of food grains from abroad was approximately 28% lower in 1974 than in the preceding year. However, the available food grains to feed people in 1974 was approximately 7% higher than it had been in 1973
Between June and October 1974	The decline in rice-exchange rate of labours was approximately 42%

Source: Alamgir & Salimullah, 1977; Alamgir, 1980; and Sen, 1981.

Appendix Table 2: Contemporaneous Consequences of the 1974 Floods

Items	**Number**
Death tolls *	1988
Number of persons affected *	29898320
Number of cattle heads lost *	46405
Flood-affected areas *(square km)* **	52,600
Flood-affected areas *(%)* **	36.84
Economic loss *(million taka)****	20,000
Loss of major crops *(000'tons)* ****	
Paddy	1500
Jute	354
Sugarcane	150

Source: * Alamgir & Salimullah (1977); ** Hofer & Messerli (2002); *** Khalequzzaman (2000); and ****Mustafi and Azad (2003).

Appendix Table 3: List of Flood Affected Districts in Bangladesh

Maximum Depth of Flood Inundation (ft)	Period of Flood Inundation (months)	Proportion of Flood-Affected Areas
Barisal	Barisal	Barisal
Bhola	Bhola	Bhola
Jhalokati	Jhalokati	Jhalokati
Pirojpur	Pirojpur	Pirojpur
Bogra	Bogra	Bogra
Joypurhat	Joypurhat	Joypurhat
Chittagong	Chittagong	Chittagong
Cox's Bazar	Cox's Bazar	Cox's Bazar
Brahmanbaria	Brahmanbaria	Brahmanbaria
Chandpur	Chandpur	Chandpur
Comilla	Comilla	Comilla
Dhaka	Dhaka	Dhaka
Gazipur	Gazipur	Gazipur
Manikganj	Manikganj	Manikganj
Munshiganj	Munshiganj	Munshiganj
Narayanganj	Narayanganj	Narayanganj
Narsingdi	Narsingdi	Narsingdi
Dinajpur	Dinajpur	Dinajpur
Panchagarh	Panchagarh	Panchagarh
Thakurgaon	Thakurgaon	Thakurgaon
Faridpur	Faridpur	Faridpur
Gopalganj	Gopalganj	Gopalganj
Madaripur	Madaripur	Madaripur
Rajbari	Rajbari	Rajbari
Shariatpur	Shariatpur	Shariatpur
Jamalpur	Bagerhat	Bagerhat
Kishoreganj	Khulna	Khulna
Mymensingh	Satkhira	Satkhira
Netrokona	Jamalpur	Chuadanga
Sherpur	Kishoreganj	Kustia
Feni	Mymensingh	Meherpur
Lakshmipur	Netrokona	Jamalpur
Noakhali	Sherpur	Kishoreganj
Pabna	Feni	Mymensingh
Sirajganj	Lakshmipur	Netrokona
Barguna	Noakhali	Sherpur
Patuakhali	Pabna	Feni
Chapai Nababganj	Sirajganj	Lakshmipur
Naogaon	Barguna	Noakhali
Natore	Patuakhali	Pabna
Rajshahi	Chapai Nababganj	Sirajganj
Gaibandha	Naogaon	Barguna
Kurigram	Natore	Patuakhali
Lalmonirhat	Rajshahi	Chapai Nababganj
Nilphamari	Gaibandha	Naogaon
Rangpur	Kurigram	Natore
Habiganj	Lalmonirhat	Rajshahi
Maulvi Bazar	Nilphamari	Gaibandha
Sunamganj	Rangpur	Kurigram
Sylhet	Habiganj	Lalmonirhat
Tangail	Maulvi Bazar	Nilphamari
	Sunamganj	Rangpur
	Sylhet	Habiganj
	Tangail	Maulvi Bazar
		Sunamganj
		Sylhet
		Tangail

Source: Author’s calculations using data on 1974 flood severity measures.

Appendix Table 4: List of Flood Unaffected Districts

Only Famine Affected Districts		
Maximum Depth of Flood Inundation (ft)	**Period of Flood Inundation (months)**	**Proportion of Flood-Affected Areas**
Bandarban	Bandarban	Bandarban
Khagrachhari	Khagrachhari	Khagrachhari
Rangamati	Rangamati	Rangamati
Bagerhat	Chuadanga	Jessore
Khulna	Kushtia	Jhenaidha
Satkhira	Meherpur	Magura
Chuadanga	Jessore	Narail
Kushtia	Jhenaidha	
Meherpur	Magura	
Jessore	Narail	
Jhenaidha		
Magura		
Narail		

Source: Author's calculations using data on 1974 flood severity measures.

Appendix Table 5: Robustness Checks

Outcome→	Literacy			Primary School Dropout		
	1972-75 Cohort (1)	1972-76 Cohort (2)	1972-74 Cohort (3)	1972-75 Cohort (4)	1972-76 Cohort (5)	1972-74 Cohort (6)
Panel A: Controlling for District-Specific Cohort Trends						
Coefficients on ↓						
Treatment Dummy× The change in rice-exchange rate of labour	-0.056***	-0.070***	-0.072***	0.063***	0.073***	0.079***
	(6.00)	(5.23)	(5.80)	(5.48)	(4.47)	(5.16)
Treatment Dummy ×The change in rice production (%)	-0.035***	-0.029*	-0.038**	0.037**	0.035	0.041*
	(2.80)	(1.71)	(2.37)	(2.31)	(1.45)	(1.90)
Number of Observations	2475054	3220132	2653520	2475054	3220132	2653520
R^2	0.080	0.112	0.089	0.076	0.136	0.097
Panel B: Controlling for Parental Characteristics						
Coefficients on ↓						
Treatment Dummy × The change in rice-exchange rate of labour	-0.057***	-0.088***	-0.087***	0.064***	0.091***	0.095***
	(6.00)	(5.88)	(6.57)	(5.45)	(4.68)	(5.54)
Treatment Dummy × The change in rice production (%)	-0.039***	-0.052**	-0.055***	0.041**	0.057*	0.058**
	(2.93)	(2.39)	(2.87)	(2.40)	(1.83)	(2.17)
Number of Observations	2475054	3220132	2653520	2475054	3220132	2653520
R^2	0.079	0.111	0.088	0.076	0.133	0.094

Notes: Estimation of Model (1) using OLS. Each specification estimates separate regressions exploiting two severity measures interacted with treatment dummies. Coefficients on interaction variables are presented. Controls: rural, male, birth year, birth year squared, religious, parental characteristics, treatment dummy interacted with age-heaping dummy, district fixed-effects, cohort fixed-effects and district-specific cohort trend. Treatment dummy 1 is equal to 1 if a person was born in 1972–1975, and is equal to 0 if born in 1976–1979 or in 1968–1971. Treatment dummy 2 is equal to 1 if a person was born in 1972–1976, and is equal to 0 if born in 1977–1981 or in 1967–1971. Treatment dummy 3 is equal to 1 if a person was born in 1972–1974, but is equal to 0 if born in 1976–1978 or 1968–1969 and 1971. Robust standard errors are clustered at the district level. Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

Appendix Table 6: Famine and Potential Selection

Outcome: Sample size difference between treatment and control group in Census Data		
	(1)	(2)
The change in rice-exchange rate of labour	-51.118	
	(0.774)	
The change in rice production (%)		54.017
		(0.454)
Number of Observations	64	64
R^2	0.009	0.008

Notes: OLS regressions. Absolute *t* statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.010. Standard errors clustered at the greater-district level.

Appendix Table A7: Using Food Access Measures Separately

Outcome→	Literacy			Primary School Dropout		
	1972-75 Cohort (1)	1972-76 Cohort (2)	1972-74 Cohort (3)	1972-75 Cohort (4)	1972-76 Cohort (5)	1972-74 Cohort (6)
Control Group Includes People Born Before And After Famine						
Panel A:						
Treatment Dummy× The change in rice-exchange rate of labour	-0.057***	-0.087***	-0.087***	0.064***	0.090***	0.094***
	(6.234)	(5.947)	(6.747)	(5.491)	(4.585)	(5.496)
Number of Observations	2475054	3220132	2653520	2475054	3220132	2653520
R^2	0.078	0.110	0.087	0.075	0.132	0.094
Panel B:						
Treatment Dummy × The change in rice production (%)	-0.038***	-0.050**	-0.053***	0.040**	0.055*	0.057**
	(2.886)	(2.251)	(2.766)	(2.366)	(1.756)	(2.112)
Number of Observations	2475054	3220132	2653520	2475054	3220132	2653520
R^2	0.078	0.110	0.087	0.075	0.132	0.093
Control Group Includes People Born After Famine						
Panel C:						
Treatment Dummy × The change in rice-exchange rate of labour	-0.103***	-0.138***	-0.141***	0.112***	0.141***	0.152***
	(6.144)	(6.254)	(7.228)	(5.144)	(4.499)	(5.524)
Number of Observations	1708020	2366218	1883963	1708020	2366218	1883963
R^2	0.066	0.115	0.084	0.067	0.149	0.098
Panel D:						
Treatment Dummy × The change in rice production (%)	-0.114***	-0.102***	-0.104***	0.119***	0.113**	0.111**
	(3.943)	(2.788)	(3.105)	(3.312)	(2.123)	(2.345)
Number of Observations	1708020	2366218	1883963	1708020	2366218	1883963
R^2	0.066	0.115	0.084	0.067	0.149	0.098

Notes: Estimation of Model (1) using OLS. Each specification estimates separate regressions exploiting two severity measures interacted with treatment dummies. Coefficients on interaction variables are presented. Controls: rural, male, birth year, birth year squared, religious, treatment dummy interacted with age-heaping dummy, district fixed-effects and cohort fixed-effects. Treatment dummy 1 is equal to 1 if a person was born in 1972–1975, and is equal to 0 if born in 1976–1979 or in 1968–1971. Treatment dummy 2 is equal to 1 if a person was born in 1972–1976, and is equal to 0 if born in 1977–1981 or in 1967–1971. Treatment dummy 3 is equal to 1 if a person was born in 1972–1974, but is equal to 0 if born in 1976–1978 or 1968–1969 and 1971. Robust standard errors are clustered at the district level. Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

Appendix Table A8: Long-Term Effects of 1974-75 Famine on Education Outcomes of Early-Life Survivors: Clustering Standard Errors at the Greater District Levels

Outcome→	**Literacy**			**Primary School Dropout**		
	1972-75 Cohort (1)	**1972-76 Cohort (2)**	**1972-74 Cohort (3)**	**1972-75 Cohort (4)**	**1972-76 Cohort (5)**	**1972-74 Cohort (6)**
Panel A: Control Group Includes People Born Before And After Famine						
Coefficients on ↓						
Treatment Dummy× The change in rice-exchange rate of labour	-0.057***	-0.088***	-0.087***	0.064***	0.091***	0.095***
	(4.368)	(4.053)	(4.649)	(4.103)	(3.235)	(4.001)
Treatment Dummy ×The change in rice production (%)	-0.039**	-0.051*	-0.054*	0.041*	0.057	0.058
	(2.220)	(1.739)	(2.055)	(1.851)	(1.444)	(1.622)
Number of Observations	2475054	3220132	2653520	2475054	3220132	2653520
R^2	0.078	0.110	0.087	0.075	0.132	0.094
Panel B: Control Group Includes People Born After Famine						
Coefficients on ↓						
Treatment Dummy × The change in rice-exchange rate of labour	-0.104***	-0.140***	-0.142***	0.113***	0.143***	0.153***
	(5.093)	(4.120)	(4.984)	(3.984)	(2.985)	(3.827)
Treatment Dummy × The change in rice production (%)	-0.116***	-0.105**	-0.106**	0.121**	0.116	0.114*
	(2.907)	(2.102)	(2.280)	(2.471)	(1.721)	(1.803)
Number of Observations	1708020	2366218	1883963	1708020	2366218	1883963
R^2	0.066	0.115	0.084	0.067	0.149	0.098

Notes: Estimation of Model (1) using OLS. Each specification estimates separate regressions exploiting two severity measures interacted with treatment dummies. Coefficients on interaction variables are presented. Controls: rural, male, birth year, birth year squared, religious, treatment dummy interacted with age-heaping dummy, district fixed-effects and cohort fixed-effects. Treatment dummy 1 is equal to 1 if a person was born in 1972–1975, and is equal to 0 if born in 1976–1979 or in 1968–1971. Treatment dummy 2 is equal to 1 if a person was born in 1972–1976, and is equal to 0 if born in 1977–1981 or in 1967–1971. Treatment dummy 3 is equal to 1 if a person was born in 1972–1974, but is equal to 0 if born in 1976–1978 or 1968–1969 and 1971. Robust standard errors are clustered at the greater district levels (**19 greater districts).** Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

Appendix Table A9: Long-Term Effects of the 1974-75 Famine: The Role of Wealth Indicators using Change in Rice-Exchange Rate of Labour

Outcome →	Literacy			Primary School Dropout		
	1972-75 Cohort (1)	1972-76 Cohort (2)	1972-74 Cohort (3)	1972-75 Cohort (4)	1972-76 Cohort (5)	1972-74 Cohort (6)
Panel A: Interactions with Brick-Wall House						
Living in a brick-wall house× The change in rice-exchange rate rate of labour	-0.016	-0.001	-0.011	0.009	0.013	0.008
	(0.277)	(0.018)	(0.219)	(0.166)	(0.295)	(0.155)
Treatment Dummy × The change in rice-exchange rate of labour	-0.057***	-0.085***	-0.085***	0.063***	0.085***	0.090***
	(6.035)	(5.273)	(6.190)	(5.041)	(3.955)	(4.857)
Treatment Dummy × Living in a brick-wall house	-1.101	-0.142	-0.442	0.193	-3.687**	-2.366
	(0.764)	(0.060)	(0.219)	(0.141)	(2.077)	(1.423)
Treatment Dummy × The change in rice-exchange rate of labour ×Living in a brick-wall house	-0.005	-0.010	-0.008	-0.001	-0.018	-0.004
	(0.174)	(0.232)	(0.205)	(0.024)	(0.554)	(0.126)
Number of Observations	2465749	3209195	2643664	2465749	3209195	2643664
R^2	0.113	0.141	0.120	0.114	0.165	0.130
Panel B: Interactions with Concrete-Roof House						
Living in a concrete-roof house× The change in rice-exchange rate of labour	-0.134	-0.110	-0.125	0.134	0.121	0.125
	(1.351)	(1.297)	(1.354)	(1.451)	(1.511)	(1.476)
Treatment Dummy × The change in rice-exchange rate of labour	-0.057***	-0.086***	-0.086***	0.065***	0.086***	0.092***
	(6.363)	(5.734)	(6.645)	(5.453)	(4.315)	(5.285)
Treatment Dummy × Living in a concrete-roof house	-2.181	-2.041	-2.116	2.224	-1.408	0.060
	(1.546)	(0.918)	(1.100)	(1.501)	(0.706)	(0.033)
Treatment Dummy × The change in rice-exchange rate of labour × living in a concrete-roof house	0.015	0.001	0.014	-0.041	-0.045	-0.046
	(0.522)	(0.023)	(0.363)	(1.315)	(1.112)	(1.159)
Number of Observations	2465749	3209195	2643664	2465749	3209195	2643664
R^2	0.096	0.126	0.104	0.096	0.150	0.113

Notes: Coefficients on interaction variables are presented. Controls: rural, male, birth year, birth year squared, religious, treatment dummy interacted with age-heaping dummy, district fixed-effects and cohort fixed-effects. Treatment dummy 1 is equal to 1 if a person was born in 1972–1975, and is equal to 0 if born in 1976–1979 or in 1968–1971. Treatment dummy 2 is equal to 1 if a person was born in 1972–1976, and is equal to 0 if born in 1977–1981 or in 1967–1971. Treatment dummy 3 is equal to 1 if a person was born in 1972–1974, but is equal to 0 if born in 1976–1978 or 1968–1969 and 1971. Robust standard errors are clustered at the district level. Absolute t-statistics are presented in parenthesis. *p<0.10, ** p<0.05, *** p<0.010.

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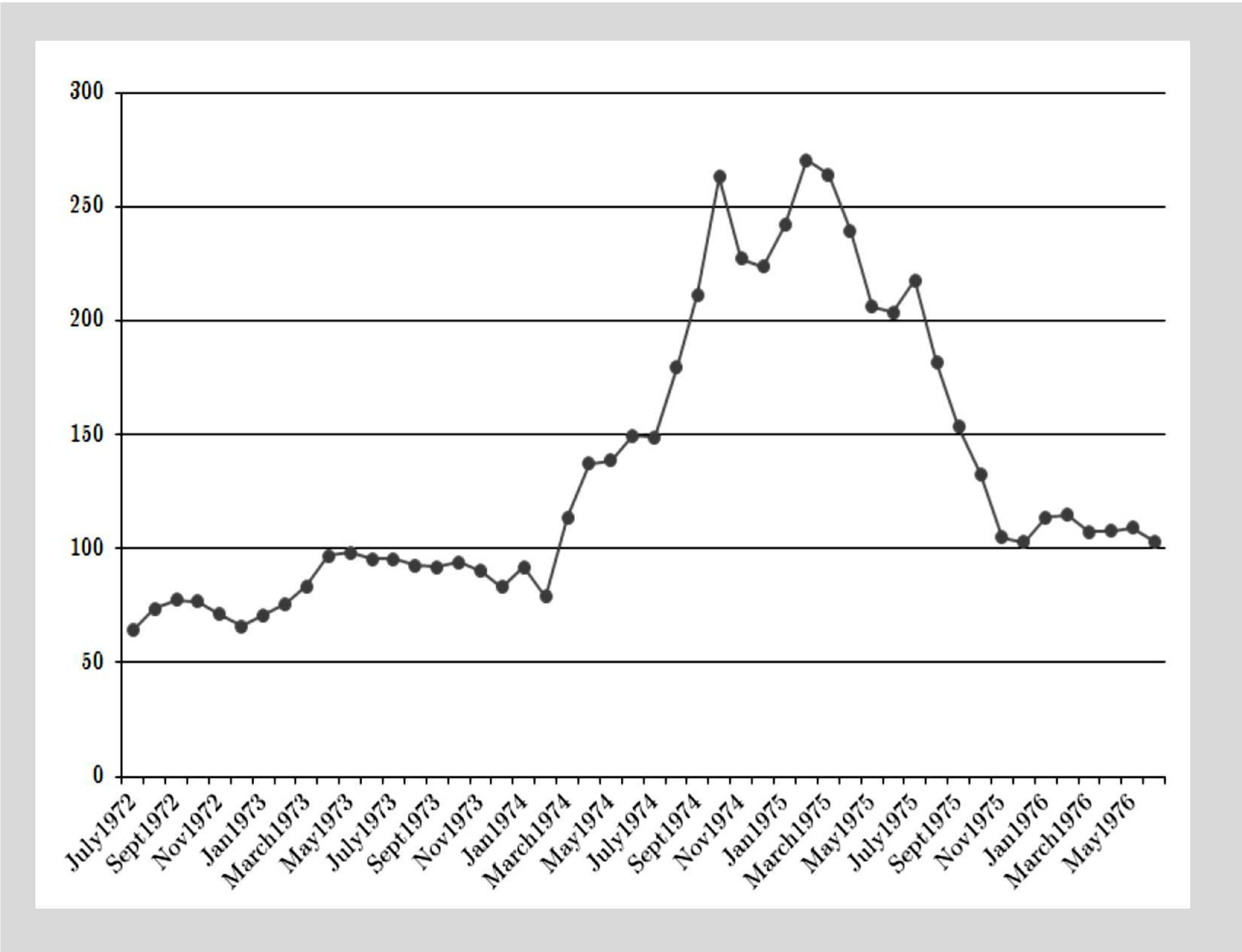
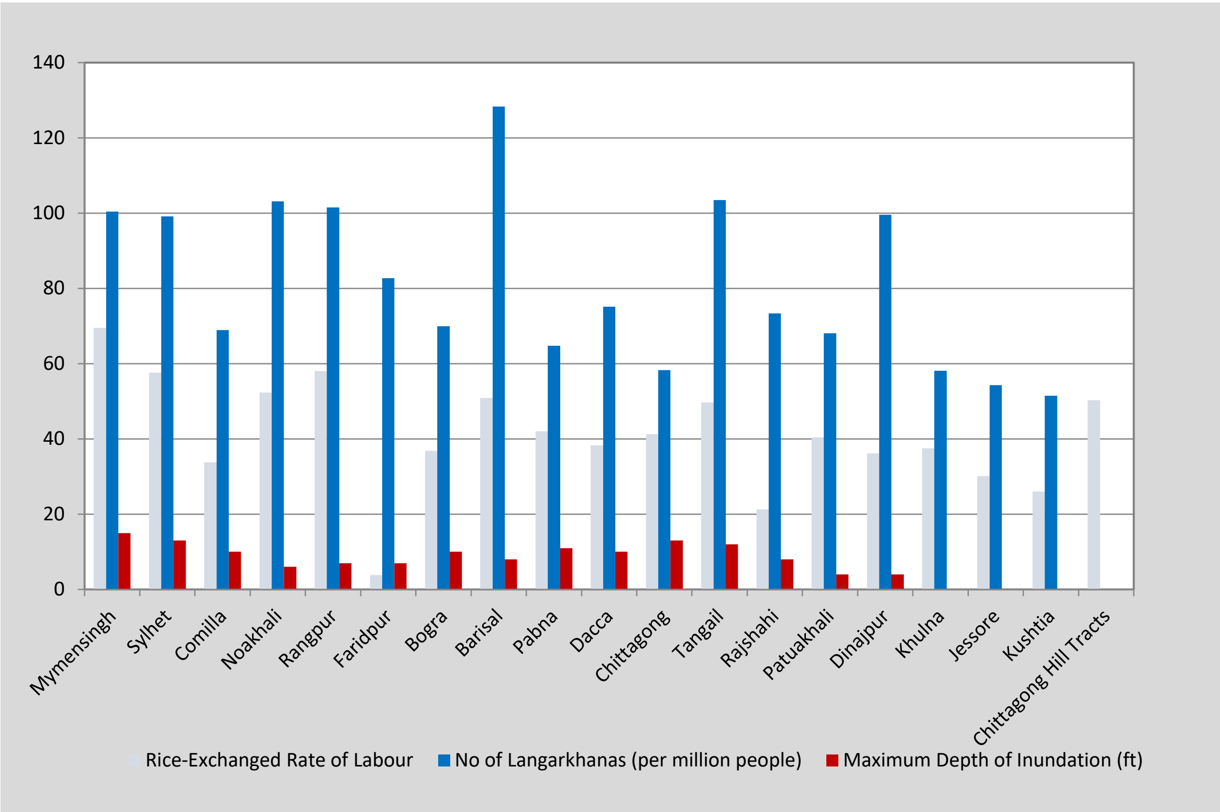
Figures

Figure 1: Average Retail Price Of Rice In Bangladesh (*In Taka Per Mound*)



Source: Hernández-Julián et al., 2013.

Figure 2: Rice-Exchange Rate Of Labour (*In Percentage*), Flood Inundation (*FT*) And Number Of Langarkhanas (*Per Million People*) Across Districts, 1974

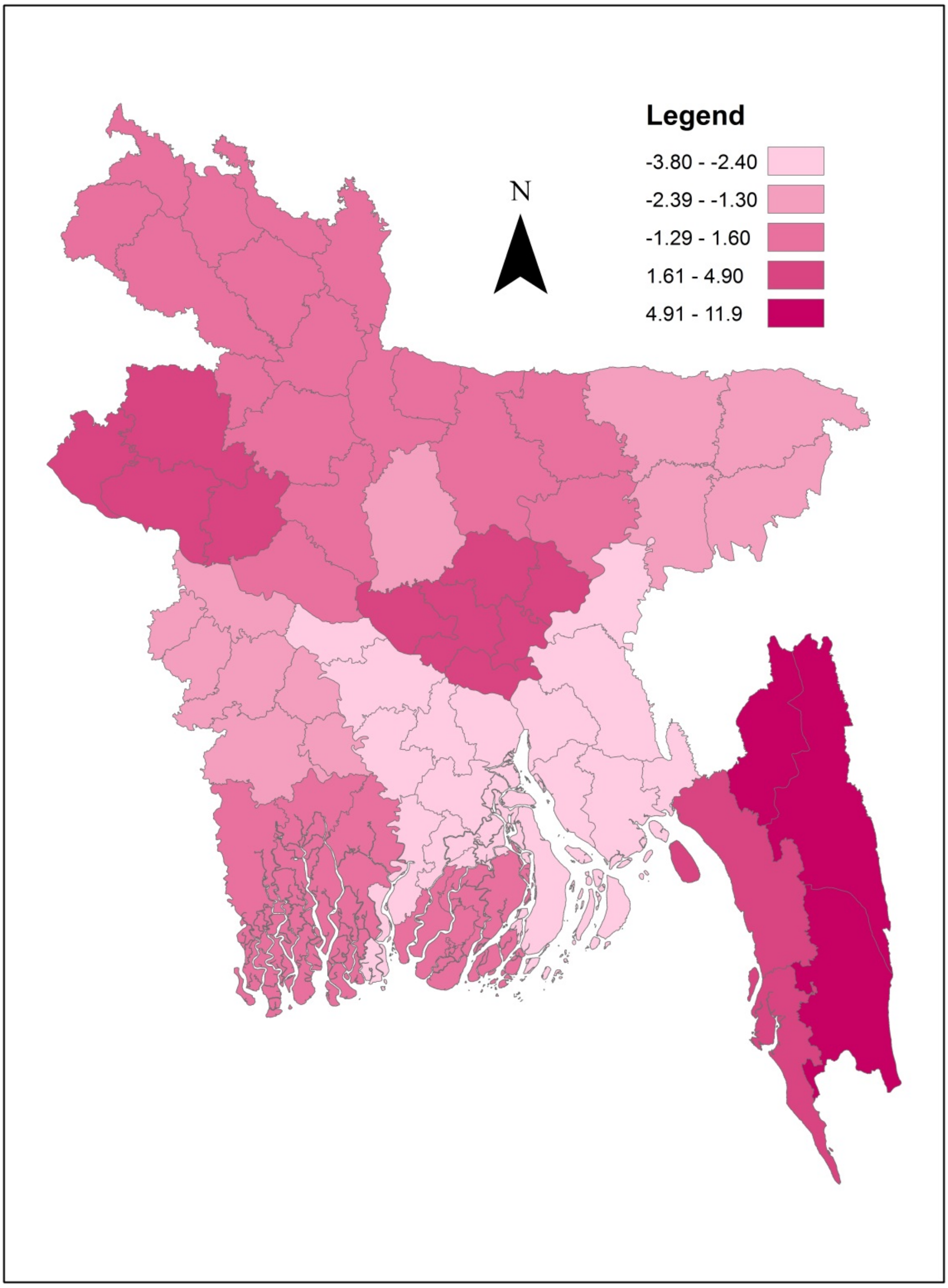


Source: Authors' calculation. Data on the district-level number of langarkhanas and maximum depth of inundation are obtained from Alamgir & Salimullah (1977) and Data on rice-exchange rate of labour are obtained from Sen (1981).

Map 1: Flooded Districts *(Greater)* In Bangladesh, 1974

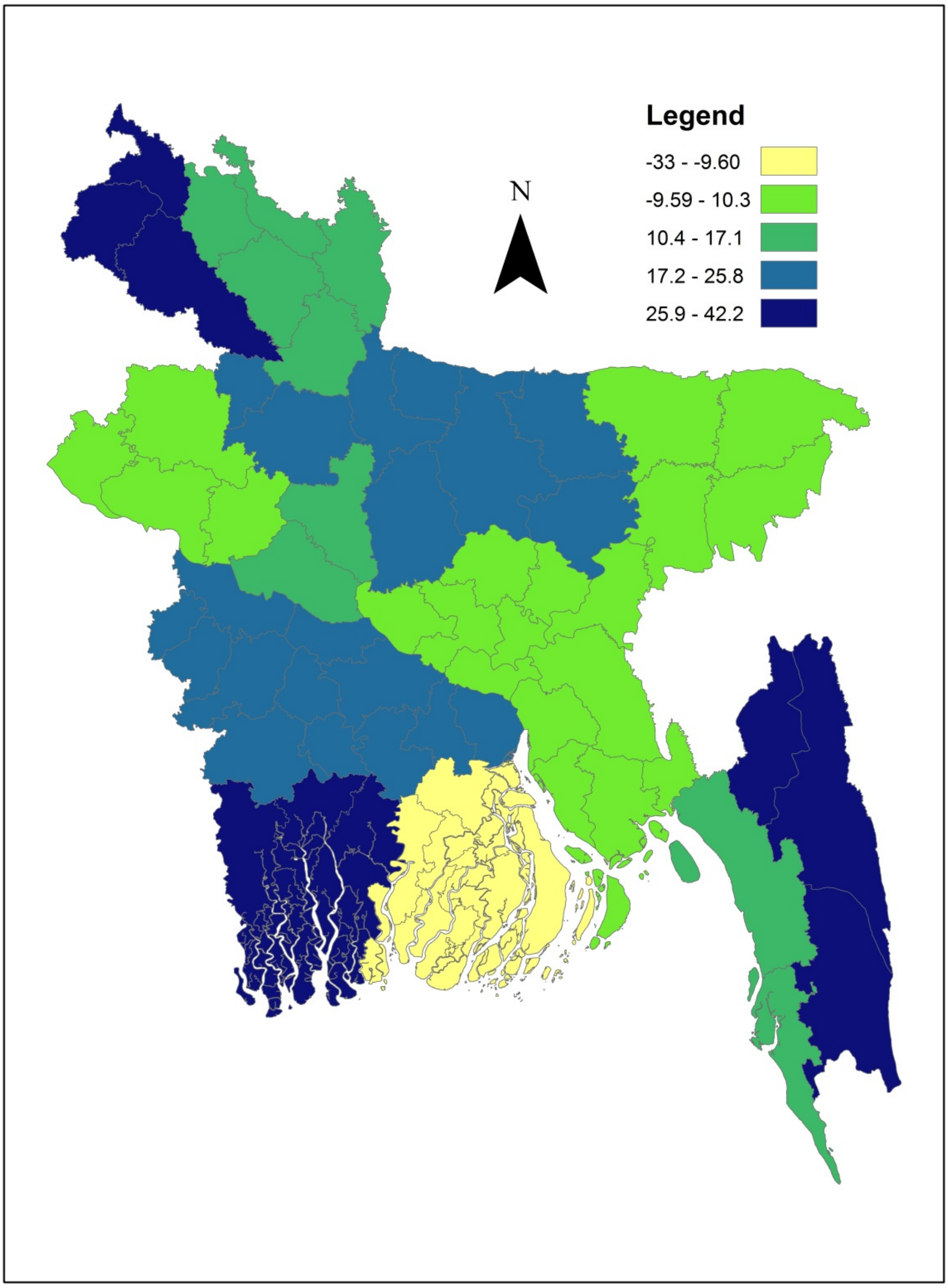
Source: http://www.banglapedia.org/httpdocs/Maps/MF_0103A.GIF.

Map 2: The Decline in Rice-Exchange Rate of Labour Across Districts, June-October 1974



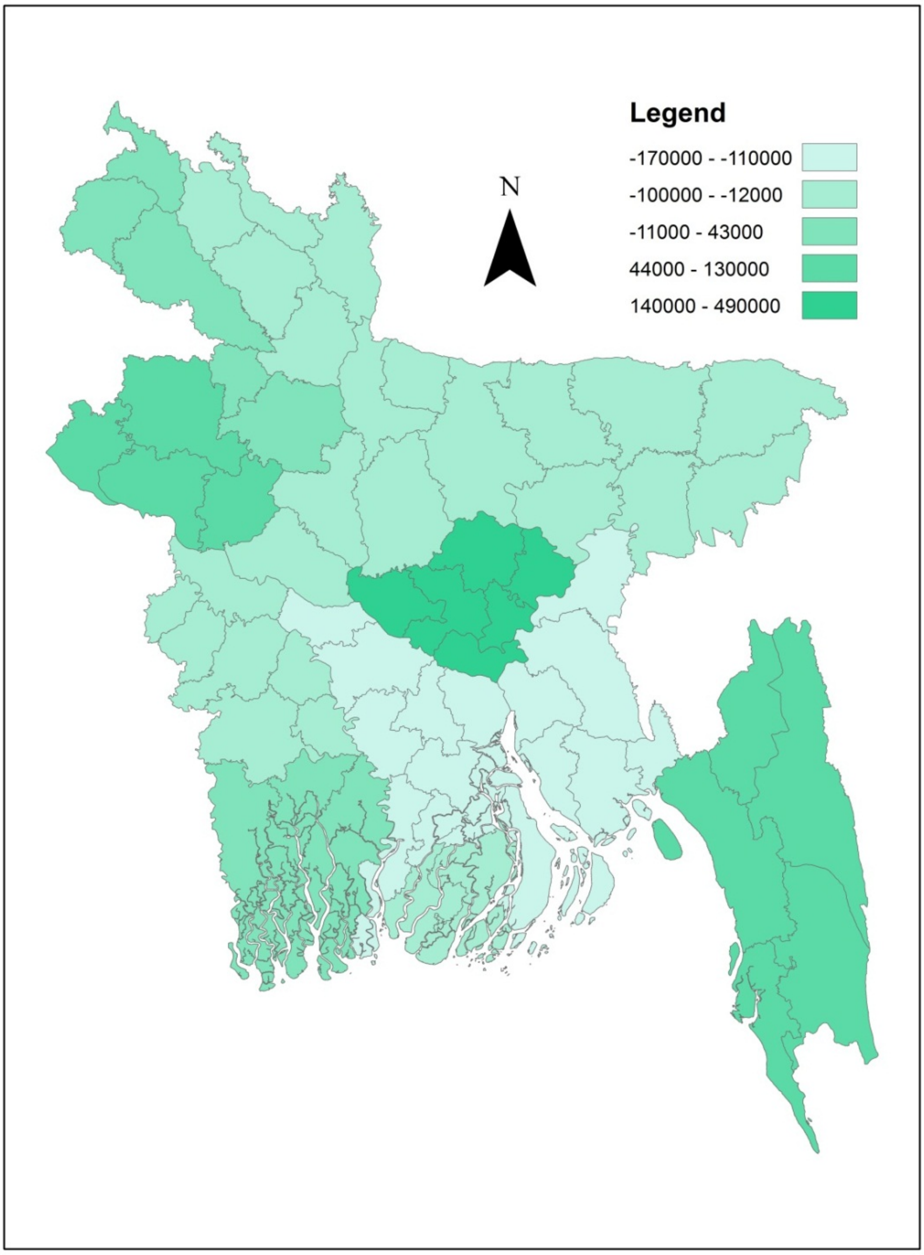
Source: Data presented in this map are obtained from Alamgir & Salimullah, (1977); and Sen (1981).

Map 3: Change in Rice Production in Districts, 1973–1974



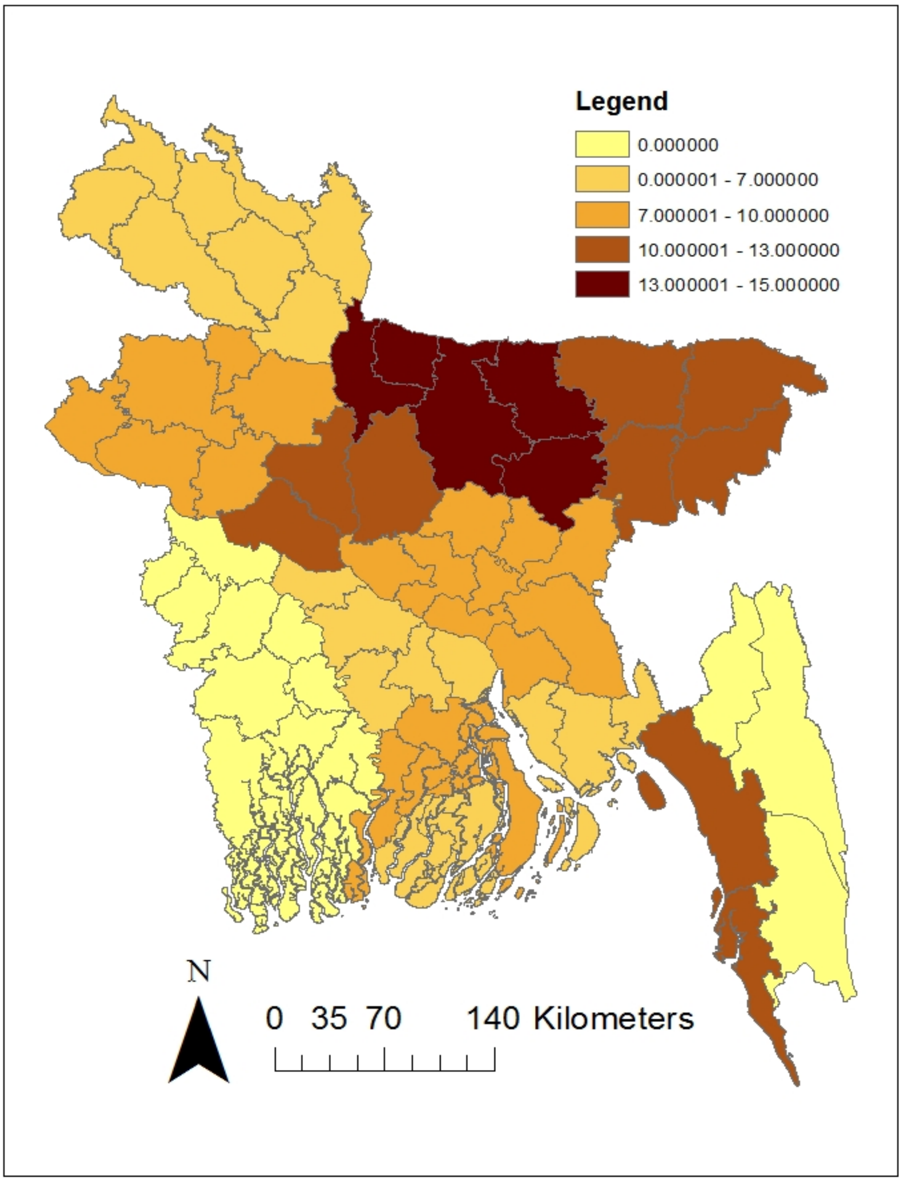
Source: Data presented in this map are obtained from Alamgir & Salimullah, (1977); and Sen (1981).

Map 4: District-Wise Net Migration, 1974-1981



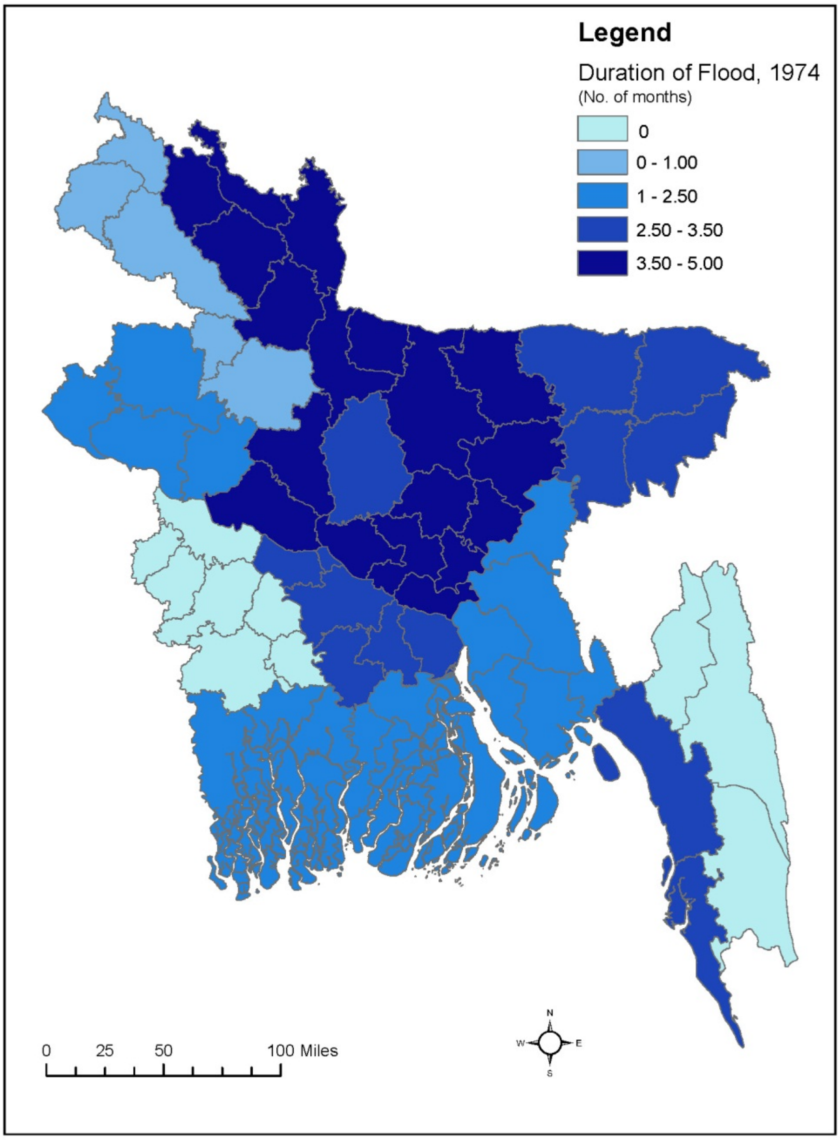
Source: Data presented in this map are obtained from Nabi (1992).

Map 5: Maximum Depth of Flood Inundation *(Ft)* in Districts, 1974



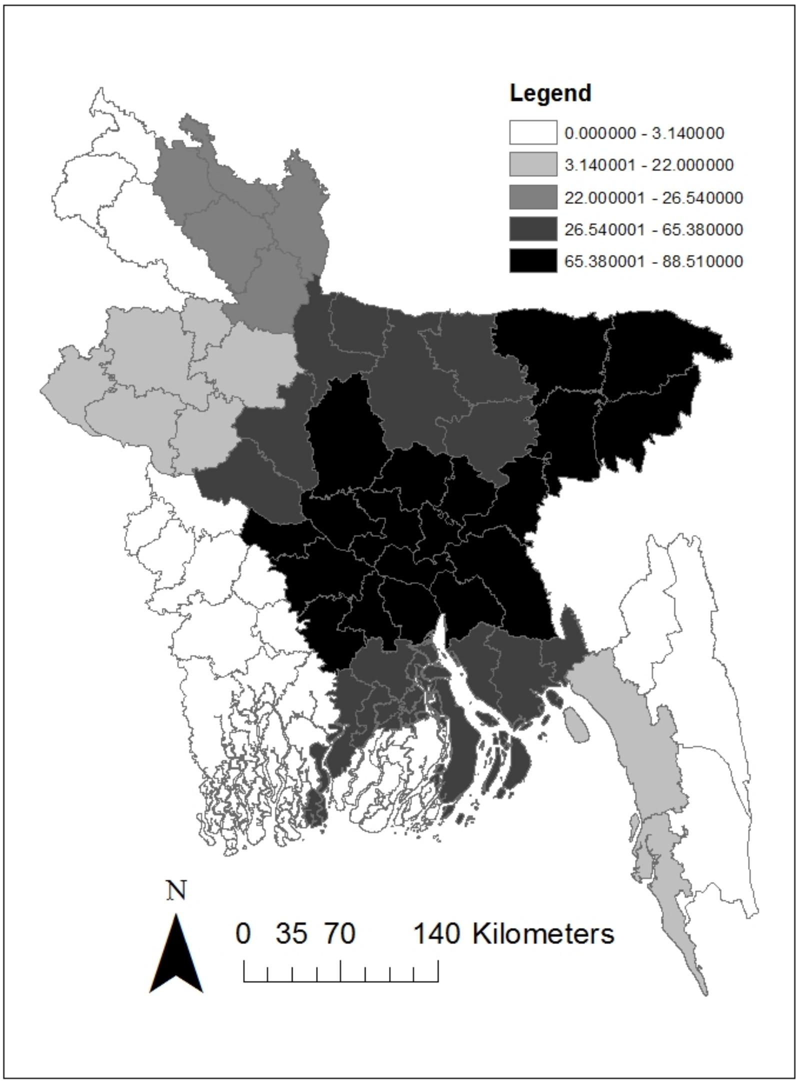
Source: Data presented in the map are obtained from Alamgir & Salimullah (1977).

Map 6: Duration of Flood Inundation *(In Months)* in Districts, 1974



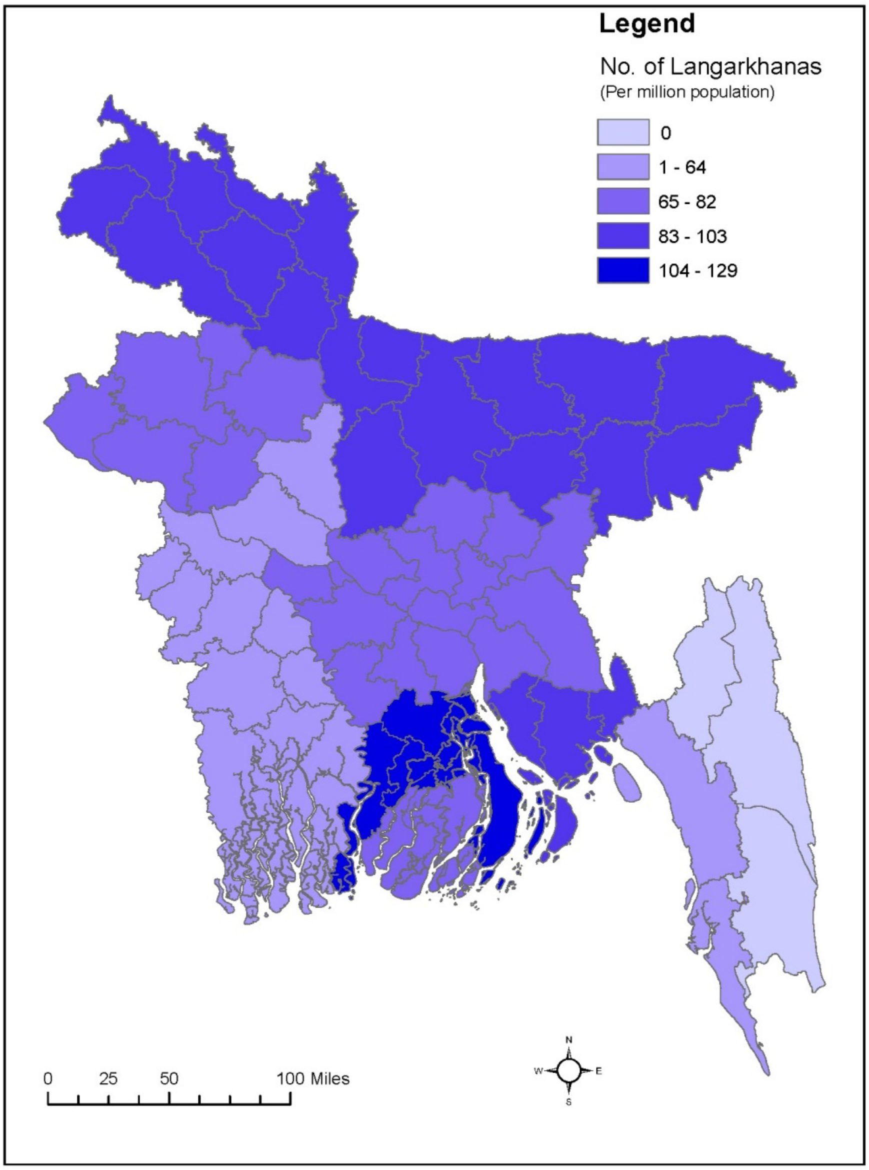
Source: Data presented in the map are obtained from Alamgir & Salimullah (1977).

Map 7: Total Flood-Affected Area in the Total Surface Area of the Districts *(%)*, 1974



Source: Data presented in the map are obtained from Alamgir & Salimullah (1977).

Map 8: The Number of Langarkhanas *(Per Million People)* in Districts, 1974



Source: Data presented in the map are obtained from Alamgir & Salimullah (1977).