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Essays on the Determinants of Women's and Children's Health in Bangladesh

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Essays on the Determinants of Women's and Children's Health in Bangladesh

by

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of the requirements for the degree of
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ABSTRACT

My dissertation is titled "The Determinants of Women's and Children's Health in Bangladesh." The first chapter studies the impact of a Bangladeshi schooling program on child immunization rates. The program provided a stipend and other incentives to attend secondary school, significantly increasing rural girls' education. I hypothesize that this would lead to higher immunization rates in the next generation since better-educated mothers have better knowledge of health practices. The study uses a regression model ("difference-in-differences"), which is based on differential exposure to the 1994 Female Secondary School Stipend Program (FSSSP) by birth cohort and rural residence. I find that the FSSSP significantly increased education among rural girls and increased their children's full immunization rates.

The second chapter examines the effect of the education stipend program on women's obesity in Bangladesh. Obesity is a growing public health problem in Bangladesh, with 32.4% of women classified as overweight or obese. My project examines whether higher education and the resulting increase in income could explain the trends in obesity. This Chapter uses the same identification strategy as in Chapter One, based on the 1994 FSSSP, to identify causal effects. The study finds that obesity rates increase more among women eligible for a 5-year stipend than among women eligible for a 2-year stipend.

The third chapter investigates the impact of tropical storms on child health in Bangladesh. Bangladesh has the world's 9th (27.90%) highest risk of natural disasters because of its geographic location, landscape, population density, and poverty. Tropical storms may affect household income/wealth and access to maternal healthcare, which, in turn, influence child health. I use linear regression with "fixed effects", which capture geographic and temporal variation in child health and tropical storm exposure. I find that in-utero exposure to tropical storms decreases the height-for-age, weight-for-height, and weight-for-age z-scores among children under five and increases the probability of stunting, wasting, and becoming underweight. The findings suggest that exposure to natural disasters can have important long-term effects on child health, and the impact depends on the timing of exposure.

This research provides new information on the determinants of women's and children's well-being in Bangladesh.

CHAPTER ONE:

THE IMPACT OF MATERNAL EDUCATION ON CHILD IMMUNIZATION: EVIDENCE FROM BANGLADESH

Md Shahjahan, Giulia La Mattina, and Padmaja Ayyagari *

Note to Reader

Portions of this chapter have previously been published in the *IZA Discussion Paper Series* (2022), IZA DP No. 15553. The copyright permission for reuse is in Appendix Figure A3.

Introduction

A large literature has documented a positive correlation between maternal education and child health in low- and middle-income countries (LMICs). Recent studies have attempted to identify causal effects by relying on quasi-experimental variation in schooling access generated by policies such as compulsory schooling laws, tuition subsidies, or school construction programs. However, the evidence for such inter-generational spillovers is mixed.[1] While some studies find

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[1] Studies based on high-income countries such as the US also find mixed results. For example, Currie and Moretti (2003) find that increasing the availability of colleges leads to significant improvements in infant health while McCrary and Royer (2011) find that school entry policies have small effects on infant health.

improvements in child health outcomes and inputs (Breierova and Duflo 2004; Chou et al. 2010; Grepin and Bharadwaj 2015; Hahn et al. 2018a; 2018b; Wu 2022; Mazumder et al. 2023), others find no impacts or only find impacts on some measures of health (Zhang 2012; Ali and Elsayed 2018, Akresh et al. 2023). Further, it is unclear whether the difference in findings across these studies is due to differences in the measures of health used, the margin of education that was targeted (e.g., primary vs secondary schooling), or contextual factors that are specific to the policy or country being studied. Thus, there is a need for further research on this topic.

We contribute to this literature by examining the inter-generational impact of a stipend program on child immunizations in Bangladesh. The Female Secondary School Stipend Program (FSSSP) was introduced in 1994 and provides a cash stipend to girls in rural areas enrolled in secondary school (grades 6-10). Several studies have shown that the FSSSP significantly increased schooling among girls eligible for the stipend (Khandker et al. 2003; Raynor 2006; Fuwa 2006; Schurmann 2009; Hong and Sarr 2012; Hahn et al. 2018a; 2018b; Khandker et al. 2021; Wu 2022; Sara and Priyanka 2022). There is also evidence of improvements in some measures of maternal and child health outcomes and inputs. Previous studies have found improvements in infant and child mortality, anthropometric measures, hemoglobin levels, antenatal care use, postnatal care use, and institutional delivery, but not in birthweight or anemia (Hahn et al. 2018a; 2018b; Wu 2022).[2] To our knowledge, no study has examined the impact of the FSSSP on child immunizations.

Our focus on child immunizations is motivated by several factors. First, immunizations are widely accepted as one of the safest and most cost-effective ways to reduce the incidence of deadly

[2] Studies have also found that the stipend program led to increases in the age at marriage, assortative mating, greater female autonomy, increased contraceptive use, improved labor market outcomes for women, increased age at first birth, decreases in the number of children (Hahn et al. 2018a; 2018b; Hong and Sarr 2012), improvements in younger siblings' education (Begum et al. 2017), and decreases in intimate partner violence (Sara and Priyanka 2022).

diseases during childhood (UNICEF).[3] Despite remarkable progress in immunizations over the past two decades, full immunization rates have remained below 90% in Bangladesh (Figure 1.1), and the country experienced 82 measles outbreaks in 2019, raising concerns about vaccination rates. Second, empirical evidence on the causal link between maternal education and child immunizations is limited and mixed. Özer et al. (2018) examine the impact of a compulsory schooling reform in Turkey and find that maternal education increases the probability that their children are fully immunized. Keats (2018) examines a Ugandan reform that eliminated primary school fees and finds that children born to women with more schooling are more likely to be fully vaccinated. In contrast, Grepin and Bharadwaj (2015) find no impact of maternal schooling on child immunizations when examining expanded access to secondary schooling in Zimbabwe, although they do find improvements in other child health outcomes. Notably, Özer et al. (2018) and Keats (2018) focus on primary schooling reforms while Grepin and Bharadwaj (2015) focus on a secondary schooling reform, suggesting that the margin of maternal education may be important when considering its impact on child health investments.

Using a difference-in-differences approach based on differential exposure to the FSSSP by birth cohort and rural residence, we find that the rate of full immunization increases by 2.7 percentage points and the rate of any immunization increases by 1.1 percentage points among children born to mothers exposed to FSSSP for 5 years, relative to children of mothers who were not exposed. In contrast, immunization rates do not change among children born to mothers exposed to FSSSP for only 2 years. We explore several potential mechanisms by which the stipend program may influence child immunizations, including income effects, quality-quantity tradeoffs, female autonomy, improved health knowledge and access to care. Although this analysis is

[3] Source: https://www.unicef.org/immunization (last accessed 3/15/2023)

descriptive and does not identify causal mechanisms, our results suggest that quantity-quality tradeoffs and improved health knowledge may be important pathways. Our findings show that the secondary schooling programs that are only targeted towards girls can have important inter-generational effects on child health.

The 1994 Female Secondary School Stipend program (FSSSP) in Bangladesh

The Female Secondary School Stipend Project (FSSSP) was originally introduced by the Bangladesh Association for Community Education (BACE) with financial support from USAID and the Asia Foundation as a pilot project in 1982 (Schurmann 2009). The pilot project began in the Shahrasti upazila of Chandpur district and Kaharole upazila of Dinajpur district.[4] From 1987 to 1992, the Norwegian Agency for Development Cooperation (NORAD) expanded the stipend program to one additional upazila every year (Khandker et al. 2021). The pilot project was successful in increasing girls' secondary school enrollment from an average of 7.9% to 14% in some project areas and reducing dropout rates from 14.7% to 3.5% (Raynor et al. 2006). This pilot project's success was the basis for launching the nationwide FSSSP in 1994, which is the focus of our study.[5] The main goal of the FSSSP was to reduce gender inequality in secondary education (grades 6-10, ages 11-15).[6] Under this program, girls attending a secondary school in rural areas were eligible for a stipend and full tuition subsidy if they satisfied the following criteria: i) attended at least 75% of all school days, ii) secured a score of at least 45% in the annual exam, and iii)

[4] An upazila is a small administrative division in Bangladesh, similar to a county in the United States.
[5] Only eight upazilas out of about 500 upazilas in Bangladesh received the stipend program before 1994. Moreover, the stipend was not uniformly provided across all schools within these upazilas before 1994. Since our focus is on the nationwide program, we categorize girls exposed to the pilot projects but not the nationwide program as part of our "unexposed" group. To the extent that the pilot project may have led to higher immunization rates among the children of some women in the unexposed group, our main specification underestimates the true effect of the stipend program.
[6] Other goals included increasing female age at marriage and improving employment capabilities. See Fuwa (2006) and Raynor et al. (2006) for a more detailed discussion of the background and goals of the FSSSP.

remained unmarried. Boys and urban residents were not eligible for the program. Figure 1.2 shows that secondary school enrollment increased much faster among girls than boys after the introduction of the FSSSP at the national level.

In 1994, only girls enrolled in grades 6 and 9 were eligible for the stipends, while in 1995, girls enrolled in all grades except grade 8 were entitled to receive the stipends. From 1996 onward, girls enrolled in all secondary education grades (grades 6–10) qualified for the stipends (Khandker et al. 2003). This generates variations in the duration of exposure to the program for rural girls: those born in 1980–1982 (aged 12–14 and enrolled in grades 7–9 in 1994) received two years of stipends, those born in 1983 or later (aged 11 or younger and enrolled in grades 1-6 in 1994) received five years of stipends, and those born before 1980 (aged 15 or older in 1994) received no stipends as they were enrolled in grade 10 or had already exceeded secondary-school ages in 1994 (Hahn et al. 2018b). Figure 1.3 illustrates the variation in exposure to the program by birth cohort and grade. For example, a girl born in 1983 would be in grade 6 in 1994 and eligible for five years of stipends whereas a girl born in 1980 would be in grade 9 in 1994 and only eligible for two years of stipends. A girl born in 1979 would be in grade 10 in 1994 and would not be eligible for FSSSP. Women born in 1983 or later who received stipends for 5 years are categorized as “Fully exposed”, women born between 1980 and 1982 are categorized as “Partially exposed” and women born in 1979 or earlier are categorized as “Unexposed”.

The stipend amounts varied by grade. In 1994, the annual stipends were equivalent to US $18 in grade 6 and US $36 in grade 9, while in 1995, stipends were US $20 in grade 7, US $45 in grade 10, and US$22 in grade 8 in 1996 (Hahn et al. 2018a). In comparison, the average annual income was US$1011.65 in rural areas and US$1920.71 in urban areas in 1993-1994.[7] The stipend was expected to cover up to 50% of direct educational expenses (textbooks, uniforms, examination fees, etc.) and was paid directly to the girls in two equal annual installments in the presence of the school teachers and officers of Agrani Bank Limited, a state bank with branches in rural Bangladesh (Liang 1996; Mahmud 2003). The tuition subsidy was paid directly to the school. The nationwide rollout of FSSSP took place rapidly between 1994 and 1995. The number of FSSSP recipients increased from 1.9 million (9.3% of girls enrolled in secondary school) in 1994 to 4.2 million (96.2% of girls enrolled in secondary school) in 2002 (BANBEIS 2006). Beginning in mid-2003, stipend awards were cut back and greater monitoring of disbursements was introduced leading to a drop in the number of recipients (Raynor et al. 2006). Figure 1.2 shows that secondary school enrolment plateaued for both sexes at the national level after 2003.[8]

The FSSSP has been widely studied and is generally considered to be successful in achieving its goal of increasing female secondary schooling (Khandker et al. 2003; Fuwa 2006; Begum et al. 2017; Hahn et al. 2018a, 2018b; Wu 2022). Using a difference-in-differences method, Hahn et al. (2018a) estimate that the FSSSP increased years of schooling by 1.2 years and secondary schooling completion by 5 percentage points among girls eligible for the stipend. There is evidence that the stipend program also increased the schooling of younger siblings (Begum et al. 2017). Xu et al. (2022) show that the FSSSP reduced the gender gap in school enrollment within households but not in total education expenditure conditional on enrollment nor in the share of education expenditure on items related to the quality of education (e.g., private tutoring).

[7] Authors' calculations based on income data from the 1995 Household Expenditure Survey and exchange rate information from the Bangladesh Bank 2008-2009.
[8] Our results are robust to restricting the range of exposed cohorts to 1975-1988, so that the younger women in the exposed cohorts were 15 in 2003.

Data

We use publicly available data from the 1993-94 to 2017-18 waves of the Bangladesh Demographic and Health Survey (BDHS). The BDHS is a nationally representative survey of ever-married women of reproductive age in Bangladesh and is a segment of the worldwide Demographic and Health Surveys (DHS).[9] The BDHS collects the childhood immunization history of all surviving children aged 59 months or younger using face-to-face interviews and records on vaccine cards. The survey includes the following questions: *i) Do you have a card or other paper/document where (NAME)'s vaccinations are written? ii) Did you ever have a vaccination card for (NAME)? iii) May I see the card or other document where (NAME) 's vaccinations are written down.* If the mother responds *"No,"* the child's vaccination status is 'unvaccinated.' If the response is *"Vaccination date on card"/"Reported by mother"/"Vaccination marked on the card,"* then the child is considered to be 'vaccinated.' We exclude observations for which the response is *"Don't know."*

The WHO recommends four vaccines (eight doses) for children in Bangladesh – a vaccine against tuberculosis (BCG), a vaccine against Diphtheria-Pertussis-Tetanus (DPT), a vaccine against Polio (OPV), and a vaccine against Measles. Table 1.1 (based on Table 1 of Sarker et al. 2019) presents the recommended vaccination schedule for all four vaccines. We use a binary indicator for being fully immunized and a binary indicator for receiving any immunization as dependent variables. Vaccination status is classified as 'fully immunized' if the child receives all eight recommended vaccine doses: one dose of BCG, three doses of DPT, three doses of OPV, and

[9] For the 1993-94 through 2004 waves, ever-married women aged 10 to 49 years were surveyed; for the 2007 and 2017-18 waves, ever-married women aged 15 to 49 years were surveyed; for the 2001 wave, ever-married women aged 12 to 49 years were surveyed. We restrict our sample to women aged 16 years or older across all waves. The data set can be obtained from DHS program website (https://dhsprogram.com/data/available-datasets.cfm) upon authorization.

one dose of the Measles vaccine. Vaccination status is classified as 'any immunization' if the child receives any one of the eight recommended vaccine doses. In Appendix Table A1.2, we present results separately for each of the eight vaccine doses. We also use the mother's years of education and a binary indicator for completing secondary school or higher as dependent variables. Information on whether a woman received the FSSSP stipend is not available in the data.

Our main analysis is limited to women born between 1975 and 1998 who are at least 16 years old at the time of the survey. We exclude 15-year-old women because they are still in grade 10 and therefore, eligible for the stipend. We exclude birth cohorts born before 1975 since the period between 1971 and 1974 was characterized by substantial change and uncertainty in Bangladesh – the country gained independence in 1971 and experienced a famine in 1974 (Sen 1981; Hernández-Julián et al. 2014). However, we also present results for samples with wider and narrower ranges of birth cohorts as a robustness check. These results are discussed in more detail in Section 5.3. Our main estimates are robust to varying the range of birth cohorts, although the confidence intervals become wider with smaller samples. We use the 1975-1998 cohort range as our preferred specification because it avoids concerns about bias due to differential effects of the 1974 famine between rural and urban areas.[10] We also restrict our sample to children aged between 12 and 59 months since children younger than 12 months are not old enough to receive the full set of recommended vaccine doses and data on immunizations is not collected for children older than 59 months. For the analysis of maternal education, we do not restrict the sample to women with children aged 12 to 59 months. Since the policy may lead to selection into fertility, this allows us to avoid concerns about sample selection bias. However, our main estimates for education are robust to using the child immunization sample (see Appendix Table A1.6). Finally, we exclude

[10] Our estimates are slightly larger in magnitude when we include the cohorts born between 1971 and 1974.

observations with missing values for any of the key variables included in our analysis. Our final sample consists of 25,465 child-mother-year observations for the child immunization analysis and 58,707 women-year observations for the maternal education analysis.[11] Appendix Table A1.1 shows the number of observations at each step of the sample selection process.

Table 1.2 presents summary statistics for the full sample and separately for the three cohort groups described above. Panel A presents the statistics for the maternal education sample and Panel B for the child immunization sample. On average, women have 5.5 years of education and about 50.5% have completed secondary or higher education. Women who were fully exposed to FSSSP have 2.2 more years of schooling than women who were not exposed to FSSSP. Women who were partially exposed to FSSSP have 0.7 more years of schooling than unexposed women. About 82.7% of all children in the child sample are fully immunized. Children born to women fully exposed to FSSSP are 11.8 percentage points more likely to be fully immunized than children born to unexposed women. Children born to women partially exposed to FSSSP are 5.7 percentage points more likely to be fully immunized than children born to unexposed women. About 90.9% of the child sample is Muslim and 69.5% reside in a rural area. The BDHS measures residence at the time of the survey and does not include information of residence at the time of schooling. We discuss the econometric issues related to the measurement of residence in further detail below.

The cross-cohort comparisons presented in Table 1.2 are at the national level and may capture the causal impact of the FSSSP on maternal education and child immunization as well as the effect of other programs or shocks that differentially affected women in different birth cohorts. In our identification strategy, we exploit variation in eligibility for FSSSP between urban and rural

[11] We use the children's recode files of the DHS to construct the sample for the immunization analysis and the individual recode files of the DHS to construct the sample for the education analysis.

areas and across cohorts to identify the causal effect of FSSSP on the outcomes of interest net of other programs and shocks. We discuss our approach in the next section.

Methodology

Our approach is closely related to the difference-in-differences approach used by Hahn et al. (2018a, 2018b) and Wu (2021). This approach exploits the plausibly exogenous variation in exposure to the FSSSP by birth cohort and rural residence to estimate the causal effect of maternal education on child immunization. Our main regression equation is:

$$Y_{ijkt} = \beta_0 + \beta_1 Fully\ Exposed_k \times Rural_{ijkt} + \ \beta_2 Partially\ Exposed_k \times Rural_{ijkt} + \beta_3 Rural_{ijkt} + \beta_4 \mathrm{X}_{ijkt} + \gamma_k + \varepsilon_{ijkt} \qquad (1)$$

Where Y_{ijkt} is an indicator for the full (or any) immunization status of child i born to mother j who was born in year k and interviewed in survey year t. In the analysis of maternal education, the dependent variable is the years of schooling or a binary indicator that equals one if mother j has completed secondary school. $Rural_{ijkt}$ is a binary indicator for residing in a rural area in year t. $Fully\ Exposed_k$ is one if the child's mother was born in 1983 or later, and zero otherwise. $Partially\ Exposed_k$ is one if the child's mother was born between 1980 and 1982 (inclusive), and zero otherwise. The reference category includes mothers born in 1979 or earlier (not exposed to FSSSP). X_{ijkt} denotes a vector of covariates including survey wave fixed effects, a binary indicator for being Muslim (the reference group includes all other religions), and division fixed effects.[12] γ_k is a vector of maternal birth year fixed effects.

The main parameters of interest in equation (1) are the coefficients on the interaction terms, β_1 and β_2. β_1 estimates the rural-urban difference in the immunization rates of children born to fully exposed mothers relative to children born to unexposed mothers. β_2 estimates the rural-urban difference in the immunization rates of children born to partially exposed mothers relative to children born to unexposed mothers.

Standard errors are clustered at the mother and maternal year of birth levels using a two-way wild cluster bootstrap method (Cameron and Miller 2015). Since we have multiple children per mother in the sample, we cluster at the mother level to account for within family correlations. We also cluster at the maternal birth year level to account for within cohort correlations since individuals in the same cohort were exposed to the stipend program at the same time. They may also be exposed to other unobserved shocks that introduce within cohort correlation. We use the Wild bootstrap approach to account for the small number of clusters at the birth year level and a two-way approach to account for the non-nested, multiple dimensions of the clusters (Cameron and Miller 2015). Since it is not always clear what the appropriate level of clustering should be, we also present results using alternative approaches to inference. These are discussed in further detail in Section 5.4.

[12] The number of administrative divisions in Bangladesh changed during our study period. At the time of the 1993-94 wave, Bangladesh was divided into five administrative divisions (Barisal, Chittagong, Dhaka, Khulna, and Rajshahi). Sylhet separated from Chittagong in 1995, Rangpur separated from Rajshahi in 2010, and Mymensingh separated from Dhaka in 2015. To have consistent regions across waves, we use the original five divisions for the maternal education analysis. For the child immunization analysis, we use data from 1996-97 onwards since respondents in the 1993-94 wave do not meet our sample selection criteria. Therefore, for the immunization analysis, we use six divisions – the original divisions and Sylhet.

We also estimate the impact of the FSSSP on individual vaccine doses and other variables to explore the mechanisms by which the program influences immunization rates. Since there are many dependent variables in these analyses, we account for multiple hypothesis testing using two approaches. First, after grouping the outcomes by domains (individual vaccine doses, health inputs, income, fertility, autonomy and media), we report Benjamini et al. (2006) sharpened q-values to control the false discovery rate (FDR) within each domain as in Anderson (2008). The FDR is defined as "the expected proportion of rejections that are type I errors" (Anderson 2008). The results are reported in Tables 1.8-1.12 (mechanisms) and Appendix Table A1.2 (individual vaccine doses). Second, we aggregate all outcomes within a domain using the simple average of z-scores (Kling et al., 2007) as a summary index.[13] We also report sharpened q-values for all the summary indexes. Appendix Table A1.7 presents the estimates for the summary indexes.

Identification is based on the assumption that had the FSSSP not been introduced, child immunization rates over maternal cohorts would have evolved similarly in rural and urban areas. As this assumption cannot be tested directly, we examine rural-urban differences in child immunizations by maternal birth cohorts using an event study regression. The event study regression replaces the cohort dummies in equation (1) with a full set of maternal birth year fixed effects (1979 is the reference group). If changes in child immunizations over maternal cohorts evolved similarly in urban and rural areas for children of unexposed mothers, this would provide indirect support for the parallel-trends assumption. In other words, we test for statistically significant coefficients on the interactions between the rural dummy and the fixed effects for birth

[13] We switch the sign of each outcome if needed so that a positive sign is associated with an improved outcome. We then demean each outcome and divide it by its standard deviation for the control group to create a z-score and construct the index by taking the simple average of z-scores.

years 1975-1978 (i.e., the unexposed cohorts). A lack of statistical significance provides support for the parallel-trends assumption.

In addition, we use a series of placebo tests to assess the plausibility of our identifying assumption. We restrict the placebo analysis to cohorts born between 1960 and 1979, who were not eligible for the stipend program.[14] We categorize these individuals into placebo fully exposed, partially exposed, and unexposed cohorts, and re-estimate equation (1) using these placebo cohorts in place of our original treatment and control groups. We estimate a series of regressions where we vary the definition of the fully exposed, partially exposed, and unexposed cohorts by one year in each subsequent regression. For example, the first regression in this series defines birth years 1966-1979 as the fully exposed cohort, 1963-1965 as the partially exposed cohort, and 1960-1962 as the unexposed cohort. The second regression defines birth years 1967-1979 as the fully exposed cohort, 1964-1966 as the partially exposed cohort and 1960-1963 as the unexposed cohort, and so on. Since none of the mothers belonging to these placebo cohorts were eligible for FSSSP, we should not find any significant differences in education or immunization rates between urban and rural residents and by birth cohorts. If instead, we find significant coefficients on the interaction terms, this would suggest that there are unobserved factors that are correlated with rural residence and birth cohort and our outcomes. The results are discussed in Section 5.2.

Finally, we conduct various robustness checks to rule out bias and assess the sensitivity of our estimates to alternative specifications. One set of robustness checks involves adding child birth year fixed effects and their interactions with the rural indicator to address concerns about differential trends caused by unobserved variables. The second set of robustness checks uses alternative samples to rule out bias due to measurement error, migration, selection into

[14] Cohorts born earlier than 1960 were excluded due to concerns about small cell sizes.

motherhood, and unobserved cohort differences. These results are discussed in further detail in Section 5.3.

Results

We first present difference-in-differences estimates for the education outcomes in Table 1.3. We find that the difference in years of schooling between rural and urban women is higher by 1.3 years for fully exposed cohorts relative to unexposed cohorts and by 0.5 years for partially exposed cohorts relative to unexposed cohorts (Column 2, Table 1.3). We also find that the rural-urban difference in the probability of completing secondary or higher schooling for fully and partially exposed cohorts relative to unexposed cohorts is higher by 14.3 percentage points and by 5.3 percentage points, respectively (Column 4, Table 1.3). These results are consistent with the findings of Hahn et al. (2018a, 2018b) and Wu (2022).[15]

Table 1.4 presents the difference-in-differences estimates for child immunizations. We find significant increases in the likelihood of full immunization and any immunization for the children born to women who were eligible for a 5-year stipend but not for children born to women eligible for a 2-year stipend relative to children of ineligible women. Specifically, the rural-urban difference in the likelihood of full immunization is higher by 2.7 percentage points for children born to fully exposed women relative to those born to unexposed women (Column 2, Table 1.4). This is equivalent to an increase of 3.7 percent relative to the sample mean for unexposed cohorts in rural areas. The corresponding estimate for any immunization is 1.1 percentage points (Column 4, Table 1.4). In contrast, the coefficient on the interaction between the rural indicator and the

[15] We find qualitatively similar results when using the child immunization sample to estimate the impact of FSSSP on maternal education which is presented in Appendix Table A6.

partially exposed indicator is not statistically significant for either outcome. In Appendix Table A1.2, we present results for each individual vaccine dose and for the vaccine index described above. We find significant increases in all vaccine doses for the children of women eligible for a 5-year stipend but not for the children of women eligible for a 2-year stipend. The table also presents sharpened q-values that account for multiple hypotheses testing. Our conclusions are robust to this correction. Figure 1.4 presents coefficient estimates and 95% confidence intervals for the effect of being fully exposed to the FSSSP on each individual vaccine dose. We find that a 5-year stipend had larger effects on second and third doses of the DPT and Polio vaccines than on the first dose of these vaccines.

Event Study Regressions

The results from the event study regressions for education and child immunization are presented in Figures 1.5 and 1.6, respectively. The graphs plot the coefficient corresponding to each rural-birth year interaction. The graph for years of schooling exhibits a relatively flat trend for birth cohorts born in 1979 or earlier and a steep increase for birth cohorts born in 1980 or later. We find similar trends for completing secondary or higher schooling. The graph for full immunization exhibits a flat trend for cohorts that were not eligible for the stipend program, and we do not see a clear trend for cohorts that were only eligible for a 2-year stipend. However, there is a sharp increase in child immunizations for cohorts that were eligible for a 5-year stipend. The graph for any immunization is noisier but the overall trend is similar to that of full immunizations. The flat trends for the cohorts born in 1979 or earlier imply that there were no differential changes by rural residence in schooling or immunizations among unexposed cohorts, supporting our identifying assumption. The full set of interaction coefficients and confidence intervals are also presented in Appendix Tables A1.3 and A1.4. For all four regressions, the Wild cluster bootstrap confidence intervals are quite wide and none of the interaction coefficients are statistically significant. We do not present confidence intervals in Figures 1.5 and 1.6 since the wide confidence intervals mask the changes in education and immunizations for fully and partially exposed cohorts. Event study graphs including the confidence intervals are presented in Appendix Figures A1 and A2. The lack of statistical significance for the interaction coefficients for birth years 1975-1978 suggests that there are no differential trends in the absence of the stipend program, i.e. it provides support for the parallel trends assumption.

Placebo Tests

Figure 1.7 presents results from a series of placebo regressions as a further check of our identifying assumption. The sample for each regression in this graph includes women born between 1960 and 1979. We excluded cohorts born earlier than 1960 due to concerns about small cell sizes and cohorts born after 1979 since they would have been exposed to the stipend program. We then varied the definition of the placebo fully exposed cohort by decreasing it by one year in each subsequent regression. Placebo partially exposed cohorts are defined as those born during the three years before the placebo fully exposed cohorts. For example, in the first regression, persons born 1966-1979 are defined as the placebo fully exposed cohort, persons born 1963-1965 belong to the placebo partially exposed cohort, and persons born 1960-1962 belong to the placebo unexposed cohort. In the last regression, persons born 1977-1979 are fully exposed, persons born 1974-1976 are partially exposed, and persons born 1960-1973 are unexposed. Since none of these cohorts were actually exposed to the stipend program, a positive and statistically significant effect would suggest that unobserved factors may be biasing our main estimates. The graph shows that the difference-in-differences estimates are not statistically significant or are the wrong sign in some cases for years of schooling. This suggests that unobserved factors that differentially affect birth cohorts and rural residents are unlikely to bias our main estimates.

Robustness Checks

As mentioned above, our identifying assumption is that child immunization rates by maternal cohorts would have evolved similarly in rural and urban areas in the absence of the FSSSP. A concern may be that unobserved policies such as immunization campaigns or investments in health infrastructure had differential effects across cohorts and by rural/urban residence. To rule out such concerns, we first estimate specifications that include child birth year fixed effects and interactions with the rural dummy. The first and fifth columns in Table 1.5 present estimates from our preferred specification for full immunizations and any immunizations, respectively. The second and sixth columns present estimates from a specification that adds child birth year fixed effects. These account for immunization campaigns or other programs that might lead to higher immunization rates among recent cohorts of children. In columns three and seven, we add interactions between child birth year fixed effects and the rural dummy. This allows for the possibility that public health programs more heavily targeted rural areas where immunization rates were lower to begin with. In columns four and eight, we add division fixed effects interacted with maternal cohort dummies. This accounts for differential trends by maternal cohort and across regions due to unobserved factors such as trends in access to health care. The point estimates for both full immunization and any immunization are quite robust across these various specifications, suggesting that our preferred estimates are not driven by unobserved factors such as public health programs. The difference-in-differences estimates for full immunization are all statistically significant at the 5% level, but, for any immunization, the estimates become insignificant once we add the interactions between child birth year fixed effects and the rural dummy.

In Table 1.6, we consider alternative sources of bias and examine whether our main estimates are robust to accounting for them. First, our estimates may be biased due to measurement error in rural residence. Ideally, we would use information on the mother's residence in a rural or urban area during her secondary schooling years (ages 11-15) since eligibility for the FSSSP is based on rural residence at the time of schooling. Unfortunately, this information is not available in the BDHS and instead we use current residence which may not be the same as residence during secondary schooling. This measurement error may introduce bias if there is substantial internal migration between urban and rural areas. According to the 2011 Bangladesh Population and Housing Census, the migration rate from rural to urban areas was 4.29% whereas the urban to rural areas migration rate was 0.36% (Bangladesh Bureau of Statistics 2012). Given the low rate, urban to rural migration is unlikely to substantially bias our estimates but rural to urban migration may be a concern. To the extent that migrants to urban areas have greater access to healthcare services or are more likely to vaccinate their children, our estimates would be a lower bound of the effect of FSSSP on child immunization. Nevertheless, we address this concern in Panel A of Table 1.6, by excluding those living in the Dhaka division, where the capital of Bangladesh is located. This division experiences a much higher rate of rural-to-urban migration (Chowdhury and Amin 2006). Therefore, excluding Dhaka allows us to assess whether our main estimates are primarily driven by internal migration. We find estimates that are similar in magnitude to our main estimates, suggesting that our results are not biased by internal migration.

In Panel B, we restrict the sample to the oldest child under 5 of each woman born between 1975 and 1998 and aged 16 years or older at the time of the survey. Hahn et al. (2018a) find that the FSSSP decreased the number of children born to eligible women, which implies that the FSSSP may affect the composition of our main sample. Restricting the sample to the oldest child allows us to examine the extent to which our main estimates are explained by such compositional changes. The estimates for full immunization are similar in magnitude to our preferred estimates but are not statistically significant, likely due to the smaller sample size. For any immunization, we find larger and statistically significant estimates.

In Panel C, we address selection into motherhood. Hahn et al. (2018a) show that the FSSSP led eligible women to delay the birth of their first child. In our sample, over 90% of women have their first child by age 24, and Appendix Table A1.5 shows that the FSSSP did not change the probability of having at least one birth among women who are older than 24. Therefore, we restrict the sample to children born to women who are older than 24 at the time of the survey so that our estimates of the impact of the FSSSP on child immunization are not confounded by differences in age at first birth. We find a statistically significant increase in the full immunization rate (2.5 percentage points) among children of fully exposed women but not among children of partially exposed women. When we restrict the sample to the oldest child under 5 of women older than 24, the coefficient estimates for full immunization become significantly larger in magnitude (Panel D) but are not statistically significant. Although these results should be interpreted with caution due to the small sample size, they suggest that, in the absence of changes in fertility behavior, the impact of the FSSSP on child immunization rates may be larger. Overall, our conclusion that the FSSSP increased full immunization rates among the children of women eligible for a 5-year stipend remains robust to these alternative specifications.

In Figure 1.8, we explore whether our difference-in-differences estimates are sensitive to the range of maternal birth cohorts included in the sample. The graph presents 95% confidence intervals and coefficient estimates for the interaction between the fully exposed cohort and rural dummies. We first show the estimates from our preferred specification (in red), which includes cohorts born between 1975 and 1998. The vertical, dashed red line corresponds to the difference-in-differences estimate from the preferred specification. We present the estimates for the sample of cohorts born between 1971 and 1998 next, and each subsequent regression is estimated over a narrower cohort range. Overall, the point estimates are robust to varying the range of cohorts included in the sample but as expected, the 95% confidence intervals become wider as the sample size decreases.

Alternative Approaches to Inference

As mentioned above, we cluster the standard errors two-ways at the mother and maternal year of birth levels in our preferred specification. Since it is not always clear what the appropriate clustering level should be, we consider alternative approaches for inference following the recommendations in MacKinnon et al. (2022). Panel A of Table 1.7 presents the coefficients and 95% confidence intervals from our preferred specification. Given the structure of the data and the research design used in this paper, we consider three other clustering dimensions. First, as treatment varies according to the mother's birth year, we consider one-way clustering at the mother's birth year using a wild cluster bootstrap method (Panel B, Table 1.7). Second, we consider clustering one-way at the division-mother's year of birth to account for the fact that the implementation of the reform may have differed across divisions (Panel C, Table 1.7). Finally, as we have multiple observations per mother, we consider two-way clustering at the mother and division-mother's year of birth (Panel D, Table 1.7). The difference-in-differences estimate for full immunizations among children of fully exposed women is statistically significant at the 5% level using all three alternative approaches while the corresponding estimate for children of partially exposed women is less precisely estimated. In summary, our conclusions remain unchanged.

Potential Mechanisms

In this section, we explore potential mechanisms by which the FSSSP may influence child immunizations. We use the difference-in-differences framework of equation (1) to estimate the impact of the FSSSP on various outcomes that may mediate the effect of the stipend program on child immunizations. It is important to note that these results are only suggestive and that the various mechanisms may interact with each other in complex ways. For example, the program may simultaneously improve immunizations and health investments, and these effects may reinforce each other.

Income Effects

Maternal education may increase household income due to higher labor earnings or positive assortative mating in the marriage market (see McCrary and Royer 2011 for a discussion of the conceptual framework). Consistent with the income channel, previous research has shown that education influences the labor supply of mothers and the characteristics of their partners (Breierova and Duflo 2004; Keats 2018; Hahn et al. 2018a, 2018b; Sara and Priyanka 2022). Although the vaccines themselves are provided for free in Bangladesh, higher income may influence child immunizations by improving the affordability of transportation costs or physician/clinic costs. Higher labor earnings also increase opportunity costs, however, which makes the theoretical effect of a mother's labor earnings on child immunization a-priori ambiguous. Since the DHS does not include information on income, we use labor supply, occupation, and husband's education to examine this channel (Table 1.8). For fully exposed women, we find that the program significantly increases the likelihood that the respondent's husband has completed secondary or higher schooling by 5.6 percentage points (Column 1), that she works in the formal sector by 1.4 percentage points (Column 3), and that her husband works in the formal sector by 4.6 percentage points (Column 4), but no significant change in the likelihood that she is currently working (Column 2).[16] These effects are only significant at the 10% level when we rely on sharpened q-values that correct for multiple hypotheses testing. For partially exposed women, we find a 3.9 percentage point increase in the likelihood that the respondent's husband has completed secondary or higher schooling but no change in the other outcomes.

Quantity-Quality Tradeoff

The FSSSP may affect child immunizations by changing fertility choices and introducing a quantity-quality tradeoff. Theoretically, a smaller number of children allows families to allocate more resources to each child (Becker and Lewis 1973; Becker and Tomes 1976; Doepke 2015) and empirical evidence on a negative relationship between the number of children and child outcomes supports the theory (see, for e.g., Millimet and Wang 2011; Kugler and Kumar 2017). Evidence that female education affects fertility patterns while simultaneously improving child health also suggests that a quality-quantity tradeoff may be an important mechanism by which female education affects intra-household allocations (Breierova and Duflo 2004; Keats 2018; Grepin and Bharadwaj 2015; Hahn et al. 2018a, 2018b). The FSSSP may also affect fertility by changing the age at marriage (Chari et al. 2017), which we discuss further below. Previous studies have shown that secondary schooling programs with some features similar to the FSSSP such as

[16] We follow Sara and Priyanka (2022) in defining the formal sector as work in professional occupations and business. The reference group includes work in agriculture, semi-skilled and unskilled labor, and no work.

conditional cash transfers (Baird et al. 2011) and scholarships (Duflo et al. 2021) are successful in improving educational outcomes and reducing fertility. In Table 1.9, we present evidence on changes in fertility patterns due to the FSSSP. For fully exposed cohorts, we find that the FSSSP increases maternal age at first birth by 0.5 years, and significantly decreases the number of (living) children and the ideal number of children reported by the woman. These results are robust to multiple hypotheses testing corrections. The decrease in fertility suggests that a quantity-quality tradeoff may explain the increase in immunizations for fully exposed cohorts.

Decision-Making and Autonomy

The program may influence child health investments by increasing women's autonomy and decision-making power within the household. There is evidence that women are more likely to invest in child health and nutrition compared to men, and female caregivers invest more in girls' human capital while male caregivers invest more in boys' human capital (Thomas 1990, 1994; Duflo 2003; Qian 2008; Nyqvist and Jayachandran 2017; Armand et al. 2020; Dizon-Ross and Jayachandran 2022). Furthermore, early marriage has been linked to worse female autonomy and child health (Garcia-Hombrados 2022; McGavok 2021; Chari et al. 2017). Table 1.10 presents evidence on FSSSP's impact on early marriage, decision-making, and autonomy. We find that the program significantly increases the age at first marriage or cohabitation by 0.7 years and decreases the likelihood of child marriage (before age 18) by 7.2 percentage points for fully exposed cohorts. We find slightly smaller impacts for partially exposed cohorts. It is plausible that increased schooling as well as the eligibility requirement to remain unmarried contribute to this effect. There is evidence that later marriage decreases desired and actual fertility (Chari et al. 2017), which suggests that the increase in age at marriage may also influence immunizations via the quantity-quality tradeoff discussed above.

Next, we examine indicators for whether the respondent has a say in decisions regarding their own health care, large household purchases, and visits to family or relatives. We also construct an index which is the sum of the individual decision-making variables. Finally, we use an indicator for whether the respondent is allowed to go to a health center or hospital alone or with children. Consistent with prior work (Sara and Priyanka 2022), we find little evidence of an improvement in these measures of decision-making and autonomy.

Knowledge and Allocative Efficiency

The allocative efficiency hypothesis suggests that better educated persons may possess greater health knowledge that enables them to pick a more efficient allocation of health inputs (Grossman 2006). Consistent with this channel, early work by Thomas et al. (1991) shows that most of the effect of maternal education on child height in Brazil can be explained by access to information via new media. As a proxy for knowledge, we examine the respondent's exposure to media (Table 1.11). We find that the FSSSP significantly increases the likelihood that a (fully exposed) woman reads a newspaper at least once a week by 7.7 percentage points, watches TV at least once a week by 10.6 percentage points, and listens to the radio at least once a week by 1.8 percentage points. We do not find strong evidence on this pathway for partially exposed cohorts. To the extent that media exposes individuals to public health announcements and other health information, these findings suggest that improved knowledge may be an important pathway for explaining the immunization effects among fully exposed cohorts. This is consistent with prior work showing that the FSSSP improved women's knowledge of AIDS (Wu 2022).

Access to Health Care

The FSSSP may also influence immunizations by increasing interactions with health care providers, who are an important source of information on preventive care. Previous studies have shown that the FSSSP improved other health inputs such as antenatal care, facility births, and postnatal care (Hahn et al. 2018b; Wu 2022). Women may learn about newborn care and recommended vaccinations during antenatal visits, facility births, and postnatal visits. In Table 1.12, we examine the impact of the FSSSP on other health inputs, finding strong evidence of increased interactions with health care providers. Specifically, we find significant increases in the probability of receiving any antenatal care (Column 1), the probability that antenatal care is provided by a doctor (Column 2), the number of antenatal care visits (Column 4), the probability that delivery occurred in a facility (Column 5), the probability that a doctor assisted with delivery (Column 8), and the probability of receiving any postnatal care (Column 10). We also find that the FSSSP increased the probability that a women received iron supplements during pregnancy (Column 5) but did not change the probability that a child was given a Vitamin A capsule in the last 6 months (Column 9).

To summarize, our results suggest that improved knowledge (via media or health care providers) and a quantity-quality tradeoff in fertility choice are potential mechanisms by which the FSSSP improved health investment in the next generation. In the case of income effects and improvements in female autonomy, although some of the individual measures are not statistically significant based on q-values, we stronger evidence in favor of these mechanisms when relying on summary indexes (Appendix Table A1.7).

Conclusion

We find that the 1994 Female Secondary School Stipend Program significantly increased education among women eligible for the stipend and increased immunization rates among their children. Specifically, the probability of full immunization increased by 2.7 percentage points (or 3.7 percent) among children of fully exposed women relative to the children of unexposed women. We do not find significant impacts for the children of partially exposed women. Multiple mechanisms appear to be at play. We find that the stipend program is associated with greater media exposure and more interactions with health care providers, suggesting that improved knowledge of vaccine benefits and recommended schedules may be an important mechanism. We also find that the stipend program reduced fertility, suggesting that a quantity-quality tradeoff may be a pathway by which the program affects child health investments.

Our findings imply that policies targeting girls' education have important spillover effects on public health and future generations. Vaccinations are some of the most effective means of protecting children from life-threatening diseases, especially in low-income countries where access to affordable health care is limited. Although Bangladesh has made tremendous progress in child immunizations over the past four decades, gaps remain (Jamil 1999; Halder and Kabir 2008; Sarkar et al. 2015). Along with investment in public health resources, educating girls may be an effective approach to addressing these concerns. Our study suggests that the FSSSP may have played a role in explaining the convergence in aggregate trends in childhood full immunization rates by urban and rural areas and by child gender that we saw in Figure 1.1.

Our findings also suggest that the mixed results in existing literature (Özer et al. 2018; Keats 2018; Grepin and Bharadwaj 2015) may reflect contextual factors specific to the country or policy being studied as well as the margin of education targeted by the programs. Grepin and

Bharadwaj (2015) estimate that an additional year of education induced by a secondary schooling reform in Zimbabwe has no impact on the probability that a child is fully immunized. To compare our estimate to that of Grepin and Bharadwaj (2015), we construct a Wald estimator using the difference-in-differences estimates for fully exposed cohorts from Tables 1.3 and 1.4. We find that an additional year of education due to the FSSSP increases the probability of being immunized by 2.1 percentage points (=0.0267/1.321).[17] In contrast, Özer et al. (2018) and Keats (2018) find larger impacts of primary schooling reforms on immunizations. Özer et al. (2018) find that an additional year of education increases the probability of completing the third dose of DPT vaccines by 13 percentage points, while Keats (2018) finds that completing one more grade increases child immunizations by 10.6 percentage points for tuberculosis, 11.6 percentage points for measles, 7.7 percentage points for polio, and 8 percentage points for diptheria. However, it is worth noting that the average immunization rates in Uganda, which is the setting of Keats' (2018) study, are lower than the average immunization rates in Bangladesh. For example, only 59% of children completed the third dose of polio vaccine in Keats (2018) compared to 89.3% of children in our sample. In conclusion, our results suggest that secondary schooling reforms significantly improve immunization rates in the next generation but further research is needed to understand the smaller magnitude is due to the margin of education or the higher baseline immunization rates.

[17] In general, we do not use an instrumental variables approach since the FSSSP may affect immunizations via multiple pathways and therefore may not satisfy the exclusion restriction. For example, the FSSSP may affect child immunizations via an increase in maternal education and a delay in maternal age at marriage. We only use the Wald estimator as a way to compare the magnitude of our estimates to previous studies.

Tables and Figures

Table 1.1. The Expanded Program on Immunizations (EPI) Schedule in Bangladesh.

Diseases	Vaccine	Recommended Age
Childhood tuberculosis (TB)	BCG	At birth/0 day
Diphtheria/ Pertussis/Tetanus	DPT 1	42 days
	DPT 2	70 days
	DPT 3	98 days
Poliomyelitis	OPV 1	42 days
	OPV 2	70 days
	OPV 3	98 days
Measles	Measles	273 days

Notes: BCG=Bacillus Calmette-Guérin; DPT= Diphtheria-Pertussis-Tetanus; OPV= Oral Polio Vaccine
Source: WHO South-East Asia: Expanded Programme on Immunization (EPI) REGIONAL FACT SHEET 2017.

Table 1.2. Study Summary Statistics.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Fully Exposed Cohorts	Partially Exposed Cohorts	Unexposed Cohorts	Difference between Fully and Unexposed Cohorts	Difference between Partially and Unexposed Cohorts
Variables	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (*t* statistic)	Mean (*t* statistic)
Panel A: Maternal Education Sample						
Years of Schooling	5.560	6.394	4.890	4.160	2.234***	0.731***
	(4.055)	(3.683)	(4.197)	(4.271)	(59.64)	(13.12)
Secondary or Higher Education	0.505	0.607	0.421	0.335	0.272***	0.0859***
	(0.500)	(0.488)	(0.494)	(0.472)	(58.35)	(13.64)
(Maternal) Age	26.090	23.741	28.131	29.944	-6.202***	-1.813***
	(6.441)	(4.633)	(6.293)	(7.518)	(-112.50)	(-19.49)
Rural	0.660	0.650	0.656	0.684	-0.0336***	-0.0283***
	(0.474)	(0.477)	(0.475)	(0.465)	(-7.36)	(-4.60)
Muslim	0.902	0.907	0.898	0.896	0.0112***	0.00220
	(0.297)	(0.291)	(0.303)	(0.306)	(3.93)	(0.55)
Observations	58,707	33,784	9,216	15,707		
Panel B: Child Immunization Sample						
Full Immunization	0.827	0.866	0.805	0.748	0.118***	0.0570***
	(0.378)	(0.341)	(0.396)	(0.434)	(21.15)	(6.71)
Any Immunization	0.971	0.979	0.967	0.954	0.0249***	0.0125**
	(0.168)	(0.143)	(0.179)	(0.209)	(10.07)	(3.14)
(Maternal) Age	24.228	23.086	25.436	26.212	-3.127***	-0.776***
	(4.707)	(3.790)	(5.206)	(5.456)	(-47.99)	(-7.16)
Rural	0.695	0.684	0.690	0.723	-0.0387***	-0.0333***
	(0.461)	(0.465)	(0.463)	(0.448)	(-5.62)	(-3.63)
Muslim	0.909	0.912	0.906	0.905	0.00654	0.000561
	(0.287)	(0.284)	(0.292)	(0.293)	(1.52)	(0.09)
Observations	25,465	15,166	4,005	6,294		

Notes: Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts are born between 1975 and 1979. Full immunization indicates that the child has received all eight doses of WHO recommended vaccines. Any immunization indicates that the child has received at least one of the eight recommended vaccine doses. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively.
Source: Bangladesh Demographic and Health Surveys, 1993-94 through 2017-18 (Panel A), Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18 (Panel B).

Table 1.3. Difference-in-Differences Estimates of the Impact of FSSSP on Maternal Education.

	(1)	(2)	(3)	(4)
	Years of Schooling		Secondary or Higher Education	
Fully Exposed × Rural	1.421***	1.321***	0.153***	0.143***
	[1.191, 1.664]	[1.061, 1.567]	[0.130, 0.176]	[0.119, 0.167]
Partially Exposed × Rural	0.552***	0.488***	0.060***	0.053***
	[0.340, 0.766]	[0.255, 0.688]	[0.0507, 0.0720]	[0.0442, 0.0641]
Covariates		×		×
Observations	58,707	58,707	58,707	58,707
Dep. Var. Mean	5.560	5.560	0.505	0.505

Notes: The sample includes women born between 1975 and 1998. Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts (reference group) are born between 1975 and 1979. Covariates include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.

Source: Bangladesh Demographic and Health Surveys, 1993-94 through 2017-18.

Table 1.4. Difference-in-Differences Estimates of the Impact of FSSSP on Child Immunizations.

	(1)	(2)	(3)	(4)
	Full Immunization		Any Immunization	
Fully Exposed × Rural	0.064***	0.02467**	0.01843***	0.01140**
	[0.046, 0.080]	[0.010, 0.043]	[0.011, 0.027]	[0.003, 0.019]
Partially Exposed × Rural	-0.001	-0.025	0.008	0.002
	[-0.028, 0.030]	[-0.046, 0.005]	[-0.016, 0.027]	[-0.017, 0.021]
Covariates		×		×
Observations	25,465	25,465	25,465	25,465
Dep. Var. Mean	0.827	0.827	0.971	0.971

Notes: The sample includes children under 5 born to women born between 1975 and 1998. Full immunization indicates that the child received all eight doses of WHO recommended vaccines, and any immunization indicates that the child received at least one of the eight recommended vaccine doses. Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts (reference group) are born between 1975 and 1979. Covariates include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table 1.5. Alternative Specifications Accounting for Unobserved Trends in Immunizations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Full Immunization				Any Immunization		
Fully Exposed × Rural	0.0267**	0.0271**	0.0243*	0.0635***	0.0110**	0.0110**	0.00808	0.0183***
	[0.0104, 0.0428]	[0.0107, 0.0431]	[-0.00202, 0.0542]	[0.0460, 0.0800]	[0.00314, 0.0192]	[0.00339, 0.0189]	[-0.00391, 0.0218]	[0.0106, 0.0271]
Partially Exposed × Rural	-0.0248	-0.0242	-0.0222	-0.00129	0.00186	0.00169	-0.000466	0.00679
	[-0.0457, 0.00488]	[-0.0473, 0.00693]	[-0.0508, 0.00698]	[-0.0276, 0.0304]	[-0.0165, 0.0205]	[-0.0168, 0.0193]	[-0.0201, 0.0199]	[-0.0156, 0.0267]
Covariates	×	×	×	×	×	×	×	×
Child's Birth Year FE		×	×	×		×	×	×
Child's Birth Year FE × Rural			×	×			×	×
Division FE × Cohort				×				×
Observations	25,465	25,465	25,465	25,465	25,465	25,465	25,465	25,465
Dep. Var. Mean	0.827	0.827	0.827	0.827	0.971	0.971	0.971	0.971

Notes: The sample includes children under 5 born to women born between 1975 and 1998. Full immunization indicates that the child received all eight doses of WHO recommended vaccines, and any immunization indicates that the child received at least one of the eight recommended vaccine doses. Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts (reference group) are born between 1975 and 1979. Covariates include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table 1.6. Additional Robustness Checks.

	(1) Full Immunization	(2) Any Immunization
Panel A: Excluding Dhaka Division		
Fully Exposed × Rural	0.0338**	0.0150**
	[0.00799, 0.0540]	[0.00289, 0.0381]
Partially Exposed × Rural	-0.0173	0.00743
	[-0.0365, 0.00532]	[-0.0168, 0.0309]
Observations	20,259	20,259
Dep. Var. Mean	0.831	0.971
Panel B: Oldest Child Under 5		
Fully Exposed × Rural	0.0254	0.0239**
	[-0.0175, 0.0623]	[0.0110, 0.0347]
Partially Exposed × Rural	-0.0113	0.0129
	[-0.0731, 0.0646]	[-0.00194, 0.0333]
Observations	10,396	10,396
Dep. Var. Mean	0.836	0.979
Panel C: Maternal Age > 24 (95th percentile of age at 1st birth)		
Fully Exposed × Rural	0.0252**	0.00561
	[0.000342, 0.0487]	[-0.00941, 0.0223]
Partially Exposed × Rural	-0.00129	-0.00303
	[-0.0556, 0.0328]	[-0.0266, 0.0203]
Observations	10,663	10,663
Dep. Var. Mean	0.864	0.974
Panel D: Oldest Child Under 5 & Maternal Age > 24		
Fully Exposed × Rural	0.102	0.00762
	[-0.0338, 0.188]	[-0.0211, 0.0439]
Partially Exposed × Rural	0.0911*	0.00539
	[-0.0231, 0.206]	[-0.0433, 0.0399]
Observations	1,361	1,361
Dep. Var. Mean	0.916	0.990

Notes: Full immunization indicates that the child received all eight doses of WHO recommended vaccines, and any immunization indicates that the child received at least one of the eight recommended vaccine doses. Fully exposed cohorts are those born between 1983 and 1998 (Panels A and B) or those born between 1983 and 1993 (Panels C and D); partially exposed cohorts are those born between 1980 and 1982, while unexposed cohorts are those born between 1975 and 1979. Covariates include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.

Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table 1.7. Alternative Clustering Approaches.

	(1) Full Immunization	(2) Any Immunization
Panel A: Two-way Wild Cluster Bootstrap at Mother and Maternal Birth Year Levels		
Fully Exposed ✕ Rural	0.0267**	0.0110**
	[0.0104, 0.0428]	[0.00314, 0.0192]
Partially Exposed ✕ Rural	-0.0248	0.00186
	[-0.0457, 0.00488]	[-0.0165, 0.0205]
Panel B: One-way Wild Cluster Bootstrap at Birth Year Level (24 groups)		
Fully Exposed ✕ Rural	[0.0104, 0.0427]**	[0.0032, 0.0192]**
Partially Exposed ✕ Rural	[-0.0456, 0.0048]	[-0.0165, 0.0205]
C: One-way Wild Cluster Bootstrap at Division-Birth Year Level		
Fully Exposed ✕ Rural	[0.0050, 0.0485]**	[-0.0005, 0.0226]*
Partially Exposed ✕ Rural	[-0.0519, 0.0024]*	[-0.0143,0.0180]
Panel D: Two-way Wild Cluster Bootstrap at Mother and Division-Birth Year Levels		
Fully Exposed ✕ Rural	[0.0051, 0.0483]**	[-0.0004, 0.0225]*
Partially Exposed ✕ Rural	[-0.0517, 0.0022]*	[-0.0141, 0.0179]

Notes: The sample includes children under 5 born to women born between 1975 and 1998. Full immunization indicates that the child received all eight doses of WHO recommended vaccines, and any immunization indicates that the child received at least one of the eight recommended vaccine doses. Fully exposed cohorts are born between 1983 and 1998; partially exposed cohorts are born between 1980 and 1982, while unexposed cohorts are born between 1975 and 1979. All regressions include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table 1.8. Income Effects as Potential Mechanisms.

	(1) Husband completed secondary or higher schooling	(2) Currently working	(3) Works in formal sector	(4) Husband works in formal sector
Fully Exposed × Rural	0.0560**	0.0218	0.0138**	0.0457**
	(0.023)	(0.147)	(0.028)	(0.020)
	[0.081]	[0.14]	[0.081]	[0.081]
Partially Exposed × Rural	0.0388*	-0.0346	0.00842	0.00556
	(0.077)	(0.117)	(0.362)	(0.693)
	[0.107]	[0.133]	[0.231]	[0.245]
Observations	28,571	28,759	28,733	28,534
Dep. Var. Mean	0.193	0.245	0.026	0.279

Notes: Formal sector employment includes work in professional occupations and business. The reference group includes work in agriculture, semi-skilled and unskilled labor, and no work. Fully exposed cohorts are born between 1983 and 1998; partially exposed cohorts are born between 1980 and 1982, while unexposed cohorts are born between 1975 and 1979. All regressions include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. P-values are reported in parentheses. Benjamini et al. (2006) sharpened q-values are computed over all 8 hypotheses (4 outcomes and 2 treatments) following Anderson (2008) and are shown in square brackets. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels based on p-values.

Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table 1.9. Quantity-Quality Tradeoff as Potential Mechanisms.

	(1) Age at first birth	(2) Number of living children	(3) Ideal number of children
Fully Exposed × Rural	0.525**	-0.227***	-0.115***
	(0.047)	(0.000)	(0.001)
	[0.044]	[0.001]	[0.003]
Partially Exposed × Rural	0.189	-0.116**	-0.0405
	(0.303)	(0.021)	(0.112)
	[0.113]	[0.029]	[0.073]
Observations	28,765	28,765	28,407
Dep. Var. Mean	17.760	2.135	2.271

Notes: Fully exposed cohorts are born between 1983 and 1998; partially exposed cohorts are born between 1980 and 1982, while unexposed cohorts are born between 1975 and 1979. All regressions include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. P-values are reported in parentheses. Benjamini et al. (2006) sharpened q-values are computed over all 6 hypotheses (3 outcomes and 2 treatments) following Anderson (2008) and are shown in square brackets. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels based on p-values.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table 1.10. Female Autonomy and Decision Making as Potential Mechanisms.

	(1) Age at first marriage or cohabitation	(2) Age at marriage < 18 years	(3) Decides on respondent's health care	(4) Decides on large household purchases	(5) Decides on visits to family or relatives	(6) Decision making index (sum)	(7) Can go to health center/hospital alone or with children
Fully Exposed × Rural	0.736***	-0.0716***	0.0259	0.0326	0.0436	0.102*	-0.00779
	(0.001)	(0.001)	(0.140)	(0.127)	(0.178)	(0.051)	(0.107)
	[0.008]	[0.008]	[0.251]	[0.251]	[0.287]	[0.164]	[0.251]
Partially Exposed × Rural	0.400***	-0.0226	-0.0131	-0.00252	-0.0181	-0.0340	0.00282
	(0.009)	(0.224)	(0.601)	(0.868)	(0.511)	(0.574)	(0.666)
	[0.038]	[0.332]	[0.454]	[0.536]	[0.454]	[0.454]	[0.454]
Observations	28,765	28,765	25,088	25,090	25,084	25,082	20,460
Dep. Var. Mean	15.719	0.778	0.627	0.605	0.624	1.856	0.074

Notes: Fully exposed cohorts are born between 1983 and 1998; partially exposed cohorts are born between 1980 and 1982, while unexposed cohorts are born between 1975 and 1979. All regressions include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. P-values are reported in parentheses. Benjamini et al. (2006) sharpened q-values are computed over all 14 hypotheses (7 outcomes and 2 treatments) following Anderson (2008) and are shown in square brackets. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels based on p-values.

Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table 1.11. Knowledge and Allocative Efficiency as Potential Mechanisms.

	(1) Reads newspaper at least once a week	(2) Watches TV at least once a week	(3) Listen to radio at least once a week
Fully Exposed × Rural	0.0772***	0.106***	0.0182*
	(0.000)	(0.000)	(0.089)
	[0.001]	[0.001]	[0.118]
Partially Exposed × Rural	0.0277	0.0209	0.0198
	(0.190)	(0.273)	(0.105)
	[0.18]	[0.188]	[0.118]
Observations	28,743	28,757	28,758
Dep. Var. Mean	0.060	0.480	0.124

Notes: Fully exposed cohorts are born between 1983 and 1998; partially exposed cohorts are born between 1980 and 1982, while unexposed cohorts are born between 1975 and 1979. All regressions include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. P-values are reported in parentheses. Benjamini et al. (2006) sharpened q-values are computed over all 6 hypotheses (3 outcomes and 2 treatments) following Anderson (2008) and are shown in square brackets. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels based on p-values.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table 1.12. Difference-in-Differences Estimates of the Impact of FSSSP on Other Health Inputs.

	(1) Any antenatal care	(2) Doctor gave antenatal care	(3) Nurse gave antenatal care	(4) Number of antenatal visits	(5) Antenatal Iron Supplements	(6) Facility delivery	(7) Home delivery	(8) Doctor delivery	(9) Vitamin A in last 6 months	(10) Any postnatal care
Fully Exposed × Rural	0.104***	0.089**	-0.002	0.646***	0.059**	0.043**	-0.020	0.060**	0.009	0.191***
	(0.006)	(0.016)	(0.946)	(0.001)	(0.012)	(0.041)	(0.356)	(0.011)	(0.527)	(0.005)
	[0.04]	[0.048]	[0.495]	[0.021]	[0.043]	[0.067]	[0.277]	[0.043]	[0.387]	[0.04]
Partially Exposed × Rural	0.0151	0.0420	-0.0137	0.398	-0.0328	0.0314	-0.0487	0.0580**	0.0209	0.178
	(0.663)	(0.325)	(0.462)	(0.206)	(0.192)	(0.119)	(0.104)	(0.019)	(0.603)	(0.043)
	[0.458]	[0.277]	[0.352]	[0.212]	[0.212]	[0.136]	[0.13]	[0.049]	[0.432]	[0.067]
Observations	12,941	12,938	12,938	4,729	8,268	14,751	14,751	14,751	26,398	8,381
Dep. Var. Mean	0.703	0.501	0.093	1.953	0.627	0.291	0.592	0.363	0.759	0.612

Notes: Fully exposed cohorts are born between 1983 and 1998; partially exposed cohorts are born between 1980 and 1982, while unexposed cohorts are born between 1975 and 1979. All regressions include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. P-values are reported in parentheses. Benjamini et al. (2006) sharpened q-values are computed over all 20 hypotheses (10 outcomes and 2 treatments) following Anderson (2008) and are shown in square brackets. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels based on p-values.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

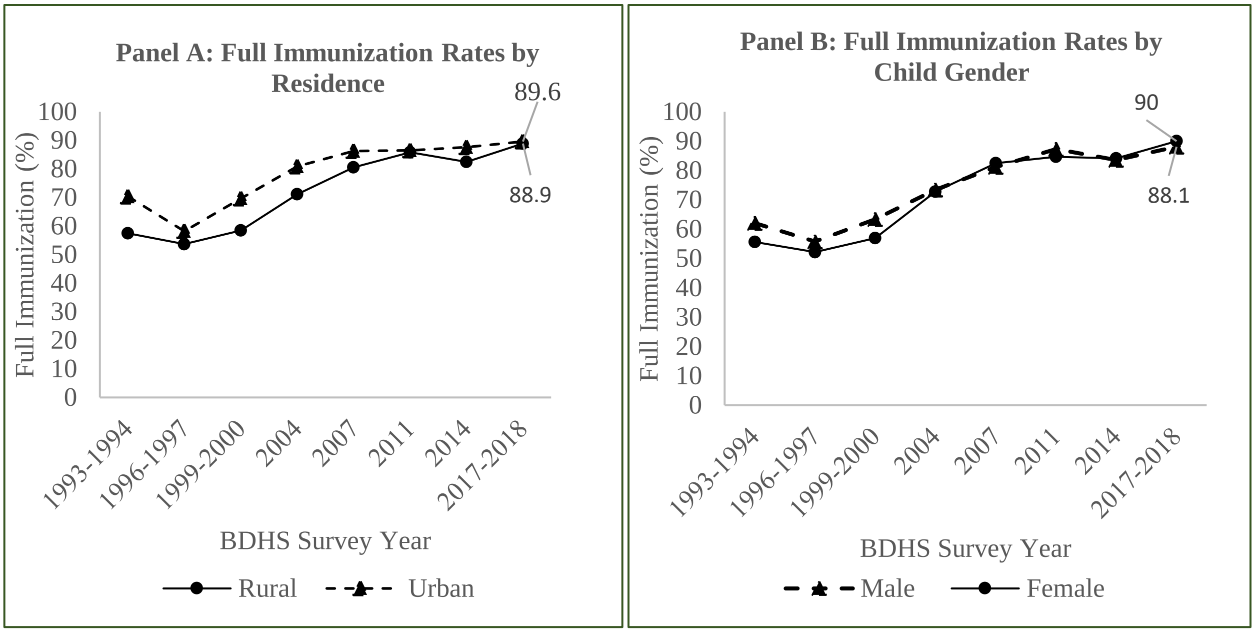

Figure 1.1. Trends in Child Immunization Rates by Residence and Gender.
Notes: Graphs present full immunization rates (%) among children aged 12–59 months in Bangladesh. Full immunization indicates that the child has received all eight doses of WHO recommended vaccines.
Source: Bangladesh Demographic and Health Surveys, 1993-94 through 2017-18.

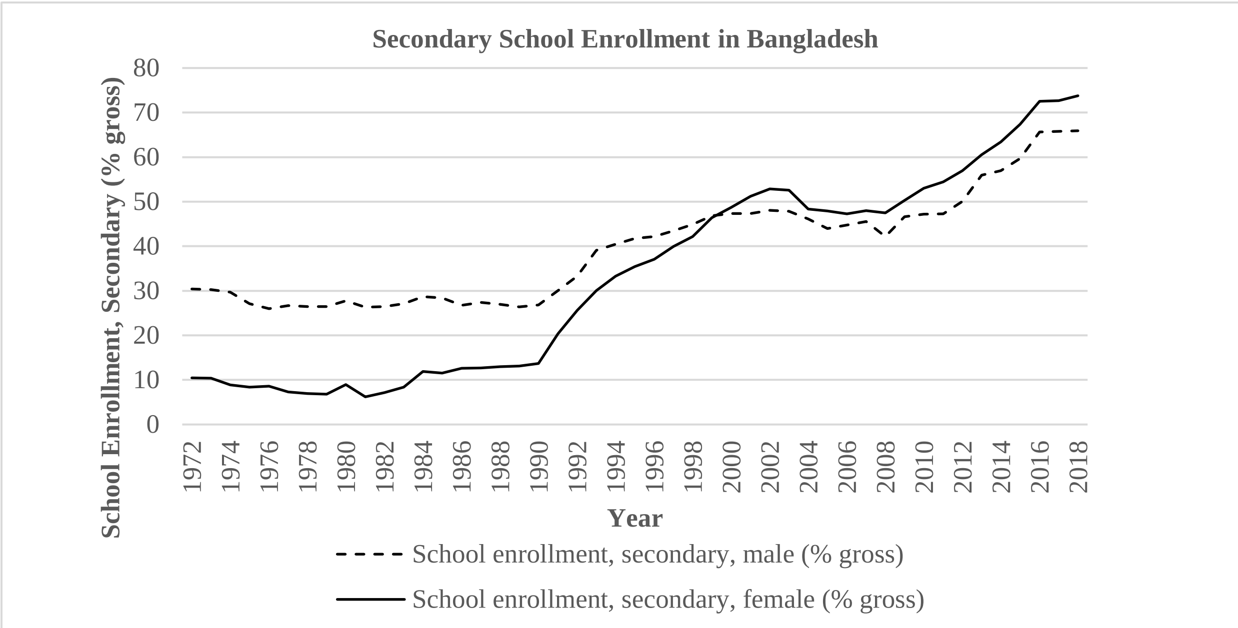

Figure 1.2. Gender Differences in School Enrollment in Bangladesh.
Notes: Secondary school enrollment by gender, 1972-2018. The solid line is for females; the dashed line is for males. The gross enrollment rate is computed by dividing the number of students in grades 6-10 by the relevant population in that age group (ages 11-15).
Source: Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2018.

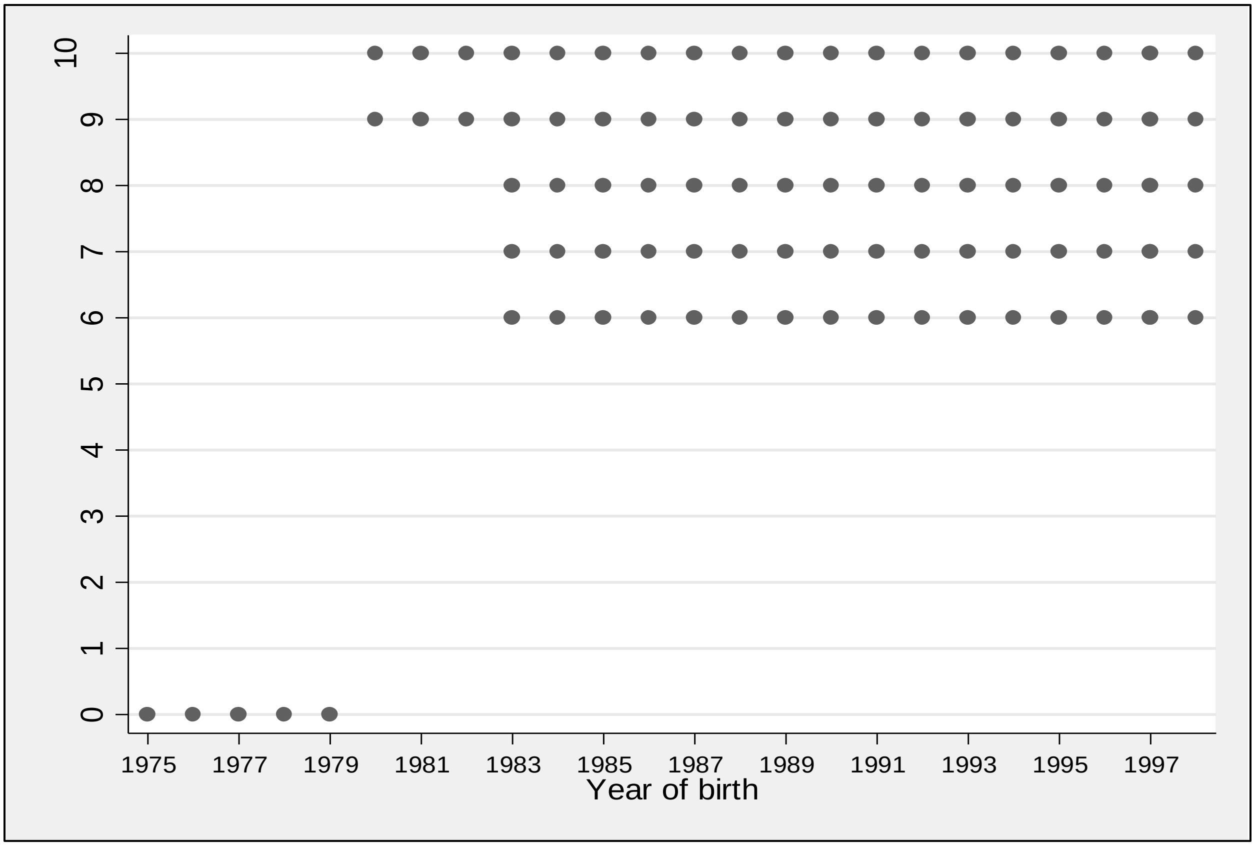

Figure 1.3. Exposure to the FSSSP by Birth Cohort.
Notes: Mothers born after 1982 were eligible for 5 years from 1994 when they were in grade 6, while mothers born between 1980 and 1982 were eligible for 2 years. Mothers born before 1980 were not eligible as they were already in grade 10 in 1994. Mothers in grades 7 in 1994 and 8 in 1995 did not become eligible for a stipend, but they were eligible for it for 2 consecutive years in 1996 and 1997 (grades 9 and 10). Mothers in grade 8 in 1994 did not become eligible for a stipend but were eligible for it for 2 years in 1995 and 1996 (grades 9 and 10). Mothers in grade 9 in 1994 received a stipend for 2 years in 1994 and 1995.

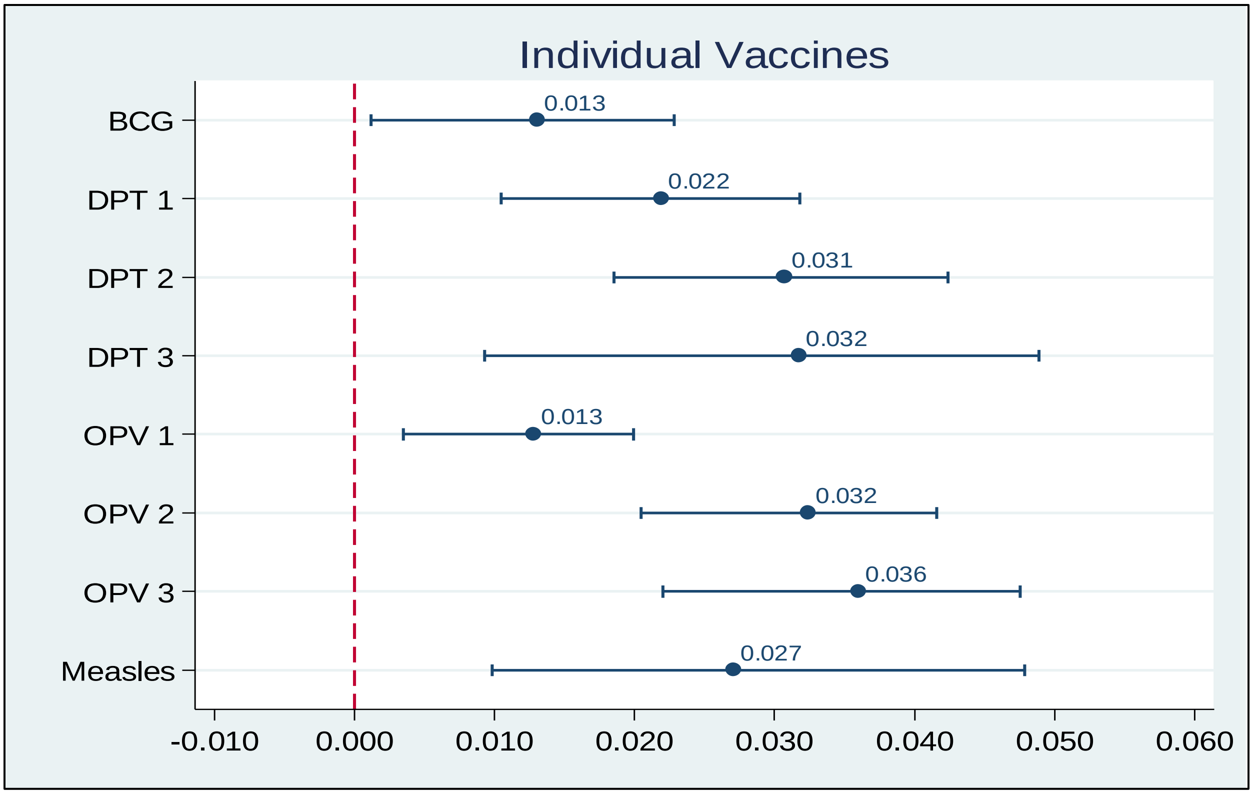

Figure 1.4. Effect of FSSSP on Individual Vaccine Doses.
Notes: Graph presents the coefficient and 95% confidence interval of the interaction between the fully exposed and rural dummies. Each point is from a separate regression of the individual vaccine dose on interactions between cohort and rural dummies, maternal birth year fixed effects, a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. The sample includes cohorts born between 1975 and 1998. Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts are born between 1975 and 1979.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

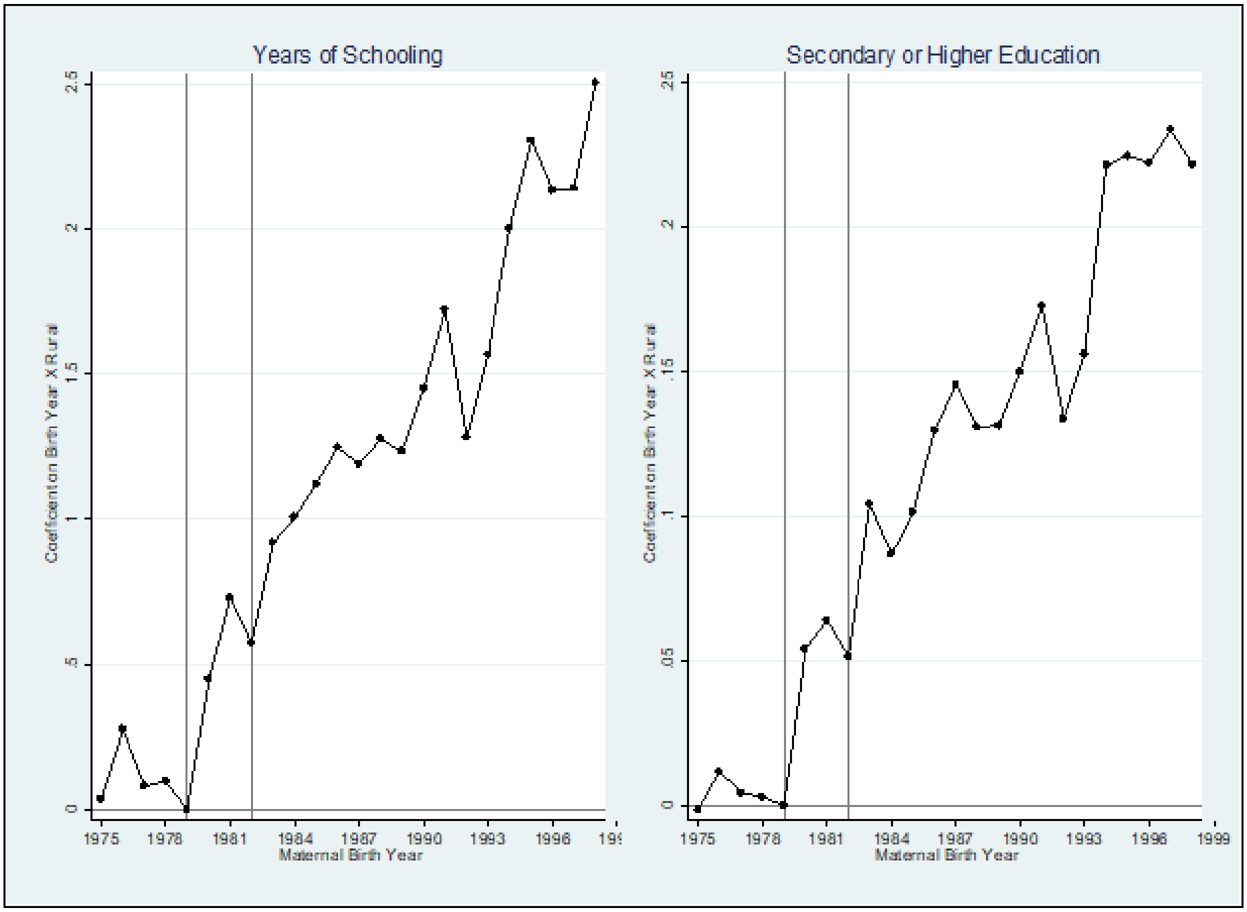

Figure 1.5. Event Study Graphs for Maternal Education.

Notes: Graphs present interaction coefficients from an event study regression of maternal education on interactions between a rural dummy and maternal birth year fixed effects, a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. The sample includes cohorts born between 1975 and 1998 (reference birth year 1979).

Source: Bangladesh Demographic and Health Surveys, 1993-94 through 2017-18.

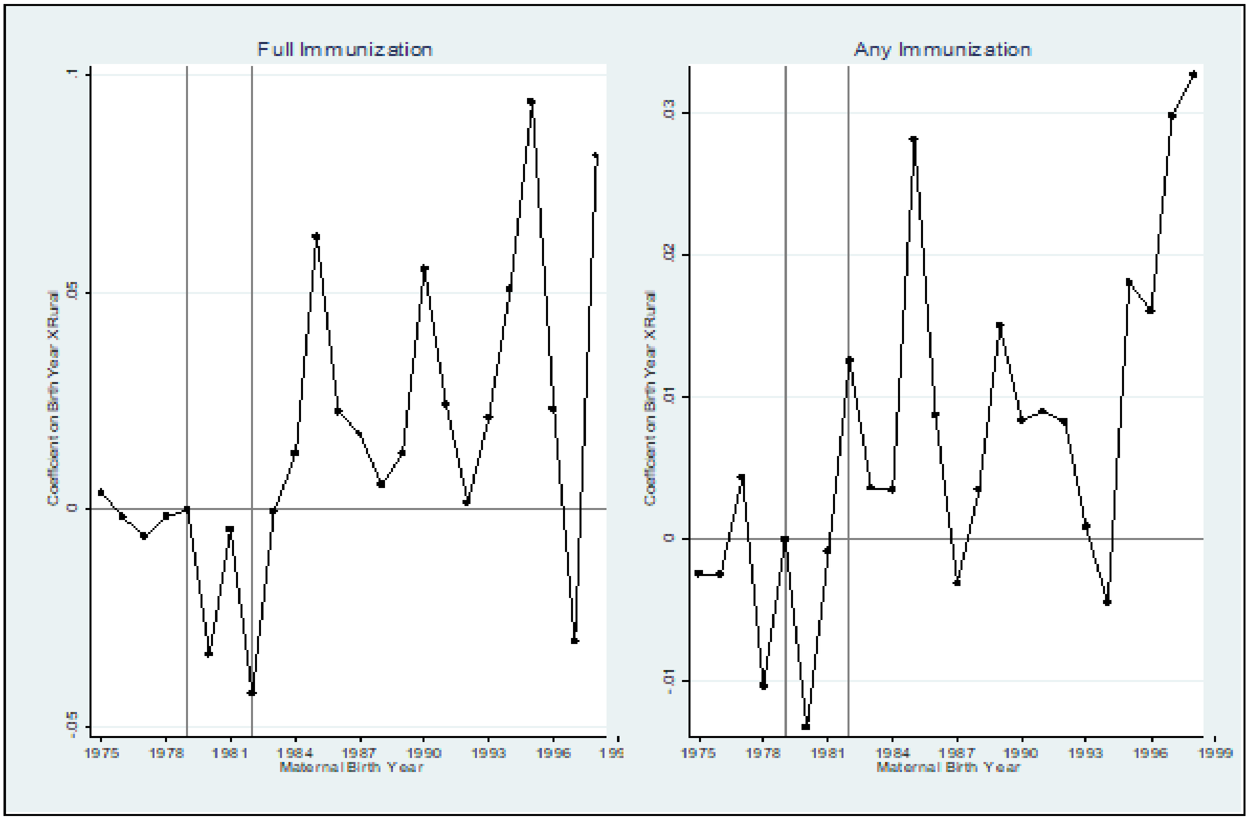

Figure 1.6. Event Study Graphs for Child Immunizations.
Notes: Graphs present interaction coefficients from an event study regression of child immunization on interactions between rural dummy and maternal birth year fixed effects, a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. The sample includes cohorts born between 1975 and 1998 (reference birth year 1979). Full immunization indicates that the child has received all eight doses of WHO recommended vaccines. Any immunization indicates that the child has received at least one of the eight recommended vaccine doses.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

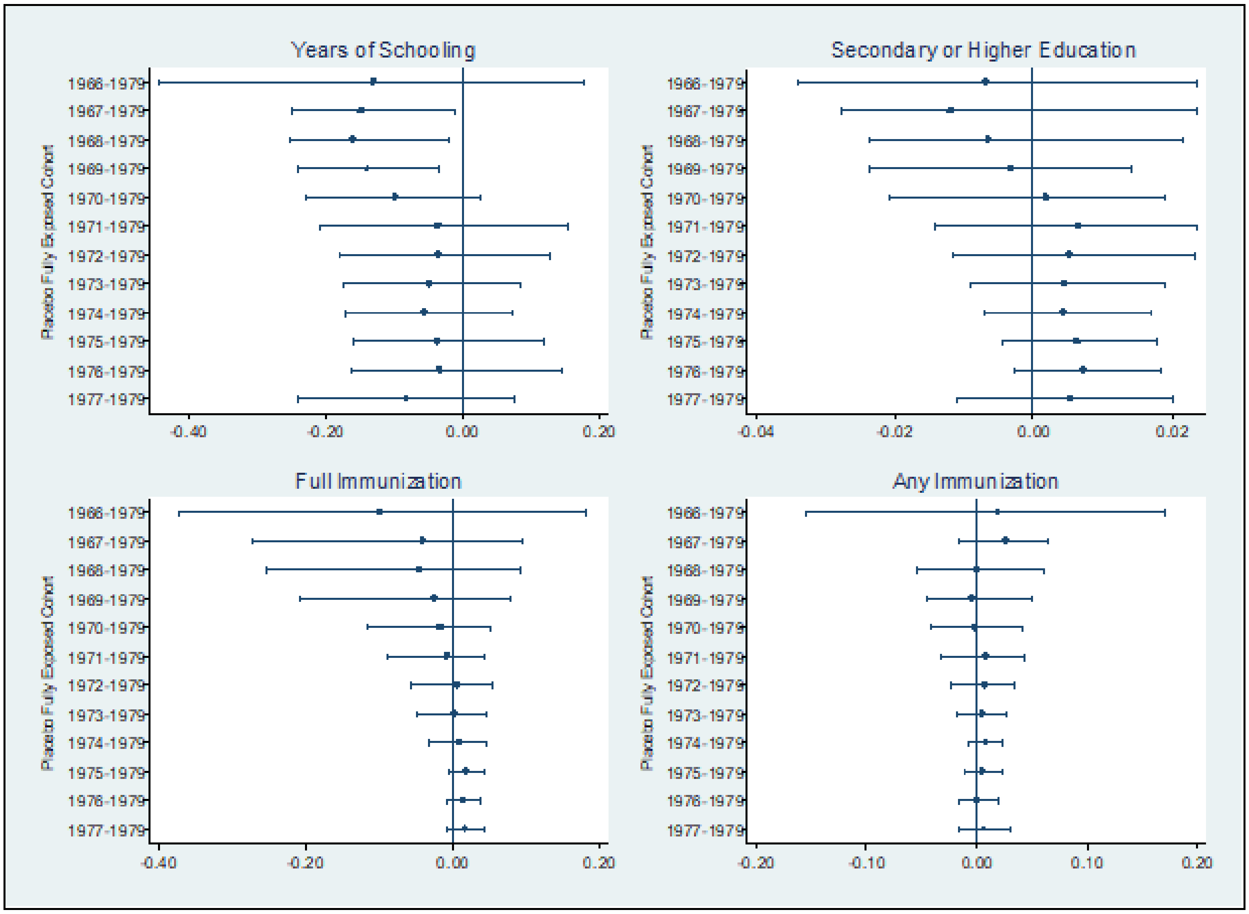

Figure 1.7. Placebo Tests.
Notes: Graphs present the coefficient and 95% confidence interval of the interaction between the fully exposed and rural dummies. Each point is from a separate regression of the dependent variable on interactions between cohort and rural dummies, maternal birth year fixed effects, a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. The sample includes cohorts born between 1960 and 1979. The definition of placebo fully exposed cohorts varies across regressions and is shown on the left axis.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

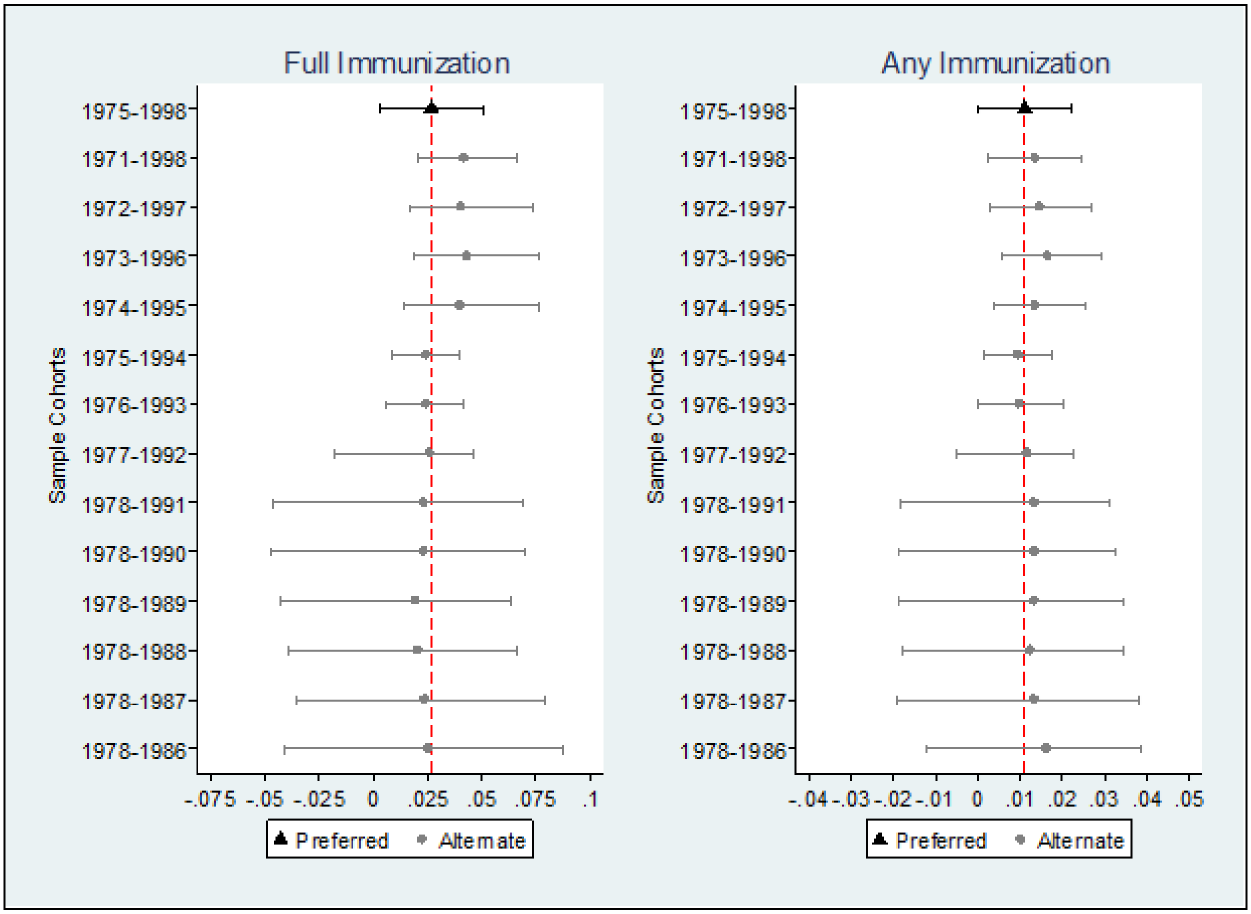

Figure 1.8. Robustness to Range of Maternal Birth Cohort.

Notes: Graphs present the coefficient and 95% confidence interval of the interaction between the fully exposed and rural dummies. The dashed red vertical line represents the estimate from our preferred specification. Each point is from a separate regression of immunizations on interactions between cohort and rural dummies, maternal birth year fixed effects, a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. The cohorts included in the sample vary across regressions and are shown on the left axis. Fully exposed cohorts are born in 1983 or later, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts are born between in 1979 or earlier.

Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

CHAPTER TWO:

THE EFFECT OF EDUCATION STIPEND PROGRAMS ON WOMEN'S OBESITY IN BANGLADESH

Md Shahjahan, and Padmaja Ayyagari [*]

Introduction

Overweight or obesity is a significant and growing health burden that creates a major public health challenge, with 39% of the world's adult population (40% of women and 39% of men) being overweight or obese in 2016 (WHO 2021). In Bangladesh, 25% of adults [18] (32.4% of women and 17.6% of men) were overweight or obese (BDHS 2017-2018). Several diseases like heart disease, diabetes, and cancers are associated with overweight or obese (Wyatt et al. 2006; Cresswell et al. 2013). Women had a higher overweight/obesity prevalence relative to men (Ng et al. 2014). Bangladesh is experiencing rapid urbanization with changing patterns of diseases among the population (Streatfield and Karar 2008), with some signifying that the country is at a progressive phase of the third stage of the epidemiological change, with deaths from chronic diseases likely to increase fast in the coming years (Ahsan et al. 2017). Education is often among the most important social predictors of women's health behaviors and outcomes, including diet, physical activity, and body weight (Liu and Guo 2015; Sobal 2011).

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[18] women aged 15-49; men age 18 and older, Bangladesh DHS 2017-18.

Since the early 1990s, several developing countries have launched programs such as tuition subsidies, conditional cash transfers, and mandatory education laws, which cause plausibly exogenous variations in admission to study. While most of the previous studies have been interested in associations, the latest research has tested to link the causal effect of schooling on women's well-being by depending on quasi-experimental methods. Analyses relying on such policies to examine the causal effect of female education on women's well-being identify diverse results. Some research explores the positive affect of education on chronic diseases - BMI levels/overweight or obesity (Howitt et al. 2015; Tansel and Karaoglan 2016; Di Chiara et al. 2017), diabetes (Ayyagari et al. 2011; Di Chiara et al. 2017; Tillmann et al. 2017), hypertension/ blood cholesterol (Di Chiara et al. 2017; Tillmann et al. 2017), some find a negative impact of education on chronic diseases - BMI levels/overweight or obesity (Brunello et al. 2013; Böckerman et al. 2017; Grabner 2009; Kemptner 2011), hypertension/blood cholesterol (Benetou et al. 2000; Powdthavee 2010), diabetes(Davies et al. 2018; Howitt et al. 2015), some find no changes of education on overweight or obesity (Barlow 2021; Xie and Mo 2014). It is not clear whether the change in results across these studies is due to exogenous differences.

Several determinants affect health. The World Health Organization (WHO, 2017) specified those well-being determinants as the economic and social environment, physical environment, and individual characteristics and behaviors. The more specific drivers are education, income, and social status (Dégano et al. 2017; Bleakley 2010; Bloom et al. 2014, 2015). Extensive literature has documented that more educated individuals receive higher wages, suffer less unemployment, and work in more prominent careers compared to their lower-educated counterparts (Cohn and Addison 1998; Psacharopoulos 1985; Card 1999). The prevalence and risk of chronic diseases are higher among educated respondents. In studies in Bangladesh (Ahmed et al. 2009) and Nepal

(Aryal et al. 2015), women with at least primary education are assumed to be at risk of being overweight/obese. It may be due to prosperity and more access to fast food, diets high in fats, salt, and sugar (Gregorio and Lee 2002). Being overweight or obese was more prevalent in non-manual than manual labor (Howitt et al. 2015). The prevalence and risk of overweight or obesity increased with higher household wealth quantiles (Al Kibria et al. 2021; Al-Zubayer et al. 2021). The studies in Bangladesh and Colombia showed that educated individuals are more likely to be at risk of being overweight or obese (Biswas et al. 2019; Hoque et al. 2014; Camacho et al. 2020). The results in this study may be due to their easy and modern way of life (Biswas et al. 2019; Camacho et al. 2020). Higher-educated people face more responsibility and pressure (Roy et al. 2021), which might lead to overweight or obesity. The mechanisms by which socioeconomic condition impacts health are not fully understood. Our study looks at the effect of education on women's obesity.

While much of the early study has focused on associations (Ahmed et al. 2009; Al-Kibria et al. 2021; Al-Zubayer et al. 2021; Aryal et al. 2015; Benetou et al. 2000; Biswas et al. 2019; Camacho et al. 2020; Gupta et al. 2010; Hoque et al. 2014; Howitt et al. 2015; Liao et al. 2021; Perova et al. 2001; Pouliou et al. 2010; Reddy et al. 2007; Singh et al. 1997; Tillmann et al. 2017; Webbink et al. 2010; Yin et al. 2017; Zaman et al. 2015), in this research, we investigate the effect of female education on women's obesity in Bangladesh. We use the 1994 Female Secondary School Stipend Program (FSSSP)[19] for causality, FSSSP provides a cash stipend, tuition fees, book

[19] In 1982, the Bangladesh Association for Community Education (BACE), a national nongovernmental organization (NGO), began the Female Secondary School Stipend Project (FSSSP) as a pilot project in the Shahrasti upazila of Chandpur district under the division of Chittagong and Kaharole upazila of Dinajpur district under the division of Rajshahi, with financial support from USAID and the Asia Foundation (Schurmann 2009). From 1987 to 1992, the Norwegian Agency for Development Cooperation (NORAD) expanded the stipend program to girls in one upazila (administrative unit) in Bangladesh every year (Khandker et al. 2021). The experience of this pilot project yielded positive outcomes: girls' secondary school enrolments increased from an average of 7.9% to 14% in some project areas, and dropout rates fell from 14.7% to 3.5% (Raynor et al. 2006). This pilot project's success was the basis for launching the nationwide FSSSP in 1994 to address gender inequality in secondary education. Figure A1 shows that secondary education admission improved much faster among girls than boys after the introduction of the FSSSP at the national level.

allowance, and examination fees to rural girls in secondary school (grades 6-10)[20]. Regarding women's health, there is a finding of a decrease in fertility (Hahn et al. 2018a, 2018b). An increase in contraception use, and an increase in the use of screen time suggest that these may be significant channels through which female education affects women's well-being in Bangladesh.

Moreover, impacting education on the overall economy (Bleakley 2010; Bloom et al. 2014, 2015), education can affect women's health through societal development (Clark and Royer, 2010; Onarheim et al. 2016). Higher education increases employment opportunities and earnings (Hahn et al. 2018a, 2018b; Bleakley 2010; Bloom et al. 2014, 2015), which, in turn, increases the age at first marriage, increases the age at first birth (Hahn et al. 2018a, 2018b), decrease the fertility rates (Hahn et al. 2018a, 2018b; Ahmed 1986; Kamal 2011; Nahar and Zahangir 2019), increase the contraception use (Islam et al. 2016; Nonvignon and Novignon 2014), increase the uses of screen time (Rehbein et al. 2010; Furthner et at. 2018), which results in weight gain and affects women's obesity. Lower fertility rates due to higher engagements in more formal work (Hahn et al. 2018a) and less informal work (Hahn et al. 2018a), which incorporated fewer physical activities (Duncan et al. 2012), leading to higher BMI or obesity (Howitt et al. 2015). Working in a skilled profession is associated with obesity (Maruf and Udoji 2015). Let's look at the data from 1996-1997 to 2017-2018 (Panel A in Figure 2.1). In the early years, we can see that 3% of women were overweight or obese, which is relatively low, while in the survey year 2017-2018, 32.4% of women were overweight or obese, which is substantially high in Bangladesh. When we look at women's obesity separately, it increased about five times in the last decade (the survey year 2004 to 2017-2018), which is a public health concern (Panel B in Figure 2.1). In this study, we ask whether the FSSSP

[20] Females enrolled in 1994 (grades 7–9) born in 1980–1982 received a 2-year stipend; those enrolled in 1994 (grades 1–6) born in 1983 or later received a 5-year stipend, and those enrolled in 1994 (grade 10) born before 1980 received no stipends as they had already exceeded the 10th grade (Hahn et al. 2018b). Figure A2 shows the FSSSP exposure by birth cohort and grade.

affects earnings through the improvement of education, which, in turn, affects women's obesity. Our paper focuses on this, and we estimate the effects of education stipend programs on women's obesity in Bangladesh. However, to our knowledge, no research has investigated the impact of female education on women's obesity in Bangladesh. Applying a difference-in-difference approach, we find significant increases in obesity by 3.9 percentage points for females eligible for a 5-year stipend and 2.6 percentage points for females eligible for a 2-year stipend.

Our research contributes to literature in particular ways. First, the previous research, mainly in developed and high-income countries, has shown the effect of education on chronic diseases-BMI, overweight or obesity, diabetes, and hypertension (Brunello et al. 2013; Davies et al. 2018; Di Chiara et al. 2017; Grabner 2009; Kemptner et al. 2011; Powdthavee 2010; Reinhold and Jürges 2010) while inadequate studies in developing countries (Barlow 2021; Tansel and Karaoglan 2016; Xie and Mo 2014). Second, previous research in developing and Southern Asian countries has shown that policies targeting primary education change obesity (Barlow 2021; Tansel and Karaoglan 2016) but have no impact on policies targeting secondary education on overweight or obesity (Xie and Mo 2014), while in Bangladesh the 1994 FSSSP, which targeted secondary education, significantly changes obesity. Third, previous research has shown that educational policies targeted boys and girls who were overweight or obese (Xie and Mo 2014), while the 1994 FSSSP only targeted rural girls.

Data

We use the Bangladesh Demographic and Health Survey (BDHS) waves of 2011 and 2017-2018 for estimating equation (2). BDHS is a worldwide Demographic and Health Surveys (DHS)[21]

[21] For the waves 2011 and 2017-2018, women were surveyed aged 15 to 49 years. The data set access from the DHS program website (https://dhsprogram.com/data/available-datasets.cfm) upon authorization.

segment publicly available nationally representative cross-sectional survey data. The BDHS collects the household and women's records on demographic and socioeconomic characteristics. The study looks at the effects of FSSSP on female health, including obesity. *Obesity:* The body mass index (BMI) can be calculated by applying weight in kilograms shared by the height in square meters. While measuring weight, a respondent is categorized as obese if the female's BMI is ≥30 kg/m^2 and otherwise not (Bista et al. 2020).

We use a dichotomous indicator for obesity, equal to 1 if the female's BMI is ≥30 kg/m2 and 0 otherwise, as dependent variables. The female's education (in years) and a dichotomous category for finishing secondary or higher education are used as dependent variables.

In this study, females were at least 16 years old and birth year from 1975 to 1998 during the interview. We also restrict our sample to women who are not pregnant during the survey. Our final sample consists of 18,664 female observations for the analysis of obesity.[22] Table 2.1 exhibits summary statistics. Overall, females have 5.5 education (in years), and almost 49.7% finished secondary or higher schooling. Females exposed to FSSSP (5 years of stipend) have 1.7 years of education more compared to those unexposed to FSSSP. About 5.1% fall under the category of obesity. Fully exposed females to stipend are 0.02 percentage points less prone to risk of obesity than unexposed females. Approximately 90% & 64% of the female sample are Muslim & reside in a rural area, and the average age is 30.

Method

We use the following method to examine the causal effect of the stipend program on female obesity.

[22] We use the BDHS's household and women recode files to construct the sample for the obesity and education analyses.

$$Y_{ikt} = \beta_0 + \beta_1 Fully\ Exposed_k \times Rural_{ikt} + \ \beta_2 Partially\ Exposed_k \times Rural_{ikt} +$$
$$\beta_3 Rural_{ikt} + + \beta_4 \mathrm{X}_{ikt} + \gamma_k + \varepsilon_{ikt} \qquad (2)$$

Where Y_{ikt} is an indicator of the obesity status of female i who was born in year k and interviewed in the survey year t. For analyzing female schooling, education (in years), a dichotomous category finished secondary or higher education as a dependent variable. $Rural_{ikt}$ is a dichotomous category for rural residence in the year t. $Fully\ Exposed_k$ is one (the female was birth year in 1983 or later), and 0 otherwise. $Partially\ Exposed_k$ is one (the female was birth year from 1980 to 1982) and zero otherwise. The comparison group is those who were birth year in 1979 or earlier (unexposed to FSSSP). X_{ikt} expresses covariates with surve wave fixed effects, Muslim- a dichotomous category (all other religions as comparison category), and division fixed effects.[23] γ_k is a vector of maternal birth year fixed effects. We applied standard errors clustered at the female birth year level by applying a one-way wild cluster bootstrap technique (Cameron and Miller 2015).

We are interested in examining the parameters in the above equation are the coefficients on the interaction terms, β_1 and β_2. β_1 and β_2 explains the obesity rates of fully and partially exposed females compared to non-exposed females by the rural-urban difference.

Identification hypothesis that in the absence of the FSSSP, female obesity rates among female groups would have progressed equally in rural and urban areas. The event study was applied in equation (2) with a full set of fixed effects for female birth year (1979 is the comparison cohort). Also, apply a falsification test to evaluate the identifying hypothesis. We consider the falsification

[23] In Bangladesh, the administrative divisions changed during our study period. Wave 2011, Bangladesh was divided into seven administrative divisions. Mymensingh division separated from Dhaka division in 2015. Wave 2017-2018, Bangladesh was divided into eight administrative. For consistency, divisions across waves, we use the seven divisions for the female education and obesity analysis. Therefore, in our analysis, we use seven divisions – Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur, and Sylhet.

test for females' birth year before 1980 (not eligible for the FSSSP). We consider females' birth years from 1974 to 1979 (the fully exposed falsification cohort), females' birth years from 1971 to 1973 (the partially exposed falsification cohort), and females born between 1965 and 1970 (the non-exposed cohort). We then use equation (2) for the falsification test.

Results

In Table 2.2, we present results for the education. We observe that education (in years) is greater by 1.6 years for fully exposed females compared to non-exposed females and partially exposed females by 0.71 years compared to non-exposed females by changing urban and rural (Table 2.2, Column 2). Moreover, we observe that the likelihood of finishing secondary or higher education for fully and partially exposed females compared to non-exposed females is larger by 17.0 and 5.5 percentage points by changing urban and rural (Table 2.2, Column 4). The findings are similar to the results of the FSSSP applied in earlier studies[24] in Bangladesh.

In Table 2.3, we display the estimated outcomes for female obesity. We observe a rise in the probability of obesity for the females eligible for 5 years of stipend and partially exposed compared to non-exposed females by changing urban and rural. Particularly, the rural-urban change in the likelihood of obesity increased by 3.9 percentage points for fully exposed females compared to unexposed females and by 2.6 percentage points for partially exposed females compared to exposed females by changing urban and rural (column 2, Table 2.3). We observe significant increases in obesity for females eligible for 5 years and 2 years of stipend.

[24] See Hahn et al. (2018a, 2018b) and Wu (2022)

Identification

Figure 2.2 and Figure 2.3 show the event study results for female obesity and education. The figures outline the coefficient comparable to each birth year × rural. The figure for education (in years) shows a comparatively flat tendency for unexposed females and a sharp rise for fully or partially exposed females. We observe analogous tendencies for finishing secondary or higher education. The obesity graph exhibits a flat tendency for females who were ineligible for the FSSSP, and we do not observe a clear tendency for females who were only eligible for 2 years of stipend. However, we observe a steep rise in obesity for females eligible for 5 years of stipend. Event study Table and graphs, including the confidence intervals, are presented in Appendix Table B1, Figures B3, and B4.

Table 2.4 shows the falsification testing to confirm our identifying hypothesis further. The results are insignificant or have the inverse sign, indicating that our identifying hypothesis is fulfilled (i.e., assuming no other factors influence birth cohorts and rural residents differently).

Robustness Checks and Alternative Approaches to Inference

We check some robustness, as shown in Table 2.5. First, internal migration (i.e., urban vs. rural areas) may change the identification strategy. Dhaka is the capital of Bangladesh, we exclude the Dhaka division (Table 2.5, Panel A). The urbanization rate is faster (Chowdhury and Amin 2006) than in the rest of the country, maybe due to migration (urban vs. rural). We narrowed the sample (females born between 1975 and 1987) in Panel B (Table 2.5). We observe similar magnitudes to our main estimates. This confirms that our results are not driven by comparisons between outlying groups. We broaden the sample (females born between 1971 and 1998) in Panel C (Table 2.5). In the broader sample, we also observe similar magnitudes. In Panel D, we exclude those breastfeeding mothers. After fertility, mothers might be slightly more obese than usual (Fernández Alba et al., 2018). We observe similar results.

Decisively, considering the proposals of MacKinnon et al. (2022), we apply substitution methods (Table 2.6). The one-way standard errors are clustered at the female's birth year level by applying the Wild cluster bootstrap method applied in our main results (Panel A, Table 2.6). Analogously, we study three other clustering. We analyzed one-way clustering at the female's birth year × rural level (Panel B, Table 2.6), at the division level (Panel C, Table 2.6), and at the female's birth year × division level (Panel D, Table 2.6) to capture reform may have differed across divisions. The results for obesity, including fully or partially exposed females, are statistically different at the 1% to 5% level applying alternative methods. In summary, our conclusions remain unchanged.

Other Measures- Quantile Regression Analysis

Table 2.7 presents the quantile regression estimates for female BMI. The quantile regression analyses showed that FSSSP is positively related to their BMI through the lower to upper quantiles of the BMI distribution. Specifically, the percentage change in BMI distribution at quantile levels 0.1, 0.2, …0.8,0.9 are 27.9%, 49.5%, ... 80.2%,94.2% for fully exposed cohorts (females eligible for a 5-year stipend) compared to unexposed cohorts. The effect of FSSSP raised moving from the lower to the upper part of the BMI distribution. It implies that higher-educated women are inclined to have higher BMIs (Hossain et al. 2021). We find a significant impact for the female eligible for a 2-year stipend only for the quantile level at 0.3, 0.8, and 0.9.

Potential Mechanisms

Possible mechanisms through which FSSSP affects earnings, which, in turn, affects women's obesity, are (a) income effect, (b) contraception use, and (c) the use of screen time. Table 2.8 presents the difference-in-differences estimates for possible mechanisms through which FSSSP affects women's obesity. It is important to state that these results are only indicative and that the various mechanisms may interact with each other in complex ways.

Income Effects

Income effects may interact in complex ways with education, labor supply, fertility, etc. Consistent with the income channel, previous research has shown that education impacts the labor supply of women and the characteristics of their partners (Breierova and Duflo 2004; Keats 2018; Hahn et al. 2018a, 2018b; Sara and Priyanka 2022). Since the DHS does not include information on income, as we used in Chapter 1, labor supply, occupation, and husband's education to examine this channel (see Chapter 1 Table 1.8) and found that the program significantly increases the probability that the respondent's husband has completed secondary or higher schooling, that respondent's works in the formal sector, and her husband works in the formal sector as well. Loss of physical activity, formal jobs, and/or businesses caused by education may increase obesity.

Contraception Use

Contraception is the highest fertility-reducing factor (Kabir et al., 2009; Majumder and Ram, 2015). Women who use hormonal contraceptives are at greater risk of overweight or obesity (Grimes 2005; Callegari 2014). Higher BMI or body weight may be associated with unintended pregnancy using oral contraceptives (Holt 2005; Dinger 2011). Overweight and obese women may keep away from contraceptive methods they believe are correlated with weight gain and are more likely to use long-acting reversible contraceptives than normal-weight women (Bhuva et al., 2017). Higher education levels and dropping poverty are critical in enhancing contraceptive use and reducing unmet family planning needs (Nonvignon and Novignon, 2014). Employed women use contraceptives more (67%) than unemployed women, creating employment opportunities for women to enhance their contraceptive use (Islam et al., 2016). Secondly, we test whether the FSSSP changed women's contraception use. We observe an increase in the likelihood of women's contraception use for the females eligible for 5 and 2 years of stipend compared to not eligible females. Particularly, the probability of women's contraception use increased by 2.2 and 4.5 percentage points for fully and partially exposed females compared to non-exposed females by the rural-urban variation (Column 1 in Table 2.8). We observe significant increases in women's contraception use.

Uses of Screen Time

The relationship between screen time and obesity is that hours spent in front of the television displace time spent in physical activity (DuRant et at., 1994; Inoue et al., 2012). Women who watch four or more hours of television per day tend to have more than double the prevalence of obesity compared to those who watch less than one hour daily (Tucker and Bagwell, 1991). This screen viewing may be correlated with a dual influence of decreased physical activity and an increased intake of dense-caloric food while sitting in front of the screen leads to a positive energy balance and a sedentary lifestyle, which results in weight gain and ultimately obesity (Hands et al., 2011; Marttinen et al., 2017; Pitanga et al., 2016; Goldfield et al., 2015; Eisenmann et al., 2008; Duncan et al., 2012; Maruf and Udoji, 2015). Lastly, we test whether the FSSSP changed women's use of screen time. We observe an increase in the likelihood of use of screen time (i.e., watching TV) for the females eligible for 5 and 2 years of stipend compared to not eligible females. Particularly, the probability of use of screen time increased by 6.0 and 0.20 percentage points for fully and partially exposed females compared to non-exposed females (Column 2 in Table 2.8) by the rural-urban variation. We observe significant increases in women's screen time use for the female eligible for 5 and no effect for the female eligible for 2 years of stipend.

In summary, the FSSSP increases earnings and decreases fertility, leading to changes in lifestyle-more consumption of fast food, and diets high in fats, salt, and sugar (Gregorio and Lee 2002), which might increase obesity.

Conclusion

Health is likely to have positive growth repercussions due to improved productivity and increased human capital (Bloom et al. 2014; WHO 2009). Better female health speeds up the demographic transition and, thereby, the take-off toward sustained economic growth, and small changes in female health can strongly impact the transition process to a higher income level in the long run (Bloom et al. 2015). In this paper, we explore the effect of female education on women's obesity in Bangladesh, applying the Difference-in-Difference method. The FSSSP significantly raised women's obesity rates. Particularly, the probability of being obese increased by about 3.9 and 2.6 percentage points among females fully exposed and partially exposed to the unexposed females.

This result highlights that in a developing country like Bangladesh, the impacts of education on obesity are different from those observed in developed countries (Brunello et al. 2013; Davies et al. 2018; Di Chiara et al. 2017; Grabner 2009; Kemptner et al. 2011; Powdthavee

2010; Reinhold and Jürges 2010). In developed countries, the studies generally imply that more educated individuals have normal ranges of BMI (Böckerman et al. 2017; Grabner 2017; Kemptner et al. 2011; Reinhold and Jürges 2010; Webbink et al. 2010). The finding that education increases women's well-being through increased income and better marital match (Hahn et al. 2018a, 2018b), increases the use of screen time (Rehbein et al. 2010; Furthner et al. 2018), which incorporated fewer physical activities (Duncan et al. 2012), leading to higher BMI or obesity (Howitt et al. 2015). Our findings suggest that women's health has important spillover effects on future generations. Women's obesity is correlated with an increased risk of early neonatal mortality (Cresswell et al., 2013), maternal health shocks increase the probability of low birth weight infants (Almond et al. 2012), and iodine deficiency decreases schooling (Field et al. 2009).

Tables and Figures

Table 2.1. Summary Statistics.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample (Birth year 1975-1998)	Fully exposed cohorts (Birth year 1983-1998)	Partially exposed cohorts (Birth year 1980-1982)	Non-exposed cohorts (Birth year 1975-1979)	Fully exposed minus non-exposed cohorts	Partially exposed minus non-exposed cohorts
Variables	Mean	Mean	Mean	Mean	Mean	Mean
Education (in years)	5.478 (3.938)	6.070 (3.625)	4.826 (4.100)	4.362 (4.292)	1.708*** (25.050)	.464*** (4.596)
Education (Secondary or Higher)	.497 (.500)	.575 (.500)	.410 (.492)	.350 (.477)	.028*** (25.754)	.0600*** (5.200)
Women's obesity	.051 (.220)	.043 (.202)	.055 (.227)	.071 (.257)	-.021*** (-7.243)	-.0163*** (-2.7858)
Women's BMI	22.382 (4.598)	22.082 (4.518)	22.855 (4.488)	22.851 (4.812)	-.769 (-9.370)	.0036 (0.032)
(Female) Age	29.637 (6.242)	25.983 (4.489)	33.076 (3.219)	36.931 (3.380)	-10.95*** (-145.64)	- 3.86*** (-48.58)
Rural	.637 (.483)	.629 (.479)	.642 (.480)	.652 (.477)	- .022 (-2.587)	-.010 (-0.835)
Muslim	.900 (.300)	.906 (.292)	.890 (.313)	.893 (.310)	.0130 (2.467)	-.0026 (-0.344)
Observations	18,664	11,405	2,925	4,334		

Notes: Obese includes females with BMIs greater than or equal to 30. Standard deviation (columns 1 - 4) and t-statistics (columns 5-6) are in the parenthesis ***, **, and * correspond to 0.01, 0.05, and 0.1 levels of statistical significance.
Source: BDHS, 2011 and 2017-18.

Table 2.2. Diff.-in-Diff. Estimations of Female Education.

	Education (in years)		Education (Secondary or higher)	
	(1)	(2)	(3)	(4)
Fully exposed × Rural	1.6495***	1.6308***	.1733***	.1701***
	[1.302, 2.024]	[1.265, 2.018]	[.1284, .225]	[.1223, .2227]
Partially exposed × Rural	.7448***	.7121**	.0613*	.0552
	[.2636, 1.256]	[.1585, 1.246]	[−.0039, .131]	[−.01666, .127]
Covariates		×		×
Observations	18,664	18,664	18,664	18,664
Dep. var. mean	5.4782	5.4782	.4972	.4972

Notes: Our sample consists of females born from 1975 to 1998. For exposure to FSSSP (Full exposure - females' birth year from 1983 to 1998; partial exposure - females' birth year from 1980 to 1982; and non-exposure - females' birth year from 1975 to 1979).). Covariates: binary indicator (rural residence, Muslim), fixed effects (female birth year, survey wave, and division). We applied standard errors clustered at the female birth year level by applying a one-way Wild cluster bootstrap method. ***, **, and * correspond to 1%, 5%, and 10% levels of statistical significance, and 95% CIs are in square brackets.
Source: BDHS, 2011 and 2017-18.

Table 2.3. Diff.-in-Diff. Estimation of Women's Obesity.

	Women's obesity	
	(1)	(2)
Fully exposed × Rural	.0392***	.0387***
	[.0198, .05509]	[.01895, .05486]
Partially exposed × Rural	.0276**	.0259**
	[.006174, .05005]	[.003212, .04761]
Covariates		×
Observations	18,664	18,664
Dep. var. mean	.0512	.0512

Notes: Obese is one if the BMI of the female is greater than or equal to 30 and zero otherwise. Our sample consists of females born from 1975 to 1998. For exposure to FSSSP (Full exposure - females' birth year from 1983 to 1998; partial exposure - females' birth year from 1980 to 1982; and non-exposure - females' birth year from 1975 to 1979).). Covariates: binary indicator (rural residence, Muslim), fixed effects (female birth year, survey wave, and division). We applied standard errors clustered at the female birth year level by applying a one-way Wild cluster bootstrap method. ***, **, and * correspond to 1%, 5%, and 10% levels of statistical significance, and 95% CIs are in square brackets.
Source: BDHS, 2011 and 2017-18.

Table 2.4. Falsification Tests.

	(1)	(2)	(3)
	Education (in years)	Education (Secondary or higher)	Women's obesity
Fully exposed × Rural	-.3517*	-.0261	-.0027
	[−.672, .0328]	[−.0757, .0329]	[-.0283, .0249]
Partially exposed × Rural	-.0076	.0003	-.0148
	[−.397, .643]	[−.0449, .0636]	[-.0467, .0438]
Covariates	×	×	×
Observations	10,490	10,490	10,490
Dep. var. mean	3.7257	.2885	.0651

Notes: The falsification sample includes only non-eligible cohorts born between 1965 and 1979. For exposure to FSSSP (Full exposure - females' birth year from 1974 to 1979; partial exposure - females' birth year from 1971 to 1973; and non-exposure - females' birth year from 1965 to 1970).). Covariates: binary indicator (rural residence, Muslim), fixed effects (female birth year, survey wave, and division). We applied standard errors clustered at the female birth year level by applying a one-way Wild cluster bootstrap method. ***, **, and * correspond to 1%, 5%, and 10% levels of statistical significance, and 95% CIs are in square brackets.
Source: BDHS, 2011 and 2017-18.

Table 2.5. Robustness Checks.

	Women's obesity	
	(1)	(2)
Panel A: Excluding Dhaka division		
Fully exposed × Rural	.0324***	.0319***
	[.01589, .04799]	[.01538, .04749]
Partially exposed × Rural	.0179***	.0162**
	[.005767, .03143]	[.004527, .03026]
Observations	14,486	14,486
Dep. var. mean	.0496	.0496
Panel B: Birth cohorts 1975-1988		
Fully exposed × Rural	.0342***	.0330***
	[.01742, .04843]	[.01592, .04836]
Partially exposed × Rural	.0276**	.0261**
	[.005837, .04936]	[.004057, .04812]
Observations	13,274	13,274
Dep. var. mean	.0580	.0580
Panel C: Birth cohorts 1971-1998		
Fully exposed × Rural	.0355***	.0364***
	[.01638, .05476]	[.01753, .05589]
Partially exposed × Rural	.0239*	.0238*
	[−.0005356, .04995]	[−.0002394, .04961]
Observations	21,808	21,808
Dep. var. mean	.0533	.0533
Panel D: Excluding breastfeeding mother		
Fully exposed × Rural	.0422***	.0412***
	[.02079, .06163]	[.0195, .06082]
Partially exposed × Rural	.0273	.0256
	[−.006566, .06046]	[−.009946, .05873]
Observations	13,652	13,652
Dep. var. mean	.0599	.0599

Notes: For exposure to FSSSP (Full exposure - females' birth year from 1983 to 1988/1998; partial exposure - females' birth year from 1980 to 1982; and non-exposure - females' birth year from 1975 to 1979 [Panel A], females' birth year from 1977 to 1979 [Panel B], females' birth year from 1971 to 1979 [Panel C]).). Covariates: binary indicator (rural residence, Muslim), fixed effects (female birth year, survey wave, and division). We applied standard errors clustered at the female birth year level by applying a one-way Wild cluster bootstrap method. ***, **, and * correspond to 1%, 5%, and 10% levels of statistical significance, and 95% CIs are in square brackets.
Source: BDHS, 2011 and 2017-18.

Table 2.6. Alternative Clustering Approaches.

	Women's obesity	
	(1)	(2)
Panel A: At birth year level		
Fully exposed × Rural	.0392***	.0387***
	[.0198, .05509]	[.01895, .05486]
Partially exposed × Rural	.0276**	.0259**
	[.006174, .05005]	[.003212, .04761]
Panel B: At birth year × rural level		
Fully exposed × Rural	[.006366, .08765]**	[.005733, .08725]**
Partially exposed × Rural	[−.01579, .08464]	[−.02426, .08477]
Panel C: At division level		
Fully exposed × Rural	[.0136, .059]***	[.01596, .05859]***
Partially exposed × Rural	[−.01524, .06228]	[−.0151, .06011]
Panel D: At birth year × division level		
Fully exposed × Rural	[.01754, .06127]***	[.01734, .0608]***
Partially exposed × Rural	[.001998, .05246]**	[−.00006094, .05118]**

Notes: Our sample consists of females born from 1975 to 1998. For exposure to FSSSP (Full exposure - females' birth year from 1983 to 1998; partial exposure - females' birth year from 1980 to 1982; and non-exposure - females' birth year from 1975 to 1979).). Covariates: binary indicator (rural residence, Muslim), fixed effects (female birth year, survey wave, and division). We applied standard errors clustered at the female birth year level by applying a one-way Wild cluster bootstrap method. ***, **, and * correspond to 1%, 5%, and 10% levels of statistical significance, and 95% CIs are in square brackets.
Source: BDHS, 2011 and 2017-18.

Table 2.7. Quantile Regression of Women's BMI.

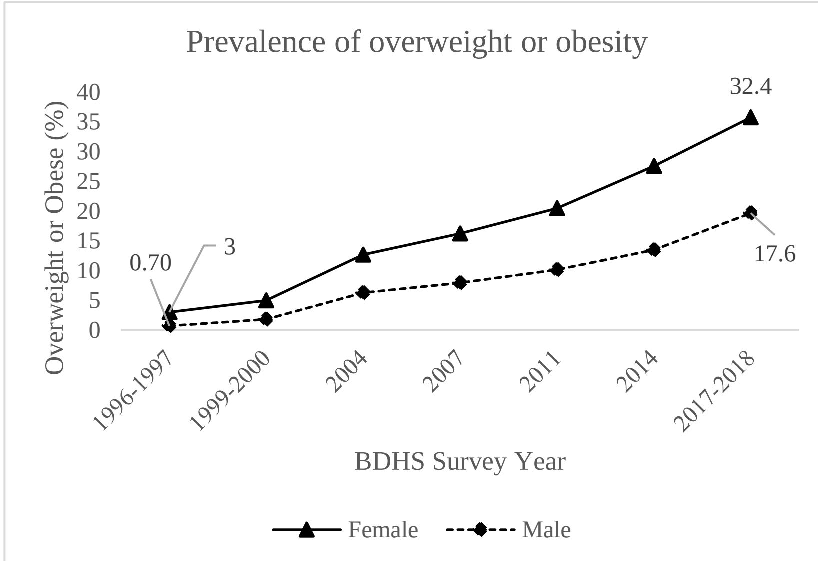
	BMI								
	quantile (.10)	quantile (.20)	quantile (.30)	quantile (.40)	quantile (.50)	quantile (.60)	quantile (.70)	quantile (.80)	quantile (.90)
	(1)	(2)	(3)						
Fully exposed × Rural	.2797	.4948***	.7004***	.7695***	.7131***	.6584***	.5870***	.8016***	.9419***
	(.1971)	(.1800)	(.1752)	(.1854)	(.1738)	(.1958)	(.1988)	(.2366)	(.2821)
Partially exposed × Rural	-.1774	-.1235	.0528**	.1507	.0384	-.0362	.2921	.5521*	.6370*
	(.2643)	(.2415)	(.2348)	(.2486)	(.2331)	(.2625)	(.2666)	(.3173)	(.3783)
Covariates	×	×	×	×	×	×	×	×	×
Observations	18,664	18,664	18,664	18,664	18,664	18,664	18,664	18,664	18,664

Notes: Our sample consists of females born from 1975 to 1998. For exposure to FSSSP (Full exposure - females' birth year from 1983 to 1988; partial exposure - females' birth year from 1980 to 1982; and non-exposure - females' birth year from 1975 to 1979). Covariates: binary indicator (rural residence, Muslim), fixed effects (female birth year, survey wave, and division). ***, **, and * correspond to 1%, 5%, and 10% levels of statistical significance, and standard errors are in parenthesis.
Source: BDHS, 2011 and 2017-18.

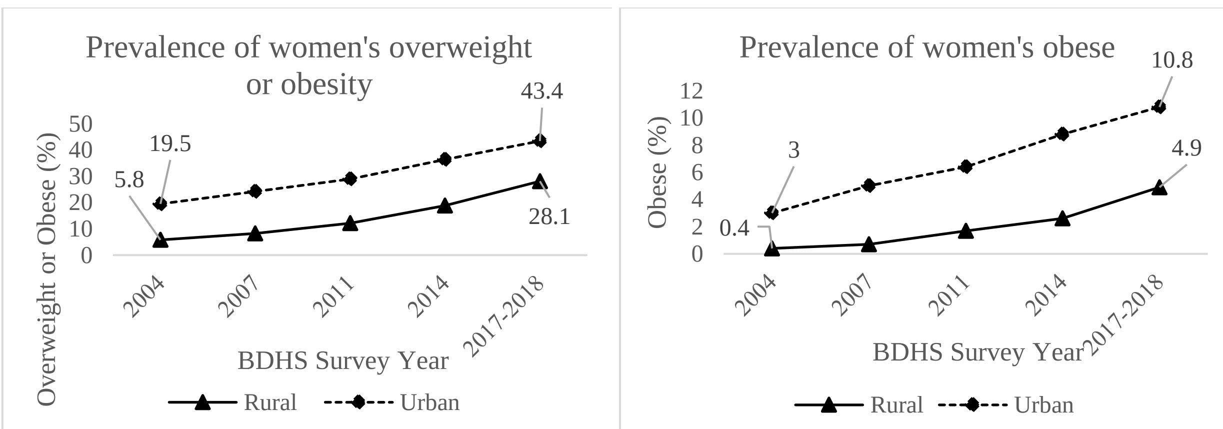
Table 2.8. Diff.-in-Diff. Estimations of Fertility, and Leisure.

	Contraceptive use	Use of screen time
	(1)	(2)
Fully exposed × Rural	.0225*	.0596***
	[−.00315, .04505]	[.03479, .08594]
Partially exposed × Rural	.0447**	.0020
	[.02077, .07531]	[−.04203, .05533]
Covariates	×	×
Observations	18,664	18,662
Dep. var. mean	.9073	.5198

Notes: Our sample consists of females born from 1975 to 1998. For exposure to FSSSP (Full exposure - females' birth year from 1983 to 1988; partial exposure - females' birth year from 1980 to 1982; and non-exposure - females' birth year from 1975 to 1979). Covariates: binary indicator (rural residence, Muslim), fixed effects (female birth year, survey wave, and division). We applied standard errors clustered at the female birth year level by applying a one-way Wild cluster bootstrap method. ***, **, and * correspond to 1%, 5%, and 10% levels of statistical significance, and 95% CIs are in square brackets.
Source: BDHS, 2011 and 2017-18.



Panel A: Overweight or Obesity Rates by Gender



Panel B: Women's Overweight or Obesity Rates by Residence

Figure 2.1. Trends in Overweight or Obesity Rates by Gender and Residence.
Notes: The graphs present overweight or obese rates (%) among males and females in Panel A (females—solid line and males- dashed line) and overweight or obese rates (%) among females by residence in Panel B (rural—solid line and urban -dashed line) aged 15 and above in Bangladesh.
Source: BDHS, from 2004 to 2017-18.

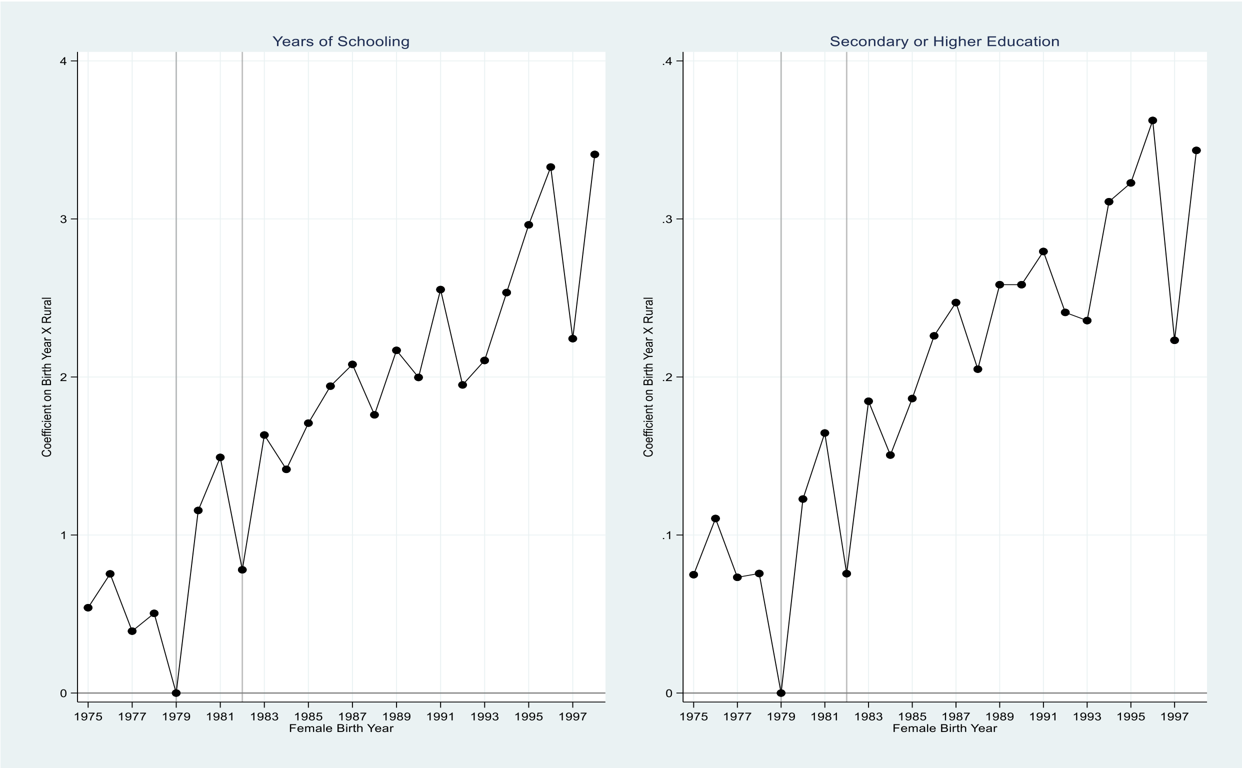


Figure 2.2. Event Study Graphs for Female Education.
Notes: Graphs show Birth Year (1975-1998) × Rural fixed effects, rural, female birth year, female age, and division fixed effects. Our sample consists of females birth year from 1975 to 1998 (in comparison to 1979).
Source: BDHS, 2011 and 2017-18.

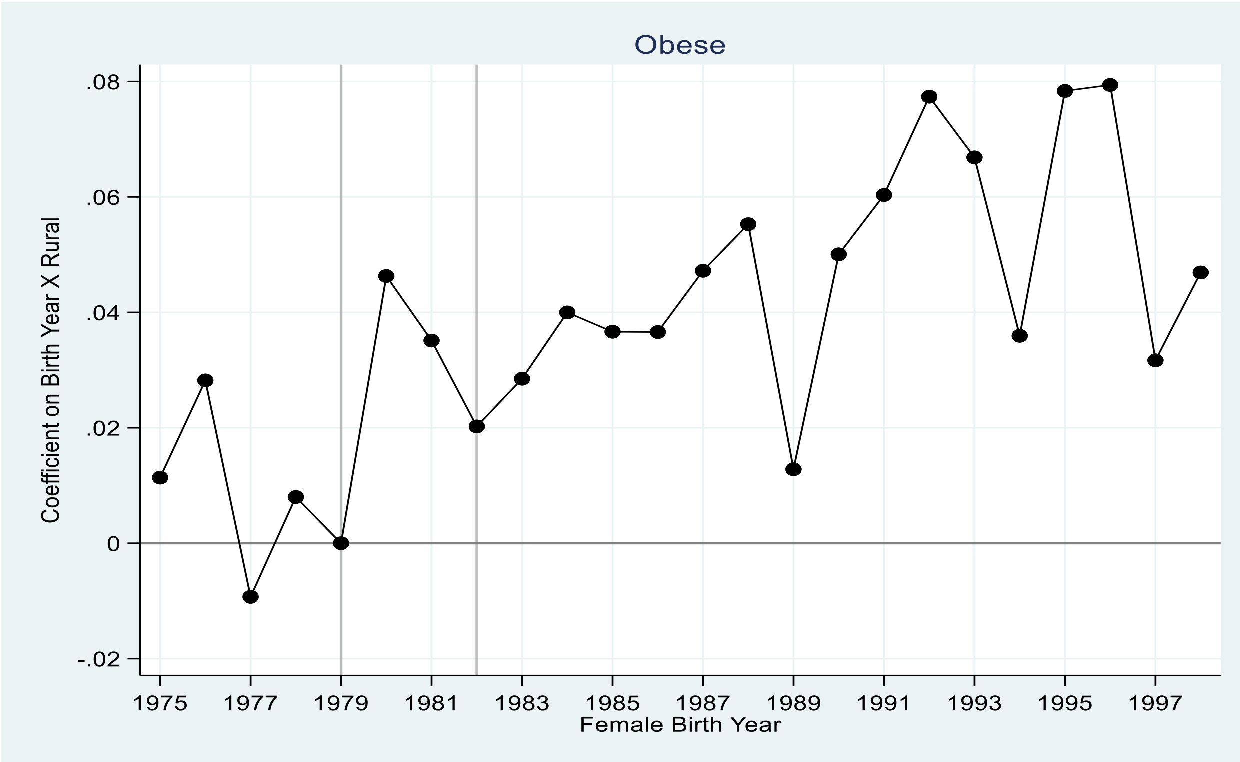


Figure 2.3. Event Study Graph for Women's Obesity.
Notes: The graph shows Birth Year (1975-1998) × Rural fixed effects, rural, female birth year, female age, and division fixed effects. Our sample consists of females birth year from 1975 to 1998 (in comparison to 1979).
Source: BDHS, 2011 and 2017-18.

CHAPTER THREE:

THE IMPACT OF TROPICAL STORMS ON EARLY CHILDHOOD HEALTH: EVIDENCE FROM BANGLADESH

Md Shahjahan, and Padmaja Ayyagari *

Introduction

Natural disasters are a growing concern that have become severe and frequent due to climate change and are harmful to developed and developing countries (Van Aalst 2006). However, people in low-income countries, specifically mothers and children, are the most vulnerable to those shocks regarding damage to lives and livelihoods (Bartlett 2009; Islam and Nguyen 2018). Disasters can cause fatalities and negatively impact infrastructures and the overall economy (Hsiang and Jina 2014; Islam 2020; Zhou and Zhang 2021). We can explain how natural disasters affect health in this way: the disasters may impact households through adverse income/wealth shocks (Karbownik and Wray 2019; Karim 2018) and restrict access to healthcare. In particular, exposure to adverse environmental effects during critical developmental phases[25], such as prenatal (in-utero) and postnatal periods, leads to lasting changes in gene expression as well as brain and body functions in early childhood (Barker 1995, 2007). It is crucial to address the nutritional status of children (Akhter et al. 2015; Barker 2003; Lumey et al. 2011; Victora et

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[25] A dynamic and productive civilization with a successful and sustainable future is developed on establishing healthy child development (Center on the Developing Child, Harvard University, 2014).

al. 2008) due to climate shock through the fetal origin hypothesis (e.g., Barker 1995; Eriksson 2005; Godfrey and Barker 2001) indicates the significance of maternal situations for fetal (during in-utero) and later growth[26] and development[27].

A vast literature has documented that natural disasters have short-term and long-term impacts on various health indicators (Currie and Vogl 2013; de Oliveira et al. 2023; Fontaine et al. 2021; Kuh et al. 2003; Lépine et al. 2021; Maccini and Yang 2009). These shocks can significantly impact the children's nutritional outcomes in the affected families (Ahmed and Eklund 2019; del Ninno et al. 2002; O'Donnell et al. 2002).

Prior studies have investigated the impact of natural disasters on children's health, focusing on single large or large vs. small-scale disaster events (Almond et al. 2018; Del Ninno and Lundberg 2005; Goudet et al. 2011; Rodriguez-Llanes et al. 2016). For example, studies have examined the effect of natural disasters, particularly flooding (Del Ninno and Lundberg 2005; Foster 1995; Karim 2018; Rodriguez-Llanes et al. 2016), droughts (Hoddinott and Kinsey 2001; Le and Nguyen 2022), earthquakes (Pun and Fontenla 2022), environmental pollution (Wang et al. 2022) and cyclones (Baez and Santos 2007; Islam 2020; Kabir et al. 2016; Paul et al. 2012) on child health.

Although the effects of large-scale disasters are influential, countries are more repeatedly affected by small-scale disasters, sometimes frequently due to climate (Van Aalst 2006), which are likely to have a significant impact. In fact, large-scale disasters typically receive substantial attention and assistance from home and abroad after natural disasters (Rahman and Bennish 1993;

[26] Disproportionate fetal growth caused mainly by environmental stress or nutritional deficiencies could be linked with metabolic or endocrine dysregulation, resulting in adverse health outcomes (Barker 1995; Gluckman et al. 2005).
[27] Health in the earliest years (i.e., beginning with the future mother's well-being) improves the developing biological organisms that enable children to flourish and become healthy adults (National Scientific Council on the Developing Child 2020).

Strömberg 2007), potentially reducing some adverse effects. In contrast, small-scale shocks often do not receive much attention and may significantly negatively affect household welfare and children's long-term health outcomes (Malak et al. 2020). Datar et al. (2013) investigated the effects of exposure to small-scale to moderate-scale natural disasters (i.e., droughts, earthquakes, epidemics, extreme temperatures, floods, mass movements, storms, and wildfires) on children's health in India and found negative effects on child's health but focused only in rural areas while Edoka (2013) explored the impact of weather shocks (i.e., droughts, extensive rain or floods, erosions, landslides, frosts, and storms) on the nutritional status of disadvantaged children in Vietnam but focused only for height-for-age z-score.

In this paper, we explore the effects of exposure to tropical storms on anthropometric measures and nutritional indicators of child health in Bangladesh. We focus on Bangladesh as relevant for particular reasons. First, Bangladesh is the world's 9th (27.90%) highest risk of natural disasters (World Risk Report 2022) due to its geographical factors, including low-lying and delta-exposed topography, and socioeconomic factors, including high population density, chronic poverty, lower coping capacities, and heavy dependency on agriculture (Matin and Taher 2001). Second, from 2008 through 2017, the period spanning our data, there were six tropical storms with maximum wind speeds ranging from 21 to 33 meters per second (m/s) formed in the Bay of Bengal, causing 368 fatalities, affecting households and people of about 1.8 million and 11.11 million, and devastating property, including 1.1 million houses and 1.5 million crops damaged (Table 3.1). Third, substantial progress in the nutritional status of stunting, wasting, and underweight has been achieved, but the nutritional status of under-five Bangladeshi children is still low, which translates to a 3.9% reduction in yearly stunting[28] and wasting[29] to <5% by 2025 and <3% by 2030 (Figure

[28] See de Onis et al.(2013).
[29] See WHO and UNICEF (2018).

3.1) and the country is off-track to achieve the recommendation rates of WHO and UNICEF. However, these tropical storms did not result in large fatalities and damage, and there has been less attention to whether exposure to these tropical storms affects child health in Bangladesh.

Possible mechanisms[30] through which tropical storms affect child health are (a) income/wealth, (b) access to maternal healthcare, (c) infectious diseases, and (d) access to children's food and vitamin or mineral supplements.

We use maximum wind speed to explore the impact of in-utero and childhood exposure to small-scale tropical storms on anthropometric measures and nutritional indicators of child health in Bangladesh. We employ linear regression models which capture geographic and temporal variation in child health and tropical storms exposure. Our models include fixed effects for district of residence and child's year of birth. The results show that maximum wind exposure to tropical storms during in-utero and childhood negatively affects the nutritional gains of children.

Our study contributes to literature in particular ways. First, previous research in Bangladesh has focused on the impact of large-scale cyclones on child health (Kabir et al. 2016; Paul et al. 2012), while we use the small-scale tropical storm (≤33 m/s) on child health. Second, a previous study found that cyclone AILA-2009 in Bangladesh positively affects child health (Islam 2020), which contradicts the findings of Kabir et al. (2016), while we find that experiencing tropical storms in the in-utero and childhood period adversely affects child health in Bangladesh. Finally, our study contributes to the literature on the effects of tropical storms by trimester exposure. A previous study found that cyclone AILA-2009 in Bangladesh during 1st and 2nd trimesters did not affect the probability of stunting, being underweight, or wasting, and 3rd trimester impacts the probability of wasting positively (Islam 2020), while our study finds 1st

[30] Explained in the mechanism section.

trimester increases the probability of stunting, and 3rd trimester increases the probability of being underweight, which adversely affects child health. The findings suggest that exposure to tropical storms can have important long-term effects on child health, and the impact depends on the timing of exposure. Our findings are consistent with the fetal origin hypothesis indicating the transmission of early-life shocks to late-life health deficits.

Data

Child health data: We use the 2012-2013 and 2019 waves of the Bangladesh Multiple Indicator Clusters Survey (MICS) for the child health data. The MICS is a publicly available[31] nationally representative cross-sectional survey conducted jointly by the Bangladesh Bureau of Statistics (BBS) and UNICEF. MICS surveys measure the situation of children and women's wide range of indicators at the level of geographical locations such as regions and districts as well as areas of residence. We used the exclusive feature in the MICS data to collect each child's birth month in the child's date of birth (CDOB) variable, which allow us to calculate[32] in-utero, trimesters, neonatal, and postnatal periods when tropical storms hit.

We use anthropometric z-scores as measures of child health, including height-for-age z-scores (HAZ), weight-for-height z-scores (WHZ), and weight-for-age z-scores (WAZ) for children under five by their age and sex. The reference population is constructed using the World Health Organization (WHO) growth standards (WHO, 2006). Children whose HAZ, WHZ, and WAZ scores are greater than two standard deviations below the median of the reference population are categorized as stunted, wasted, and underweight, respectively. The anthropometric z-scores, in particular, HAZ, show long-term health conditions, while WAZ indicates current health conditions

[31] Upon approval at: http://mics.unicef.org/surveys
[32] See Islam (2020) for a more detailed discussion of the calculation.

(WHO, 2008). Prolonged exposure to environmental stressors affects stunting (i.e., HAZ <-2 SD), while wasting (i.e., WHZ<-2 SD) is caused by inadequate nutrient intake and illness infection in the short term. Underweight (i.e., WAZ<-2 SD) is influenced by both current and long-term conditions (WHO, 2008).

Tropical storm data: The tropical storm's wind data for Bangladesh are retrieved from the NASA Langley Research Center (LaRC), POWER[33] Project financed by the NASA Earth Science/Applied Science Program[34]. According to Hsiang and Narita (2012), neither wind speed nor energy is a perfect measure of tropical storm wind exposure; however, each has its benefits (i.e., it is easier to interpret units of "meters per second" compared to "meters-cubed per second-squared"). This study uses maximum wind speed to measure exposure to tropical storms, measured in meters per second (m/s). We calculate the maximum wind speed during each tropical storm/year for each district and then merge wind speed data with child health data using the district and childbirth year. The maximum wind speed exposure for years without tropical storms is set to zero. We used ArcMap to visualize the geographic location of Bangladesh in the global context and district-wise maximum wind speed during tropical storms from 2008 through 2017 across Bangladesh (Figure 3.2 and Figure C1).

We study children under 60 months born between 2008 and 2019 exposed to tropical storms through maximum wind speed and compared to unexposed to tropical storms. Our estimation sample consists of 41,193 children. Table 3.2 presents summary statistics for Panels A and B's dependent and independent variables. Panel A presents the average HAZ, WHZ, and WAZ scores, which are -1.5106, -0.6887, and -1.3498 standard deviations, respectively. On average, the stunting, wasting, and underweight are 34.41%, 9.85%, and 26.90%.

[33] The Prediction of Worldwide Energy Resources (POWER)
[34] Available at: https://power.larc.nasa.gov/data-access-viewer/

Moving on to Panel B, the average wind speed in our sample is 5.15 m/s, the average household members are 5.48, approximately 89.42% are Muslim, and around 82.81% of households live in rural areas. The average value of the household wealth index's bottom two quantiles is 48.40%, referred to as a poor household. The mean child's age is about 2.04 years, and 51.45% of children are male. Approximately 40.74% of children are in prenatal (9 months in-utero period), and 15.78%, 14.15%, and 12.51% are in the 1st trimester, 2nd trimester, and 3rd trimester while 8.12% and 12.00% of children are in the neonatal and postnatal periods, respectively.

Methodology

We employ the following linear regression with "fixed effect", which captures geographic and temporal variation in child health and tropical storms exposure:

$$Y_{idt} = \beta_0 + \beta_1 WindExposure_{dt} + \beta_2 \mathbf{X}_{idt} + \lambda_d + \delta_t + u_{idt} \qquad (3)$$

Where the subscripts i is for the child, d is for the district, and t is for the child's birth year. The variable Y_{idt} indicates the outcome of interest, including anthropometric measures (i.e., HAZ, WHZ, WAZ) scores and nutritional indicators (i.e., stunting, wasting, underweight). $WindExposure$ is an explanatory variable of wind exposure to tropical storms in district d and birth year t. $\mathbf{X}_{idt}$ denotes a vector of covariates including a binary indicator for Muslim (the reference group includes all other religions), number of household members, and child age in years; λ_d and δ_t represent district and childbirth year fixed effects to avoid omitted variable bias. Child birth year fixed effects account for unobserved factors at the birth year levels that could have affected the child's health. District fixed effects account for district-specific factors that do not change over time but could have affected the child's health. By incorporating the childbirth year and district-fixed effects, tropical storms' impact on the child's health is identified within the location and the year of birth. u_{idt} is an error term, and at the district level, standard errors are clustered to account for the concerns of serial correlation (random observations). We are interested in estimating the coefficient β_1 that captures the impact of wind exposure to tropical storms on early childhood health. Our identifying assumption is that, conditional on districts and child birth year fixed effects and demographics, there are no unobserved factors correlated with wind exposure and child health.

The exclusive feature of the MICS data is that it records each child's birth month in the CDOB code, allowing us to observe the impact of prenatal (in-utero) and postnatal wind exposure to tropical storms on child health by trimesters (first, second, and third), neonatal, and postnatal analysis when tropical storms hit[35]. Neonatal represents the first four weeks or one month, and postnatal is the first eight weeks or two months of a baby being exposed to tropical storms.

Empirical Results and Discussion

Prenatal (in-utero) Exposure

A healthy pregnancy is a blessing that promotes a healthy birth[36]. Children exposed to extreme climate shocks such as tropical storms in the utero stage experience a reduction in HAZ score and are more prone to be stunted and underweight (Eskander and Barbier 2019). Table 3.3 shows the impact of prenatal (in-utero) wind exposure to tropical storms on child health. All

[35] For example, tropical storm RASMI dissipated in October 2008. Mothers were exposed to tropical storms during the prenatal period of their children born between February and October 2008. Mothers exposed to tropical storms during 1st trimester if their children were born between February and April 2008. Similarly, 2nd trimester and 3rd trimester include children born between May & July 2008 and August & October 2008, respectively. Children exposed to tropical storms during neonatal period if children born in October 2008 and children exposed to tropical storms during postnatal period if children born between October and November 2008, respectively.

[36] Health in the earliest years (i.e., beginning with the future mother's well-being) improves the developing biological organisms that enable children to flourish and become healthy adults (National Scientific Council on the Developing Child, 2020).

regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. Evident from Panel A in Table 3.3, under-five children exposed to tropical storms during the in-uterine period decrease the HAZ, WHZ, and WAZ by about 0.0211(column 2), 0.0091(column 4), and 0.0127(column 6) standard deviations by increasing maximum wind by a meter per second (m/s). As apparent from Panel B in Table 3.3, it increases the probability of stunting, wasting, and being underweight by about 0.43,0.14, and 0.32 percentage points.

Prenatal (in-utero) Exposure — Heterogeneous Effects

Tropical storms in Bangladesh significantly impact disadvantaged backgrounds, including poor households, rural areas, coastal regions, and children, particularly girls. Studies have shown that the vulnerability of households to tropical storms is higher in marginalized communities and lower-income groups (Rahman et al. 2023; Islam et al. 2021); vulnerability of rural communities to tropical storms experience extensive damage (Farukh et al. 2019), livelihoods are severely affected (Islam et al. 2021) which is further intensified by socio-economic factors (Kulatunga et al. 2014); the coastal regions of Barisal, Chittagong, and Khulna (southern region) are particularly vulnerable to tropical storms disasters (Haque and Jahan 2016); tropical storms adversely affect the asset holdings of household heads, and influence fertility preferences, which may indirectly impact child gender preferences (Eskander and Barbier 2019; Haq and Md 2023).

Table 3.4 represents the heterogeneous effects of tropical storms during the in-utero period on child health. In Table 3.4, first, we examine the impacts of wind exposure to tropical storms on child health by household wealth. Poor and wealthy households belong to the bottom and top two quantiles of the household's wealth index. For children of poor mothers, in-utero exposure to tropical storms leads to reductions in WAZ, WHZ, and WAZ scores by 0.0258, 0.0121, and 0.0164 standard deviations by increasing maximum wind speed by a m/s while for the wealthy mothers, the magnitude of the estimates are lower for anthropometric measures compared to poor mothers. It increases the probability of stunting, wasting, and being underweight by about 0.71, 0.26, and 0.48 percentage points by increasing maximum wind speed by m/s, while the estimates for wealthy mothers are statistically insignificant, and the magnitudes of the estimates are lower for nutritional status compared to poor mothers. Second, we examine the heterogeneous effect of tropical storms on the mother's place of residence. In-utero exposure to tropical storms decreases the HAZ, WHZ, and WAZ scores by 0.0226, 0.0083, and 0.0127 standard deviations by increasing maximum wind speed by a m/s for children born to rural mothers. In contrast, for children born to urban mothers, the magnitude of the estimates is lower for anthropometric measures compared to rural mothers. It increases the probability of stunting, wasting, and underweight by about 0.52, 0.19, and 0.30 percentage points by increasing maximum wind speed by a m/s. At the same time, the estimates for urban mothers are statistically insignificant from zero for nutritional status compared to rural mothers. Third, we examine the heterogeneous effect of tropical storms on the mother's regions of residence. In-utero exposure to tropical storms decreases the HAZ, WHZ, and WAZ scores by 0.0265, 0.0072, and 0.0161 standard deviations by increasing maximum wind speed by a m/s for children born in southern regions. In contrast, for children born in northern regions, the magnitude of the estimates is lower for anthropometric measures compared to rural mothers. It increases the probability of stunting, wasting, and underweight by about 0.58, 0.17, and 0.42 percentage points by increasing maximum wind speed by a m/s. At the same time, the estimates for northern regions' magnitude are lower or statistically insignificant from zero for nutritional status compared to southern regions. Finally, we examine the heterogeneous effect of tropical storms on child health by child gender. Wind exposure to tropical storms decreases the HAZ and WAZ scores of female children by approximately 0.0295 and 0.0159 standard deviations by increasing maximum wind speed by m/s, while for the male children, the magnitude of the estimates are lower for anthropometric measures compared to female children. It increases the probability of stunting and underweight by about 0.56 and 0.48 percentage points by increasing maximum wind speed by a m/s while the magnitudes of the estimates for male children are lower or statistically insignificant from zero for nutritional status compared to female children. Overall, in-utero wind exposure to tropical storms harms the child health of disadvantaged backgrounds.

Prenatal (in-utero) Exposure — Trimester Analysis

We found negative impacts of prenatal (in-uterine period) wind exposure to tropical storms on child health. A full-term pregnancy has three trimesters; the fetus meets specific development in each trimester. The prevalence of antenatal depressive symptoms is one of the probable association factors affected by tropical storms, which can adversely affect the health and well-being of women and their babies (Begum and Biswas 2020). In this segment, we further estimate if wind exposure to tropical storms at different trimesters (1st trimester-during 0-12 weeks, the baby's nerves and muscles begin to work together and head growth shown, 2nd trimester- during 13-28 weeks, the baby's skin begins to form and footprint and fingerprint formed, 3rd trimester-during 29-40 weeks, the baby received minerals-iron and calcium) of pregnancy affects child health differently. The estimated findings are reported in Table 3.5. All regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. Evident from Panel A in Table 3.5, wind exposure to tropical storms during the 1st trimester period decreases children's HAZ and WHZ scores by about 0.0147 and 0.0078 standard deviations by increasing the maximum wind speed by m/s. Wind exposure to storms during the 2nd and 3rd trimesters adversely affects child health, and one unit increase in maximum wind speed decreases the WHZ score by approximately 0.0091 standard deviations and WAZ scores by 0.0128 standard deviations in the 3rd trimester. In Panel B in Table 3.5, the impacts of wind exposure to tropical storms during the trimester increase the probability of stunting and underweight by 0.43 and 0.70 percentage points in the 1st trimester and 3rd trimester. We don't find a significant impact on child health in the 2nd-trimester wind exposure to tropical storms; at the same time, we don't find a significant effect of stunting & wasting for children in the 3rd-trimester wind exposure to tropical storms and wasting & underweight in the 1st-trimester wind exposure to tropical storms.

Prenatal (in-utero) Exposure — By Child Age

Children exposed to Hurricane Mitch in Nicaragua found that children younger than two and a half years old when the hurricane hit had reduced HAZ, and increased probability of stunting compared to expected levels (Cowan et al. 2022). In this segment, we further estimate if wind exposure to tropical storms during the in-uterine period of under-five children at different child ages (<12 months, 12-23 months, 24-35 months, 36-47 months, and >48 months) affects child health differently. The estimated findings are reported in Table 3.6. All regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. As evident from Table 3.6, children aged 0-11 months who were exposed to tropical storms during the in-uterine period increased the probability of wasting by 1.68 percentage points by increasing the maximum wind by a meter per second (m/s). Children aged 36-47 months who were exposed to tropical storms during the in-uterine period decreased the HAZ and WAZ by about 0.0484 and 0.093 standard deviations and increased the probability of stunting by 1.03 percentage points by increasing the maximum wind by a meter per second (m/s). Children aged 48-59 months who were exposed to tropical storms during the in-uterine period increased the probability of wasting by 0.60 percentage points by increasing the maximum wind by a meter per second (m/s). We find a significant negative impact on child health, while for children aged 12-23 months and 24-35 months, we don't find a significant negative impact. Therefore, earlier-aged children who were exposed to tropical storms during the in-uterine period are more impacted than the older ages under-five children.

Childhood Exposure to Tropical Storms

Table 3.3 examines the impact of prenatal (in-utero period) wind exposure to tropical storms on children's health, while Table C2 estimates the effects of childhood wind exposure to tropical storms on their health. All regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. Evident from Panel A in Table C2, childhood experience of tropical storms decreases children's HAZ scores by about 0.0204 standard deviations by increasing maximum wind speed by m/s. As apparent from Panel B in Table C2, it raises the probability of stunting by 0.54 percentage points. Wind exposure to tropical storms during childhood is harmful to children's health.

Childhood Exposure — Neonatal and Postnatal Period Analysis

Children experiencing extreme climate events such as tropical storms during the newborn stage experience a reduction in HAZ and increase the probability of stunting and being underweight (Eskander and Barbier 2019). This part investigates whether wind exposure to tropical storms during the neonatal and postnatal[37] period affects child health differently. Table C3 indicates the adverse effects of tropical storms on child health during the childhood period. In Panel A in Table C3, childhood wind exposure to tropical storms decreases the HAZ scores by approximately 0.0169 and 0.0154 standard deviations in the neonatal and postnatal periods by increasing maximum wind by a m/s. In Panel B in Table C3, childhood wind exposure to tropical storms for the neonatal and postnatal period increases the probability of stunting by 0.62 and 0.61 percentage points by increasing maximum wind by a m/s. We don't find a significant impact of WAH, WAZ, wasting & underweight in the neonatal and postnatal period exposure to tropical storms.

Prenatal (in-utero) and Childhood Exposure — Single Regression Analysis

Children experience tropical storms in in-utero and during the newborn stage experience a reduction in HAZ score and an increase in the likelihood of stunting and being underweight (Eskander and Barbier 2019). In a single regression, this part investigates how wind exposure to tropical storms during the prenatal (in-utero), neonatal, and postnatal[38] periods affect child health differently, and the results are presented in Table C4. All regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. In Panel A in Table C4, wind exposure to tropical storms decreases the HAZ, WHZ, and WAZ scores by approximately 0.0221, 0.0096, and 0.0139 standard deviations in prenatal (in-utero) periods while HAZ scores decrease by approximately 0.0221

[37] Neonatal and postnatal wind exposure represent the first four weeks or one month of a baby with wind exposure to tropical storm and the first eight weeks or two months of a baby with wind exposure to tropical storms.
[38] Prenatal, neonatal, and postnatal wind exposure represents the nine months uterine period, the first four weeks or one month of a baby with wind exposure to tropical storms, and the first eight weeks or two months of a baby with wind exposure to tropical storms.

standard deviations in postnatal periods by increasing the maximum wind by a m/s. In Panel B in Table C4, prenatal (in-utero) and postnatal period wind exposure to tropical storms increases the probability of stunting by 0.47 and 0.72 percentage points while the probability of wasting and underweight increase by 0.15 and 0.36 percentage points only for children of prenatal period by increasing the maximum wind by a m/s. We don't find a significant impact on the neonatal period and WHZ score, WAZ score, wasting & underweight in the postnatal period exposure to tropical storms. In brief, employing alternative measures of prenatal, neonatal, and postnatal period wind exposure to tropical storms in a single regression leaves our conclusions unchanged.

Whole-life Tropical Storms Exposure

In this study, our study is limited to under-five children born between 2008 and 2019 exposed to six tropical storms (i.e., 2008, 2009, 2013, 2015, 2016, 2017). We calculate how many tropical storms children face based on their birth year and examine the impact on their health. Table C5 shows the estimated impacts of whole-life tropical storm exposure on child health. All regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. In Panel A in Table C5, the experience of tropical storms reduces a child’s HAZ & WAZ by approximately 0.4217 & 0.2164 standard deviations by increasing maximum wind by a m/s. In Panel B in Table C5, the experience of a tropical storm increases the probability of stunting and being underweight by 11.01 and 4.92 percentage points, while wasting decreases by 3.12 percentage points. Experiencing more tropical storms one's whole life has a larger effect on children’s anthropometrics and nutritional measures.

Placebo Test

In addition, we conducted a placebo test. We provide a falsification test to examine unbiased estimates using only the sample that includes children without exposure to tropical storms. In this test, we calculate the maximum wind speed during each tropical storm for each district where the maximum wind speed by the district is the same but in different years (2008→2010, 2009→2011, 2013→2012, 2015→2014, 2016→2018, 2017→2019) and then merge wind speed data with child health data using the district and childbirth year. We then re-estimate equation (3) using this placebo sample instead of our original sample. Since none of the children from the placebo sample were exposed to tropical storms, we should not find any significant impact on anthropometric measures, z-scores (i.e., HAZ, WHZ, WAZ), and nutritional indicators (i.e., stunting, wasting, underweight). If anything, the coefficient estimates are the wrong sign compared to our main results. If, instead, we find significant coefficients, this would suggest that there are unobserved factors that are correlated with our outcomes.

Table 3.7 presents the placebo tests of the impact of wind exposure to tropical storms on child health. All regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. Panel A presents the results for anthropometric measures z-scores and Panel B for nutritional indicators of under-five children. The estimates are insignificant or wrong sign in these placebo regressions, suggesting that child health is not differentially affected by unobserved factors.

Robustness Checks

First, Bangladesh experienced flooding yearly from 2008 to 2019, except in 2009, 2018, and 2019. Del Ninno and Lundberg (2005) examine the long-term effect of flood on child nutrition in Bangladesh and find that flood adversely affects children's health (i.e., HAZ score). To address this concern, in Panel A of Table 3.8, we exclude the districts (Table C1) exposed to floods from 2018 to 2019. This restriction ensures that our main estimates are not driven by other natural disasters (i.e., flooding). All regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. After restricting the sample, the estimates are similar in magnitude and sign to our main estimates (Panel A of Table 3.8). Second, occupations are severely affected by cyclones, leading to changes in primary occupations and migration to nearby cities for better opportunities (Islam et al. 2012; Jakariya et al. 2016; Saha 2017). Our estimates may be biased due to internal migration between divisional districts. To address this interest, in Panel B of Table 3.8, we exclude those living in the divisional districts[39]. This restriction ensures that our main estimates are not driven by internal migration. All regressions control for a binary indicator Muslim (a reference to other religions), number of household members, child age in years; childbirth year, and district-fixed effects. After restricting the sample, the estimates are similar in magnitude and sign to our main estimates (in Panel B of Table 3.8). Therefore, our results are robust, and the conclusion remains unchanged.

Potential Mechanisms

Tropical storms in Bangladesh have significantly impacted various aspects of life. This section explores four key mechanisms by which wind exposure to tropical storms may influence child health.

[39] Divisional districts include Barisal, Chittagong, Dhaka, Khulna, Mymensing, Rongpur, Rajshai, Sylhet.

Income/Wealth Effects

Tropical storms can cause widespread damage to property and infrastructure, leading to production shortfalls and job losses (Lenzen et al. 2019). The southern regions of Bangladesh (coastal regions of Barisal, Chittagong, and Khulna) are particularly vulnerable to tropical storms, resulting in the highest loss of output in Chittagong and the highest income and employment losses in Barisal, with the affected sectors being housing, agriculture, construction, and industrial activities (Haque and Jahan 2016). The main livelihood sources in affected areas, such as agriculture and fisheries, are severely affected by tropical storms, leading to changes in primary occupations and migration to nearby cities for better livelihood opportunities (Islam et al. 2012; Jakariya et al. 2016). The effects of tropical storms on the socioeconomic condition of the affected households have serious consequences on their health status (Jakariya et al. 2016). Tropical storms can affect child health in the affected families (Ahmed and Eklund 2019; del Ninno et al., 2002; O'Donnell et al., 2002). We use ownership of houses, agricultural land, and poultry (i.e., chickens-ducks) to examine this channel (Table 3.9). We identified the adverse impacts of the wind experience of tropical storms on household income/wealth. Exclusively, increasing the maximum wind by a meter per second (m/s) during tropical storms decreases ownership of houses and agricultural land by 0.32 and 0.22 percentage points (Columns 2 and 4) and decreases the number of poultry (i.e., chickens-ducks) by approximately 0.02 (Column 6). After restricting the southern region (i.e., tropical storms-prone regions), we find a significantly inverse impact of wind exposure to tropical storms on household wealth by 0.43 and 0.49 percentage points for ownership of houses and agricultural land and 0.0532 quantity of chickens-ducks. Overall, experiencing tropical storms harms household income/wealth and consequently declines household consumption, childcare, and health.

Access to Maternal Healthcare Effects

Tropical storms have a significant impact on access to maternal healthcare. The loss of geographical accessibility due to tropical storms leads to decreased accessibility coverage of functional health facilities, resulting in longer travel times for pregnant women seeking care (Hierink et al. 2020). In tropical storm-affected districts, the accessibility of maternal healthcare coverage decreased due to damaged transport, and obstacles to travel (Badiuzzaman and Murshed 2016; Zhou 2019; Ampofo et al. 2022). These findings highlight the need to ensure access to maternal healthcare services during and after tropical storms (Matovelo et al. 2021). So, tropical storms make it challenging for mothers to access healthcare and obtain acceptable nutrition during pregnancy (Welton et al., 2020). We examine this channel using antenatal care visits and tetanus doses (Table 3.10). We identified the negative impacts of wind exposure to tropical storms on access to maternal healthcare for tetanus doses. Exclusively, increasing the maximum wind by a m/s during tropical storms increases the number of antenatal care visits by 0.0134 (Column 2), while decreasing the number of tetanus doses by 0.0144 (Column 4). After restricting the southern region (i.e., tropical storms prone regions), we find a significant decrease in the number of tetanus doses of wind exposure to tropical storms by 0.0437, while we do not find a significant impact on antenatal care visits, which, in turn, affects child nutrition. In rural areas, where home delivery is preferred, the coverage of ANC remains poor (Jahan et al. 2022). Women who live in rural areas, have poor education, belong to disadvantaged and vulnerable subgroups, and have unintended pregnancies are less likely to use ANC services and have fewer ANC visits (Aktar et al. 2020). Therefore, it is crucial to prioritize activities encouraging women to receive quality ANC services, deliver in functional hospitals, and ensure universal coverage of ANC, tetanus toxoid (TT) vaccination, and Iron–Folic Acid (IFA) supplementation among pregnant women, especially in areas affected by tropical storms (Bucher et al. 2015).

Infectious Diseases Effects

Tropical storms have mixed effects on the risk of infectious diseases. In the United States, cyclone experience increases hospitalization rates for respiratory diseases, infectious and parasitic diseases, and injuries (Caillouët and Robertson 2020; Zheng et al. 2017). Changes in the ecological system, land use, and transportation also contribute to the spread of infectious diseases (António et al. 2018). Also, water supply and sanitation facilities are disrupted during cyclones, leading to waterborne diseases like diarrhoea and dysentery (Chakraborty et al. 2016; Kabir 2014). The vulnerability to health problems before and after tropical storms is influenced by age, gender, income, education level, and number of living children in the family (Kabir and Khan 2017). We examine this channel with diarrhea, cough, and fever (Table 3.11). However, we do not find significant impacts of wind exposure to tropical storms on infectious diseases - diarrhea (Column 2), cough (Column 4), and fever (Column 6). The Bangladesh Multiple Indicator Cluster Survey (MICS) 2012 and 2019 was conducted from December 2012 to April 2013 and from 19 January to 1 June 2019 as part of the global MICS programme by the Bangladesh Bureau of Statistics (BBS) in collaboration with UNICEF Bangladesh, and the question asked '*At any time in the last two weeks, has (name) been ill with a diarrhoea/ cough/ fever?'*. At the time of the tropical storms, no surveys were conducted in Bangladesh. That's why we may not observe any impact of experiencing tropical storms on infectious diseases.

Access to Children's Food and Vitamin or Mineral Supplements Effects

Tropical storms in Bangladesh have caused damage to rural and agricultural engineering infrastructures (Hossain et al. 2008) and destruction of food crops, including rice, potatoes, and vegetables, leading to food insufficiency (Farukh et al. 2019). Salinity intrusion caused by cyclones has drastically affected rice and vegetable production in coastal districts (southern region), decreasing local rice production (Rabbani et al. 2015). Natural disasters, including tropical storms, have also resulted in changes in food availability, accessibility, and consumption at the household level (Islam et al. 2012; Islam and Ahmed 2017) and increased health risks due to low household food consumption (Alamgir et al. 2009). However, nutritional insecurity was more prevalent in certain areas, such as the island village and among fishermen (Clayton 2012). We use children's access to meals and vitamin or mineral supplements to examine this channel (Table 3.12). We identified the negative impacts of wind exposure to tropical storms on access to food and vitamin or mineral supplements. Exclusively, increasing the maximum wind by a m/s during tropical storms decreases the number of meals by 0.0085 (Column 2) and vitamin or mineral supplements by 0.0026 (Column 4) percentage points. After restricting the southern region (i.e., tropical storms-prone regions), we find an increase in the number of meals by 0.0002 (Column 2) and a decrease in vitamin or mineral supplements by 0.0017 (Column 4) percentage points of wind exposure to tropical storms, but we do not find a significant impact on meals and vitamin or mineral supplements. The government of Bangladesh, along with national and international NGOs like CARE Bangladesh and BRAC have been actively involved in cyclone disaster management, providing emergency response, recovery, rehabilitation activities, relief assistance including food, cash, other non-food materials, and reconstruction of community services for the tropical storms affected population (Islam et al. 2017; Islam et al. 2012; Sukhi 2014) and question asked '*Did* *(name) drink or eat vitamin or mineral supplements yesterday, during the day or night?'* Unfortunately, we don’t have information about the types and quality of meals. That's why we might not observe any impact of experiencing tropical storms on children's food and vitamin or mineral supplements. The destruction caused by tropical storms, such as damage to crops and livestock, can also contribute to food insufficiency and further health risks (Farukh et al. 2019; Islam and Ahmed 2017).

Thus, tropical storms have caused direct damage to property and infrastructure, resulting in loss of income and employment, particularly in coastal regions such as Barisal, Chittagong, and Khulna (Tasdik Hasan et al. 2020). Also, tropical storms have adversely affected maternal healthcare, with vulnerable populations experiencing difficulties accessing necessary healthcare services (Hasan 2014). Additionally, tropical storms have contributed to food insecurity, exacerbating the health risks-nutritional deficiency faced by the population (Hossain et al. 2008; Paul et al., 2012). Therefore, our results suggest that household income/wealth and access to maternal healthcare are potential mechanisms by which wind exposure to tropical storms may influence child health in Bangladesh.

Conclusion

Tropical storms are likely to be unaccompanied by a fast or widespread loss of lives or extensive devastation of property and public infrastructures (Lenzen et al. 2019), which is often seen in extreme natural disasters. Conversely, repeated experiences of tropical storms are likely to have notable long-term adverse effects on households (Karbownik and Wray 2019; Karim 2018), potentially making child health vulnerable (Hierink et al. 2020; Welton et al. 2020).

Wind exposure to tropical storms that increase the maximum wind by a meter per second decreases ownership of houses, agricultural land, and the number of poultry (i.e., chickens-ducks) and restricts access to maternal healthcare, which might negatively affect household income, consumption, childcare, and health. We have reported the effects of in-utero and childhood wind experiences of tropical storms on the health of Bangladeshi children. Particularly, the in-utero experience of tropical storms makes children 0.0211 standard deviations shorter for their age, 0.0091, and 0.0127 standard deviations thinner for their height and age, respectively. Moreover, it increases the probability of stunting, wasting, and underweight. In the examination of the heterogeneous effects of tropical storms, we found that child health adversely affects those children born to poor mothers, mothers living in rural areas, southern regions, and female children. Examining the differential effects of experiencing tropical storms by trimesters, we show that experiencing tropical storms during the 1st trimester increases the likelihood of stunting, and 3rd trimester increases the likelihood of being underweight, adversely affecting child health. Exposure to tropical storms during childhood increases the likelihood of stunting but does not affect wasting or underweight. Our results are consistent with earlier literature (Baez and Santos 2007; Goel 2013; Nowak-Szczepanska et al. 2021; Paul et al. 2012).

Our findings suggest that experience of natural disasters can have important long-term effects on child health, and the impact depends on the timing of exposure. Our findings indicate that the in-utero period significantly impacts an individual's developmental health and well-being outcomes from infancy to adulthood (e.g., Barker 1995; Eriksson 2005; Godfrey and Barker 2001). Our results indicate that such shocks have long-term harmful effects (Bartlett 2009; Islam and Nguyen 2018) on the development of children (Barker 1995; Gluckman et al. 2005).

Tables and Figures

Table 3.1. The Tropical Storms Over Bangladesh, 2008 through 2017.

Year	Tropical storms	Winds (m/s)	No. of fatality	No. of affected households	No. of affected people	No. of damaged house	Damaged crops (Acres)
October 27, 2008	RASMI	23.61	15	92,701	321,839	16,764	22,382
May 25, 2009	AILA	33.33	190	948,621	3,928,238	243,000	340,660
May 16, 2013	MAHASEN	23.61	17	222,815	1,498,579	151,005	205,907
July 30, 2015	KOMEN	20.83	113	346,389	1,584,942	510,000	667,221
May 21, 2016	ROANU	27.78	24	139,852	699,260	83,978	133,261
May 30, 2017	MORA	30.56	9	59,258	2,811,465	104,830	93,106
Tropical storm impact			368	1.8 million	11 million	1 million	1.5 million
Saffir–Simpson scale, 1-minute maximum sustained winds							
Category	5	4	3	2	1	Tropical storm	Tropical depression
m/s	≥70	58-69.7	49.6-57.7	42.9-49.2	33.1-42.5	18-32.4	10.3-17.5

Note: m/s indicates meters per second.
Source: Bangladesh Meteorological Department, 2008-2017; Ministry of Disaster Management and Relief (ModMR), Bangladesh. Taylor, H.T., Ward, B., Willis, M. and Zaleski, W., 2010. The saffir-simpson hurricane wind scale. *Atmospheric Administration: Washington, DC, USA*.

Table 3.2. Summary Statistics.

	(1)	(2)	(3)	(4)
Panel A: Outcome variables	Mean	Std. dev.	Min.	Max.
Height-for-age z-score	-1.511	1.378	-6	6
Weight-for-height z-score	-.689	1.131	-4.99	4.98
Weight-for-age z-score	-1.350	1.116	-5.9	4.68
Stunting	.344	.475	0	1
Wasting	.099	.298	0	1
Underweight	.269	.443	0	1
Panel B: Independent variables	Mean	Std. dev.	Min.	Max.
Wind speed	5.148	5.533	0	20.59
Muslim	.894	.308	0	1
Household members	5.482	2.219	2	29
Rural	.828	.377	0	1
Southern region	.434	.495	0	1
Poor household	.484	.50	0	1
Prenatal (9-month utero period)	.408	.491	0	1
1st Trimester	.158	.364	0	1
2nd Trimester	.142	.348	0	1
3rd Trimester	.125	.331	0	1
Neonatal	.081	.273	0	1
Postnatal	.120	.325	0	1
Male child	.515	.50	0	1
Child age in years	2.040	1.4116	0	4
Observations	41,193	41,193	41,193	41,193

Note: The sample includes under-five children born between 2008 and 2019. Mother's education includes secondary or higher education. Poor households indicate the bottom two quantiles of the household wealth index. Height-for-age/weight-for-height/weight-for-age is a measure of linear growth. Children whose height-for-age/weight-for-height/weight-for-age is more than two standard deviations below the median of the reference population are considered shorter for their age/thinner for their height/thinner for their age and are classified as moderately or severely stunting, wasting, and underweight.
Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

Table 3.3. Impact of Prenatal (in-utero) Wind Exposure to Tropical Storms on Child Health.

	Panel A: Anthropometrics measure z-scores					
	HAZ score		WHZ score		WAZ score	
	(1)	(2)	(3)	(4)	(5)	(6)
Prenatal wind exposure	-.022***	-.021***	-.013***	-.009***	-.014***	-.013***
	(.004)	(.004)	(.003)	(.003)	(.040)	(.003)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	-1.511	-1.511	-.690	-.690	-1.350	-1.350
	Panel B: Anthropometrics measure nutritional indicators					
	Likelihood of stunting		Likelihood of wasting		Likelihood of underweight	
	(1)	(2)	(3)	(4)	(5)	(6)
Prenatal wind exposure	.004***	.004***	.002**	.001*	.004***	.003***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	.344	.344	.099	.099	.270	.270
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×		×

Notes: The sample includes under-five children born between 2008 and 2019. Prenatal wind exposure represents 9-month uterine period[40] with wind exposure to tropical storms. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

[40] For example, tropical storm RASMI dissipated in October 2008. Mothers exposed to tropical storms during the prenatal period of their children born between February and October 2008.

Table 3.4. Impact of Prenatal (in-utero) Wind Exposure to Tropical Storm on Child Health — Heterogeneity Analysis.

	HAZ score	WHZ score	WAZ score	Likelihood of stunting	Likelihood of wasting	Likelihood of underweight
	(1)	(2)	(3)	(4)	(5)	(6)
Poor mothers						
Prenatal wind	-.026***	-.012***	-.016***	.007***	.003**	.005***
exposure	(.007)	(.004)	(.005)	(.002)	(.001)	(.002)
Observations	19,936	19,936	19,936	19,936	19,936	19,936
Dep.Var.Mean	-1.745	-.799	-1.566	.418	.114	.330
Wealthy mothers						
Prenatal wind	-.017***	-.007	-.010**	.002	.00005	.002
exposure	(.006)	(.005)	(.004)	(.002)	(.001)	(.002)
Observations	13,582	13,582	13,582	13,582	13,582	13,582
Dep.Var.Mean	-1.179	-.519	-1.036	.249	.078	.185
Rural mothers						
Prenatal wind	-.023***	-.008**	-.013***	.005***	.002**	.003**
exposure	(.004)	(.003)	(.003)	(.001)	(.001)	(.001)
Observations	34,111	34,111	34,111	34,111	34,111	34,111
Dep.Var.Mean	-1.553	-.717	-1.395	.355	.101	.279
Urban mothers						
Prenatal wind	-.017**	-.012*	-.014*	.001	-.001	.004
exposure	(.007)	(.006)	(.007)	(.003)	(.002)	(.003)
Observations	7,082	7,082	7,082	7,082	7,082	7,082
Dep.Var.Mean	-1.305	-.555	-1.133	.293	.089	.220
Southern region						
Prenatal wind	-.027***	-.007	-.016***	.006***	.002	.004**
exposure	(.006)	(.004)	(.005)	(.002)	(.001)	(.002)
Observations	17,863	17,863	17,863	17,863	17,863	17,863
Dep.Var.Mean	-1.467	-.712	-1.337	.327	.101	.263
Northern region						
Prenatal wind	-.017**	-.011***	-.010***	.003*	.001	.0024
exposure	(.006)	(.004)	(.003)	(.002)	(.001)	(.002)
Observations	23,330	23,330	23,330	23,330	23,330	23,330
Dep.Var.Mean	-1.540	-.671	-1.360	.358	.096	.274
Female child						
Prenatal wind	-.030***	-.005	-.016***	.006***	.001	.005***
exposure	(.0051)	(.003)	(.004)	(.002)	(.001)	(.002)
Observations	19,996	19,996	19,996	19,996	19,996	19,996
Dep.Var. Mean	-1.509	-.676	-1.361	.341	.090	.271
Male child						
Prenatal wind	-.012**	-.013***	-.009**	.003*	.002	.001
exposure	(.005)	(.004)	(.004)	(.002)	(.001)	(.002)
Observations	21,197	21,197	21,197	21,197	21,197	21,197
Dep.Var.Mean	-1.512	.701	-1.339	.347	.107	.267

Table 3.4 (Continued)

District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates	×	×	×	×	×	×

Notes: The sample includes under-five children born between 2008 and 2019. The southern region of Bangladesh includes Barisal, Chittagong, and Khulna divisions. Prenatal wind exposure represents 9 months uterine period with wind exposure to tropical storms. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

Table 3.5. Impact of Prenatal (in-utero) Wind Exposure to Tropical Storm on Child Health — Trimester Analysis.

	Panel A: Anthropometrics measure z-scores					
	HAZ score		WHZ score		WAZ score	
	(1)	(2)	(3)	(4)	(5)	(6)
1st trimester wind exposure	$-.015^{***}$	$-.015^{***}$	$-.008^{**}$	$-.008^{*}$	-.006	-.006
	(.005)	(.005)	(.004)	(.004)	(.004)	(.004)
2nd trimester wind Exposure	-.010	-.009	$-.011^{***}$	$-.009^{**}$	-.007	-.006
	(.006)	(.006)	(.004)	(.003)	(.005)	(.005)
3rd trimester wind exposure	-.003	-.003	-.004	-.005	$-.012^{*}$	$-.016^{**}$
	(.008)	(.008)	(.006)	(.006)	(.006)	(.006)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	-1.511	-1.511	-.689	-.689	-1.350	-1.350
	Panel B: Anthropometrics measure nutritional indicators					
	Likelihood of stunting		Likelihood of wasting		Likelihood of underweight	
	(1)	(2)	(3)	(4)	(5)	(6)
1st trimester wind exposure	$.004^{***}$	$.004^{*}$	.001	.001	.0002	.0001
	(.002)	(.002)	(.001)	(.001)	(.001)	(.001)
2nd trimester wind Exposure	-.001	-.001	.0001	.0001	.0002	-.0002
	(.002)	(.002)	(.001)	(.001)	(.002)	(.002)
3rd trimester wind exposure	.004	.004	.001	.001	$.007^{***}$	$.007^{***}$
	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	.344	.344	.099	.099	.269	.269
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×		×

Notes: The sample includes under-five children born between 2008 and 2019. Trimester wind exposure represents 3 months uterine period[41] with wind exposure to tropical storms. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

[41] For example, tropical storm RASMI dissipated in October 2008. Mothers exposed to tropical storms during 1st trimester period of their children born between February and April 2008. Similarly, 2nd trimester and 3rd trimester periods include children born between May & July 2008 and August & October 2008, respectively.

Table 3.6. Impact of Prenatal (in-utero) Wind Exposure to Tropical Storms on Child Health — By Child Age.

	HAZ score	WHZ score	WAZ score	Likelihood of stunting	Likelihood of wasting	Likelihood of underweight
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Child age= 0-11 months						
Prenatal wind exposure	-.019	-.066	.012	.015	.017*	.006
	(.038)	(.050)	(.030)	(.014)	(.009)	(.011)
Observations	7,865	7,865	7,865	7,865	7,865	7,865
Dep.Var.Mean	-.978	-.431	-1.005	.204	.097	.182
Panel B: Child age= 12-23 months						
Prenatal wind exposure	.010	.008	.011	-.005	.004	-.004
	(.024)	(.015)	(.015)	(.008)	(.005)	(.006)
Observations	8,164	8,164	8,164	8,164	8,164	8,164
Dep.Var.Mean	-1.538	-.728	-1.286	.356	.118	.259
Panel C: Child age= 24-35 months						
Prenatal wind exposure	.001	.029*	.022	-.006	-.001	-.013**
	(.020)	(.016)	(.016)	(.005)	(.006)	(.006)
Observations	8,103	8,103	8,103	8,103	8,103	8,103
Dep.Var.Mean	-1.777	-.706	-1.472	.421	.093	.305
Panel D: Child age= 36-47 months						
Prenatal wind exposure	-.048***	.002	-.029***	.010***	-.002	.006
	(.013)	(.002)	(.008)	(.004)	(.002)	(.004)
Observations	8,572	8,572	8,572	8,572	8,572	8,572
Dep.Var.Mean	-1.694	-.706	-1.466	.399	.085	.296
Panel E: Child age= 48-59 months						
Prenatal wind exposure	-.004	-.016	-.013	-.003	.006**	.004
	(.0125)	(.0123)	(.0130)	(.0055)	(.0026)	(.0053)
Observations	8,489	8,489	8,489	8,489	8,489	8,489
Dep.Var.Mean	-1.539	-.856	-1.496	.334	.100	.298
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates	×	×	×	×	×	×

Notes: The sample includes under-five children born between 2008 and 2019 with specific ages. Prenatal wind exposure represents 9-month uterine period[42] with wind exposure to tropical storms. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

[42] For example, tropical storm RASMI dissipated in October 2008. Mothers exposed to tropical storms during the prenatal period of their children born between February and October 2008.

Table 3.7. Placebo Estimates of the Impact of Wind Exposure to Tropical Storms on Child Health.

	Panel A: Anthropometrics measure z-scores					
	HAZ score		WHZ score		WAZ score	
	(1)	(2)	(3)	(4)	(5)	(6)
Prenatal wind	.020***	.016**	.002	-.001	.001	-.001
exposure	(.006)	(.006)	(.005)	(.005)	(.004)	(.004)
Neonatal wind	-.008	-.008	.013*	.014*	.001	.001
exposure	(.011)	(.011)	(.008)	(.008)	(.008)	(.008)
Postnatal wind	-.012	-.011	.001	.002	-.008	-.008
exposure	(.008)	(.008)	(.007)	(.007)	(.006)	(.006)
Observations	19,977	19,977	19,977	19,977	19,977	19,977
Dep.Var.Mean	-1.418	-1.418	-.649	-.649	-1.286	-1.286
	Panel B: Anthropometrics measure nutritional indicators					
	Likelihood of stunting		Likelihood of wasting		Likelihood of underweight	
	(1)	(2)	(3)	(4)	(5)	(6)
Prenatal wind	-.006***	-.005***	.0001	.0002	.001	-.001
exposure	(.002)	(.002)	(.001)	(.001)	(.002)	(.002)
Neonatal wind	.006***	.001	-.003	-.003	-.0003	-.0003
exposure	(.002)	(.003)	(.002)	(.002)	(.004)	(.004)
Postnatal wind	.004	.004	.001	.001	.002	.002
exposure	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)
Observations	19,977	19,977	19,977	19,977	19,977	19,977
Dep.Var.Mean	.321	.321	.104	.104	.256	.256
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×		×

Notes: The sample is restricted to under-five children born between 2008 and 2019 with no exposure to tropical storms where the maximum wind speed by the district is the same but different birth year (2008→2010, 2009→2011, 2013→2012, 2015→2014, 2016→2018, 2017→2019). Prenatal wind exposure represents a 9-month uterine period[43] with wind exposure to tropical storms. Neonatal and postnatal[44] wind exposure represents the first four weeks or one month of a baby with wind exposure to tropical storms and the first eight weeks or two months of a baby with wind exposure to tropical storms. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

[43] For example, tropical storm RASMI dissipated in October 2008. Mothers exposed to tropical storms during the prenatal period of their children born between February and October 2008.

[44] For example, tropical storm RASMI dissipated in October 2008. Children exposed to tropical storms during the neonatal period if children born in October 2008 and children exposed to tropical storms during the postnatal period if children born between October and November 2008, respectively.

Table 3.8. Robustness Checks.

	HAZ score	WHZ score	WAZ score	Likelihood of stunting	Likelihood of wasting	Likelihood of underweight
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Excluding flood-affected districts						
Prenatal wind exposure	-.021***	-.009***	-.015***	.004**	.001	.004***
	(.005)	(.003)	(.004)	(.002)	(.001)	(.001)
Neonatal wind exposure	-.027**	.001	-.017	.009**	.001	.008*
	(.011)	(.012)	(.011)	(.004)	(.003)	(.004)
Postnatal wind exposure	-.021**	.002	-.012*	.008***	-.0004	.005
	(.009)	(.009)	(.007)	(.003)	(.002)	(.003)
Observations	31,068	31,068	31,068	31,068	31,068	31,068
Dep.Var.Mean	-1.508	-.677	-1.344	.343	.096	.266
Panel B: Excluding divisional districts						
Prenatal wind exposure	-.023***	-.009***	-.013***	.005**	.001*	.003**
	(.011)	(.003)	(.003)	(.002)	(.001)	(.001)
Neonatal wind exposure	-.020*	-.004	-.016	.007**	.001	.006
	(.011)	(.011)	(.010)	(.004)	(.002)	(.004)
Postnatal wind exposure	-.017**	.003	-.009	.007**	-.001	.003
	(.009)	(.009)	(.007)	(.003)	(.002)	(.003)
Observations	35,373	35,373	35,373	35,373	35,373	35,373
Dep.Var.Mean	-1.520	-.691	-1.357	.347	.098	.271
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates	×	×	×	×	×	×

Notes: The sample includes under-five children born between 2008 and 2019. Panel A: Flood-affected districts (see Table A1) are those that were exposed to any floods from 2008 to 2019; Panel B: Divisional districts include Barisal, Chittagong, Dhaka, Khulna, Mymensing, Rongpur, Rajshai, Sylhet. Prenatal represents a 9-month uterine period with wind exposure to tropical storms. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

Table 3.9. Income/Wealth Effects as a Potential Mechanism.

	Ownership of house		Agricultural land		Poultry	
	(1)	(2)	(3)	(4)	(5)	(6)
Wind exposure	$-.003^{**}$	$-.003^{**}$	-.002	-.002	-.022	-.019
	(.001)	(.001)	(.001)	(.001)	(.029)	(.029)
Observations	41,187	41,187	41,168	41,168	26,849	26,849
Dep.Var.Mean	.863	.863	.392	.392	5.274	5.274
Southern region==1						
Wind exposure	$-.005^{***}$	$-.004^{**}$	$-.005^{***}$	$-.005^{***}$	$-.055^{*}$	$-.053^{*}$
	(.002)	(.002)	(.002)	(.002)	(.030)	(.028)
Observations	17,862	17,862	17,846	17,846	11,929	11,929
Dep.Var.Mean	.881	.881	.386	.386	5.680	5.680
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×	×	×

Notes: The sample includes under-five children born between 2008 and 2019. Ownership of house represents the household owning the house; agricultural land represents household member's own land that can be used for agriculture; poultry represents the number of chickens or ducks. The southern region of Bangladesh includes Barisal, Chittagong, and Khulna divisions. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.
Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

Table 3.10. Access to Maternal Healthcare Effects as a Potential Mechanism.

	Antenatal care visits		Tetanus doses	
	(1)	(2)	(3)	(4)
Wind exposure	.013	.013	-.014	-.014
	(.019)	(.019)	(.011)	(.011)
Observations	10,807	10,807	8,805	8,805
Dep.Var.Mean	3.533	3.533	3.737	3.737
Southern region==1				
Wind exposure	.004	.005	-.044***	-.044***
	(.023)	(.023)	(.012)	(.012)
Observations	5,096	5,096	3,968	3,968
Dep.Var.Mean	3.488	3.488	3.561	3.561
District FE	×	×	×	×
Childbirth year FE	×	×	×	×
Covariates		×		×

Notes: The sample includes under-five children born between 2008 and 2019. Maternal healthcare includes the number of antenatal care visits and tetanus toxoid injections received during pregnancy. The southern region of Bangladesh includes Barisal, Chittagong, and Khulna divisions. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

Table 3.11. Infectious Diseases Effects as a Potential Mechanism.

	Diarrhea		Cough		Fever	
	(1)	(2)	(3)	(4)	(5)	(6)
Wind exposure	-.001	-.001	-.003	-.003	-.001	-.001
	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
Observations	41,187	41,187	41,168	41,168	21,924	21,924
Dep.Var.Mean	.056	.056	.241	.241	.232	.232
Southern region==1						
Wind exposure	-.0004	-.0004	-.003	-.003	-.003	-.003
	(.001)	(.001)	(.003)	(.002)	(.003)	(.003)
Observations	17,863	17,863	17,863	17,863	9,536	9,536
Dep.Var.Mean	.068	.068	.386	.386	.262	.262
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×	×	×

Notes: The sample includes under-five children born between 2008 and 2019 where children have infectious diseases (diarrhea, cough, fever) last two weeks. The southern region of Bangladesh includes Barisal, Chittagong, and Khulna divisions. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.
Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

Table 3.12. Access to Children's Food and Vitamin Effects as a Potential Mechanism.

	Meals		Vitamin (or mineral supplements)	
	(1)	(2)	(3)	(4)
Wind exposure	-.008	-.008	-.003	-.003
	(.0145)	(.0142)	(.0022)	(.0022)
Observations	22,221	22,221	12,831	12,831
Dep.Var.Mean	3.249	3.249	.102	.102
Southern region==1				
Wind exposure	.0001	.0002	-.002	-.002
	(.014)	(.013)	(.003)	(.003)
Observations	9,579	9,579	5,661	5,661
Dep.Var.Mean	3.039	3.039	.095	.095
District FE	×	×	×	×
Childbirth year FE	×	×	×	×
Covariates		×		×

Notes: The sample includes under-five children born between 2008 and 2019. Meals include the number of meals taken per day and vitamin represent child drank or ate vitamin or mineral supplements yesterday. The southern region of Bangladesh includes Barisal, Chittagong, and Khulna divisions. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

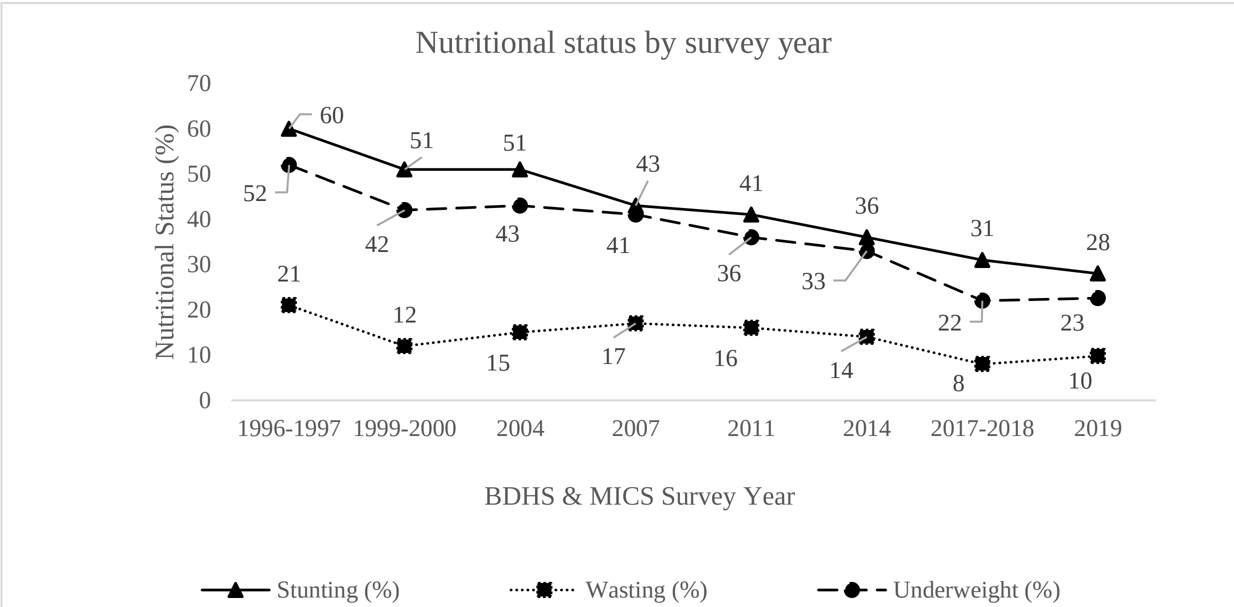

Figure 3.1. Nutritional Status of Under-five Children.
Notes: The graph presents nutritional status rates (%) among under-five children (stunting—solid line and wasting—dotted line and underweight—dashed line) in Bangladesh.
Source: Bangladesh Demographic and Health Surveys (BDHS) between 1996-1996 through 2017-2018 and Multiple Indicators Cluster Surveys (MICS) 2019.

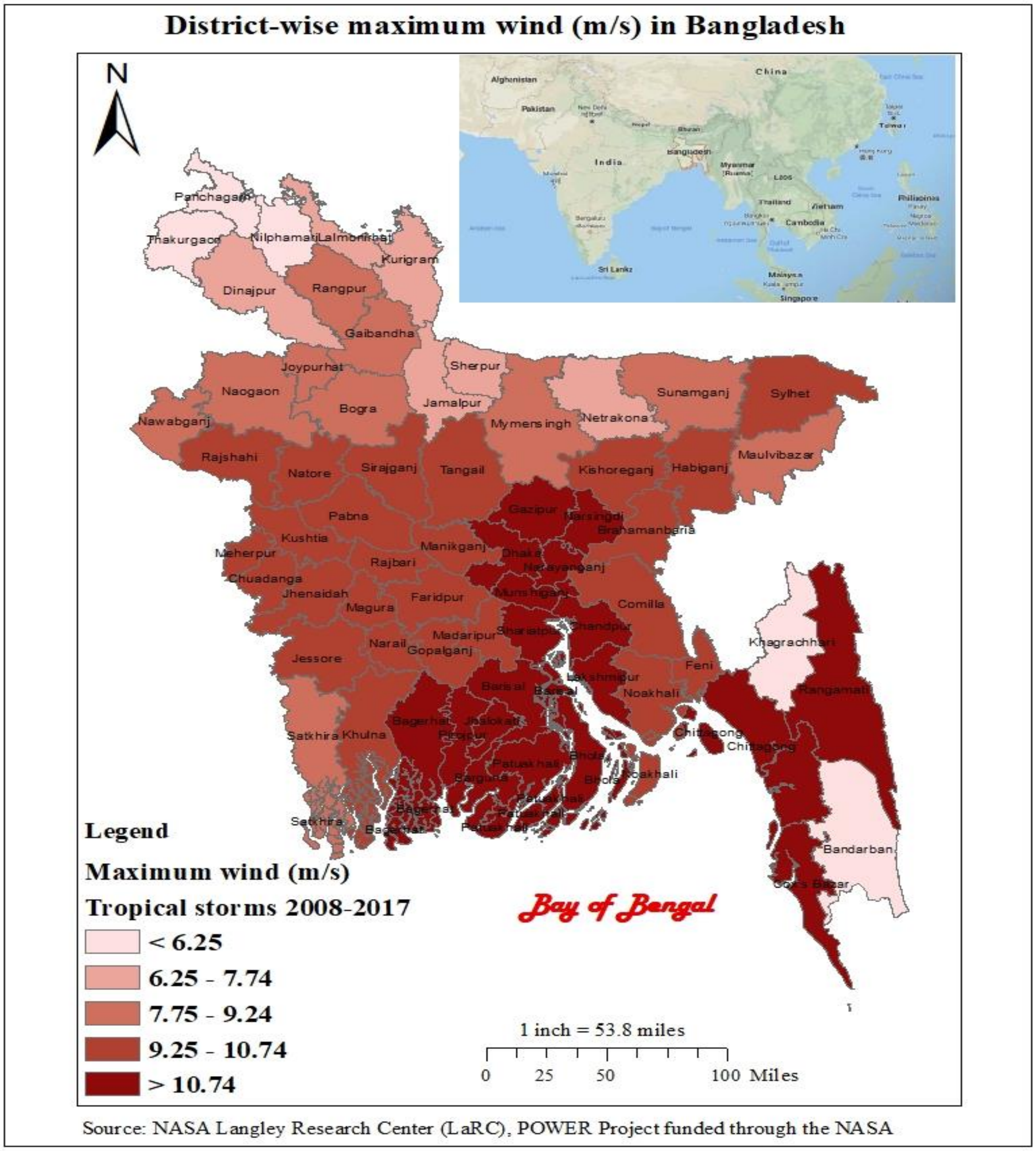

Figure 3.2. Bangladesh in the Global Context and District-wise Maximum Wind During Tropical Storms 2008 – 2017.

Notes: The figure is created using the ArcMap. Maximum wind (m/s) is calculated from the sum of each tropical storm's maximum wind (m/s) divided by the number of tropical storms. The base map layer is from the Database of Global Administrative Areas and downloadable @ https://gadm.org/download_country.html.

Source: NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

CHAPTER FOUR:

CONCLUSION

The health of women and children in Bangladesh is a concern, given the various factors I have highlighted in this research. This study, therefore, holds relevance not only for local policymakers and educators but also for public health researchers worldwide.

First, this study, of significant importance, estimates the impact of maternal education on child immunization rates in Bangladesh. It does so by leveraging the Female Secondary School Stipend Program (FSSSP), a pivotal initiative introduced in 1994. The FSSSP provides a cash stipend to girls in rural areas, encouraging them to attend secondary school. This study, adopting a difference-in-differences approach, explores differential exposure by birth year and differences between urban and rural areas. The latter is particularly relevant as only girls in rural areas are eligible for stipends. The study's key finding is that the FSSSP increased secondary schooling among girls and improved immunization rates among children born to mothers exposed to the program. These findings align with the allocative efficiency hypothesis, suggesting that better-educated mothers have greater knowledge and/or efficacy in combining health inputs to improve child health. Importantly, these findings propose that maternal education, as exemplified by the FSSSP, can be a powerful policy/tool for improving health/vaccination rates among children.

Secondly, Overweight or obesity is a significant and escalating health burden and poses a major public health challenge, with 39% of the world's adult population (women:40% and men:39%) being overweight or obesity in 2016 (WHO 2021). In Bangladesh, 25% of adults (32.4% of women and 17.6% of men) were overweight or obesity (BDHS 2017-2018). Women had a higher overweight or obesity frequency compared to men (Ng et al. 2014). Education, a crucial social predictor, significantly influences women's food intake, physical involvement, and body weight (Liu and Guo 2015; Sobal 2011). This study finds that the FSSSP increased secondary schooling among girls and obesity rates among females exposed to the program. These findings highlight that in Bangladesh, the effects of education on obesity are rather different than those found in developed countries.

Thirdly, Natural disasters are harmful to both developed and developing countries. However, people with low incomes in developing countries, specifically mothers and children, are the most distressed by those disasters (Islam and Nguyen 2018; Bartlett 2009). Natural disasters have short-term and long-term impacts on various health indicators. This study finds that in-utero exposure to tropical storms decreases the HAZ, WHZ, and WAZ scores among under-five children and increases the probability of stunting, wasting, and being underweight. Exposure to tropical storms during childhood decreases the height-for-age z-scores and increases the probability of stunting but does not affect WHZ, WAZ scores, wasting, or underweight. Also, in the trimester of exposure to tropical storms, we find 1st trimester increases the probability of stunting, and 3rd trimester increases the probability of being underweight. Therefore, findings suggest that exposure to tropical storms can have important long-term effects on child health, and the impact depends on the timing of exposure.

This study highlights new evidence on the determining factor of women's and children's well-being in Bangladesh.

REFERENCES

Ahmed, A.U., 1986. Socioeconomic determinants of age at first marriage in Bangladesh. *Journal of biosocial science*, *18*(1), pp.35-42.

Ahmed, S. and Eklund, E., 2019. Rural accessibility, rural development, and natural disasters in Bangladesh. *Journal of Developing Societies*, *35*(3), pp.391-411.

Ahmed, S.M., Hadi, A., Razzaque, A., Ashraf, A., Juvekar, S., Ng, N., Kanungsukkasem, U., Soonthornthada, K., Van Minh, H. and Huu Bich, T., 2009. Clustering of chronic non-communicable disease risk factors among selected Asian populations: levels and determinants. *Global health action*, *2*(1), p.1986.

Ahsan, K.Z., Arifeen, S.E., Al-Mamun, M.A., Khan, S.H. and Chakraborty, N., 2017. Effects of individual, household and community characteristics on child nutritional status in the slums of urban Bangladesh. *Archives of Public Health*, *75*(1), pp.1-13.

Akhter, S.R., Sarkar, R.K., Dutta, M., Khanom, R., Akter, N., Chowdhury, M.R. and Sultan, M., 2015. Issues with families and children in a disaster context: a qualitative perspective from rural Bangladesh. *International Journal of Disaster Risk Reduction*, *13*, pp.313-323.

Akresh, R., Halim, D. and Kleemans, M., 2023. Long-term and intergenerational effects of education: Evidence from school construction in Indonesia. *The Economic Journal*, *133*(650), pp.582-612.

Aktar, S., Majumder, U.K. and Khan, M.S., 2020. Antenatal and postnatal care practices among indigenous people in Bangladesh: A case study in Dinajpur. *Asian Journal of Education and Social Studies*, *8*(3), pp.38-56.

Al Kibria, G.M., Hashan, M.R., Hossain, M.M., Zaman, S.B. and Stennett, C.A., 2021. Clustering of hypertension, diabetes, and overweight/ obesity according to socioeconomic status among Bangladeshi adults. *Journal of biosocial science*, *53*(2), pp.157-166.

Alamgir, F., Nahar, P., Collins, A.E., Ray-Bennett, N.S. and Bhuiya, A., 2009. Climate change and food security: health risks and vulnerabilities of the poor in Bangladesh. *The International Journal of Climate Change: Impacts and Responses*, *1*(4), p.37.

Ali, F.R.M. and Elsayed, M.A., 2018. The effect of parental education on child health: Quasi-experimental evidence from a reduction in the length of primary schooling in Egypt. *Health Economics*, *27*(4), pp.649-662.

Almond, D., Currie, J. and Duque, V., 2018. Childhood circumstances and adult outcomes: Act II. *Journal of Economic Literature*, *56*(4), pp.1360-1446.

Almond, D., Currie, J. and Herrmann, M., 2012. From infant to mother: Early disease environment and future maternal health. *Labour Economics*, *19*(4), pp.475-483.

Al-Zubayer, M.A., Ahammed, B., Sarder, M.A., Kundu, S., Majumder, U.K. and Islam, S.M.S., 2021. Double and triple burden of non-communicable diseases and its determinants among adults in Bangladesh: Evidence from a recent demographic and health survey. *International Journal of Clinical Practice*, *75*(10), p.e14613.

Ampofo, P.O., Tenkorang-Twum, D., Adjorlolo, S., Chandi, M.G., Wuni, F.K., Asiedu, E., Kukula, V.A. and Opoku, S., 2022. The impact of strike action by Ghana registered nurses and midwives on the access to and utilization of healthcare services. *Plos one*, *17*(10), p.e0275661.

Anderson, Michael L. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American statistical Association* 103.484 (2008): 1481-1495.

António, D.C., Sanseverino, I., Pozzoli, L. and Lettieri, T., 2018. Toward Climate Change Impact: Vectors carrying viral infection. *Joint Research Centre (JRC), the European Commission's science and knowledge service.*

Anttila-Hughes, J. and Hsiang, S., 2013. Destruction, disinvestment, and death: Economic and human losses following environmental disaster. *Available at SSRN 2220501*.

Armand, A., Attanasio, O., Carneiro, P. and Lechene, V., 2020. The effect of gender-targeted conditional cash transfers on household expenditures: Evidence from a randomized experiment. *The Economic Journal*, *130*(631), pp.1875-1897.

Aryal, K.K., Mehata, S., Neupane, S., Vaidya, A., Dhimal, M., Dhakal, P., Rana, S., Bhusal, C.L., Lohani, G.R., Paulin, F.H. and Garg, R.M., 2015. The burden and determinants of non communicable diseases risk factors in Nepal: findings from a nationwide STEPS survey. *PloS one*, *10*(8), p.e0134834.

Ayyagari, P., Grossman, D. and Sloan, F., 2011. Education and health: evidence on adults with diabetes. *International journal of health care finance and economics*, *11*(1), pp.35-54.

Badiuzzaman, M. and Murshed, S.M., 2016. *Impact of post-conflict development interventions on maternal healthcare utilization* (No. 2016/82). WIDER Working Paper.

Baez, J.E. and Santos, I.V., 2007. Children's vulnerability to weather shocks: A natural disaster as a natural experiment. *Social science research network, New York*, pp.1-28.

Baird, Sarah, Craig McIntosh, and Berk Ozler. (2011). “Cash or condition? Evidence from a Randomized Cash Transfer Program”, *Quarterly Journal of Economics*, 126(4), 1709-1753.

BANBEIS 2006, 2013, 2018. *Bangladesh Educational Statistics*. Dhaka: Bangladesh Bureau of Educational Information and Statistics (BANBEIS), Ministry of Education, the Government of Bangladesh. (http://www.banbeis.gov.bd)

BANBEIS 2006, 2013, 2018. *Bangladesh Educational Statistics*. Dhaka: Bangladesh Bureau of Educational Information and Statistics (BANBEIS), Ministry of Education, the Government of Bangladesh. (http://www.banbeis.gov.bd)

Bangladesh Bank 2008-2009. *Statistics department.* Dhaka: Bangladesh central bank, Ministry of Finance, the Government of Bangladesh.

Bangladesh Bank 2008-2009. *Statistics department.* Dhaka: Bangladesh Central Bank, Ministry of Finance, the Government of Bangladesh.

Bangladesh Bureau of Statistics (BBS) and UNICEF. 2014, 2019. *Multiple Indicator Cluster Survey 2012-2013, 2019: Progotir Pathey.* Dhaka, Bangladesh: BBS and UNICEF.

Bangladesh Bureau of Statistics 1995. *Household Expenditure Survey (HES) 1995.* Dhaka: Bangladesh Bureau of Statistics, Ministry of Planning, the Government of Bangladesh.

—— 2012. *Population and Housing Census.* Dhaka: Bangladesh Bureau of Statistics, Ministry of Planning, the Government of Bangladesh.

Barker, D.J., 1995. Fetal origins of coronary heart disease. *Bmj*, *311*(6998), pp.171-174.

Barker, D.J., 2003. The developmental origins of adult disease. *European journal of epidemiology*, pp.733-736.

Barker, D.J., 2007. The origins of the developmental origins theory. *Journal of internal medicine*, *261*(5), pp.412-417.

Barlow, P., 2021. The effect of schooling on women's overweight and Obesity: A natural experiment in Nigeria. *Demography*, *58*(2), pp.685-710.

Bartlett, S. 2009. Children in the context of climate change: A large and vulnerable population. *Population Dynamics and Climate Change*, *80*, 133.

Becker, G.S. and Lewis, H.G., 1973. On the interaction between the quantity and quality of children. *Journal of Political Economy*, *81*(2, Part 2), pp.S279-S288.

Becker, G.S. and Tomes, N., 1976. Child endowments and the quantity and quality of children. *Journal of Political Economy*, *84*(4, Part 2), pp.S143-S162.

Begum, L., Islam, A., and Smyth, R. 2017. Girl power: stipend programs and the education of younger siblings. *The Journal of Development Studies*, *53*(11), 1882-1898.

Begum, M.R. and Biswas, S.C., 2020. Changes in depressive symptoms during the antenatal period: a cohort study from Bangladesh. *Indian Journal of Psychological Medicine*, *42*(6), pp.519-524.

Benetou, V., Chloptsios, Y., Zavitsanos, X., Karalis, D., Naska, A. and Trichopoulou, A., 2000. Total cholesterol and HDL-cholesterol in relation to socioeconomic status in a sample of 11,645 Greek adults: the EPIC study in Greece. *Scandinavian journal of public health*, *28*(4), pp.260-265.

Benjamini, Y., Krieger, A., and Yekutieli, D. (2006), "Adaptive Linear Step-Up

Bhuva, K., Kraschnewski, J.L., Lehman, E.B. and Chuang, C.H., 2017. Does body mass index or weight perception affect contraceptive use?. *Contraception*, *95*(1), pp.59-64.

Bista, B., Dhungana, R.R., Chalise, B. and Pandey, A.R., 2020. Prevalence and determinants of non-communicable diseases risk factors among reproductive aged women of Nepal: Results from Nepal Demographic Health Survey 2016. *PloS one*, *15*(3), p.e0218840.

Biswas, T., Townsend, N., Islam, M.S., Islam, M.R., Gupta, R.D., Das, S.K. and Al Mamun, A., 2019. Association between socioeconomic status and prevalence of non-communicable diseases risk factors and comorbidities in Bangladesh: findings from a nationwide cross-sectional survey. *BMJ open*, *9*(3), p.e025538.

Bleakley, H., 2010. Health, human capital, and development. *Annu. Rev. Econ.*, *2*(1), pp.283-310.

Bloom, D.E., Canning, D. and Fink, G., 2014. Disease and development revisited. *Journal of Political Economy*, *122*(6), pp.1355-1366.

Bloom, D.E., Kuhn, M. and Prettner, K., 2015. *The contribution of female health to economic development* (No. w21411). National Bureau of Economic Research.

Böckerman, P., Viinikainen, J., Pulkki-Råback, L., Hakulinen, C., Pitkänen, N., Lehtimäki, T., Pehkonen, J. and Raitakari, O.T., 2017. Does higher education protect against obesity? Evidence using Mendelian randomization. *Preventive medicine*, *101*, pp.195-198.

Breierova, L., and Duflo, E. 2004. The impact of education on fertility and child mortality: Do fathers really matter less than mothers? *NBER Working Paper*, (w10513). National Bureau of Economic Research, Inc.

Brunello, G., Fabbri, D. and Fort, M., 2013. The causal effect of education on body mass: Evidence from Europe. *Journal of Labor Economics*, *31*(1), pp.195-223.

Bucher, S., Marete, I., Tenge, C., Liechty, E.A., Esamai, F., Patel, A., Goudar, S.S., Kodkany, B., Garces, A., Chomba, E. and Althabe, F., 2015. A prospective observational description of frequency and timing of antenatal care attendance and coverage of selected interventions from sites in Argentina, Guatemala, India, Kenya, Pakistan and Zambia. *Reproductive health*, *12*, pp.1-11.

Caillouët, K.A. and Robertson, S.L., 2020. Temporal and spatial impacts of hurricane damage on West Nile virus transmission and human risk. *Journal of the American Mosquito Control Association*, *36*(2s), pp.106-119.

Callegari, L.S., Nelson, K.M., Arterburn, D.E., Prager, S.W., Schiff, M.A. and Schwarz, E.B., 2014. Factors associated with lack of effective contraception among obese women in the United States. *Contraception*, *90*(3), pp.265-271.

Camacho, P.A., Gomez-Arbelaez, D., Otero, J., González-Gómez, S., Molina, D.I., Sanchez, G., Arcos, E., Narvaez, C., García, H., Pérez, M. and Hernandez-Triana, E., 2020. Self-reported prevalence of chronic non-communicable diseases in relation to socioeconomic and educational factors in Colombia: a community-based study in 11 departments. *Global Heart*, *15*(1).

Cameron, A. C., and Miller, D. L. 2015. A practitioner's guide to cluster-robust inference. *Journal of human resources*, *50*(2), 317-372.

Cameron, A. C., and Miller, D. L. 2015. A practitioner's guide to cluster-robust inference. *Journal of human resources*, *50*(2), 317-372.

Card, D., 1999. Chapter 30 The causal effect of education on earnings. I: ORLEY, CA & DAVID, C.(eds.) Handbook of Labor Economics.

Center on the Developing Child, Harvard University, 2014. InBrief: The foundations of lifelong health. https://developingchild.harvard.edu/science/deep-dives/lifelong-health/

Chakraborty, T.K., Kabir, A.H.M.E. and Ghosh, G.C., 2016. Impact and adaptation to cyclone AILA: focus on water supply, sanitation and health of rural coastal community in the south west coastal region of Bangladesh. *J Health Environ Res*, *2*(3), pp.13-19.

Chari, A.V., Heath, R., Maertens, A. and Fatima, F., 2017. The causal effect of maternal age at marriage on child wellbeing: Evidence from India. *Journal of Development Economics*, *127*, pp.42-55.

Chou, S. Y., Liu, J. T., Grossman, M., and Joyce, T. 2010. Parental education and child health: evidence from a natural experiment in Taiwan. *American Economic Journal: Applied Economics, 2(1),* 33-61.

Chowdhury, F.J. and Amin, A.N., 2006. Environmental assessment in slum improvement programs: some evidence from a study on infrastructure projects in two Dhaka slums. *Environmental Impact Assessment Review*, *26*(6), pp.530-552.

Chowdhury, F.J. and Amin, A.N., 2006. Environmental assessment in slum improvement programs: some evidence from a study on infrastructure projects in two Dhaka slums. *Environmental Impact Assessment Review*, *26*(6), pp.530-552.

Clark, D. and Royer, H., 2010. *The effect of education on adult health and mortality: Evidence from Britain* (No. w16013). National Bureau of Economic Research.

Clayton, A., 2012. Destructive Storms, Dormant Policies: The Impact of Cyclones on Food Security in Madagascar. *South African Institute of International Affairs (SAIIA).*

Cohn, E. and Addison, J.T., 1998. The economic returns to lifelong learning in OECD countries. *Education economics*, *6*(3), pp.253-307.

Cowan, K.N., Pennington, A.F., Gregory, T. and Hsu, J., 2022. Impact of hurricanes on children with asthma: a systematic literature review. *Disaster medicine and public health preparedness*, *16*(2), pp.777-782.

Cresswell, J.A., Campbell, O.M., De Silva, M.J. and Filippi, V., 2013. Effect of Maternal Obesity on Neonatal Death in Sub-Saharan Africa: Multivariable Analysis of 27 National Data Sets. *Obstetric Anesthesia Digest*, *33*(4), pp.197-198.

Currie, J. and Moretti, E., 2003. Mother's education and the intergenerational transmission of human capital: Evidence from college openings. *The Quarterly Journal of Economics*, *118*(4), pp.1495-1532.

Currie, J. and Vogl, T., 2013. Early-life health and adult circumstance in developing countries. *Annu. Rev. Econ.*, *5*(1), pp.1-36.

Datar, A., Liu, J., Linnemayr, S. and Stecher, C., 2013. The impact of natural disasters on child health and investments in rural India. *Social Science & Medicine*, *76*, pp.83-91.

Davies, N.M., Dickson, M., Davey Smith, G., Van Den Berg, G.J. and Windmeijer, F., 2018. The causal effects of education on health outcomes in the UK Biobank. *Nature human behaviour*, *2*(2), pp.117-125.

de Oliveira, V.H., Lee, I. and Quintana-Domeque, C., 2023. Natural disasters and early human development: Hurricane Catarina and infant health in Brazil. *Journal of Human Resources*, *58*(3), pp.819-851.

de Onis, M., Dewey, K.G., Borghi, E., Onyango, A.W., Blössner, M., Daelmans, B., Piwoz, E. and Branca, F., 2013. The World Health Organization's global target for reducing childhood stunting by 2025: rationale and proposed actions. *Maternal & child nutrition*, *9*, pp.6-26.

Dégano, I.R., Marrugat, J., Grau, M., Salvador-González, B., Ramos, R., Zamora, A., Martí, R. and Elosua, R., 2017. The association between education and cardiovascular disease incidence is mediated by hypertension, diabetes, and body mass index. *Scientific reports*, *7*(1), pp.1-8.

Del Ninno, C., and Lundberg, M. 2005. Treading water: the long-term impact of the 1998 flood on nutrition in Bangladesh. *Economics & Human Biology*, *3*(1), 67-96.

del Ninno, C., Dorosh, P.A. and Islam, N., 2002. Reducing vulnerability to natural disasters: lessons from the 1998 floods in Bangladesh. *IDS Bulletin*, *33*(4), pp.98-107.

Di Chiara, T., Scaglione, A., Corrao, S., Argano, C., Pinto, A. and Scaglione, R., 2017. Education and hypertension: impact on global cardiovascular risk. Acta cardiologica, 72(5), pp.507-513.

Dinger, J., Do Minh, T., Buttmann, N. and Bardenheuer, K., 2011. Effectiveness of oral contraceptive pills in a large US cohort comparing progestogen and regimen. *Obstetrics & Gynecology*, *117*(1), pp.33-40.

Dizon-Ross, R. and Jayachandran, S., 2022. *Dads and daughters: Disentangling altruism and investment motives for spending on children* (No. w29912). National Bureau of Economic Research.

Doepke, M., 2015. Gary Becker on the quantity and quality of children. *Journal of Demographic Economics*, *81*(1), pp.59-66.

Duflo, E., 2003. Grandmothers and granddaughters: old-age pensions and intrahousehold allocation in South Africa. *The World Bank Economic Review*, *17*(1), pp.1-25.

Duflo, Esther, Pascaline Dupas, and Michael Kremer. The impact of free secondary education: Experimental evidence from Ghana. No. w28937. National Bureau of Economic Research, 2021.

Duncan, M.J., Vandelanotte, C., Caperchione, C., Hanley, C. and Mummery, W.K., 2012. Temporal trends in and relationships between screen time, physical activity, overweight and obesity. *BMC Public Health*, *12*(1), pp.1-9.

DuRant, R.H., Baranowski, T., Johnson, M. and Thompson, W.O., 1994. The relationship among television watching, physical activity, and body composition of young children. *Pediatrics*, *94*(4), pp.449-455.

Edoka, I.O., 2013. Weather shocks and nutritional status of disadvantaged children in Vietnam. *Health Econometrics and Data Group, The University of York, WP*, *13*(10).

Effects," *Econometrica*, 75, 83–119.

Eisenmann, J.C., Bartee, R.T., Smith, D.T., Welk, G.J. and Fu, Q., 2008. Combined influence of physical activity and television viewing on the risk of overweight in US youth. *International journal of obesity*, *32*(4), pp.613-618.

Eriksson, J.G., 2005. The fetal origins hypothesis—10 years on. *BMJ*, *330*(7500), pp.1096-1097.

Eskander, S. and Barbier, E., 2019. Legacies of gusts and bloods: long-term impacts of the series of 1970-74 disasters in Bangladesh. *In: 10th Annual Faculty Research Conference: Contemporary Issues in Business and Social Sciences in a period of uncertainty; 03 - 04 Jun 2019, Kingston upon Thames, U.K.. (Submitted).*

Farukh, M.A., Hossen, M.A.M. and Ahmed, S., 2019. Impact of extreme cyclone events on coastal agriculture in Bangladesh. *Progressive Agriculture*, *30*, pp.33-41.

Fernández Alba, J.J., Paublete Herrera, C., Vilar Sanchez, A., Gonzalez-Macias, C., Castillo Lara, M., Torrejón, R. and Moreno Corral, L.J., 2018. Indications of caesarean section in overweight and obese versus normal-weight pregnant women: a retrospective cohort study. *The Journal of Maternal-Fetal & Neonatal Medicine*, *31*(3), pp.357-363.

Field, E., Robles, O. and Torero, M., 2009. Iodine deficiency and schooling attainment in Tanzania. *American Economic Journal: Applied Economics*, *1*(4), pp.140-169.

Fontaine, I., Garabedian, S., Nortes-Martinez, D. and Veremes, H., 2021. *Tropical Cyclones And Fertility: New Evidence From Madagascar* (No. 2021-02). TEPP.

Foster, A. D. 1995. Prices, credit markets and child growth in low-income rural areas. *The economic journal*, *105*(430), 551-570. https://doi.org/10.2307/2235017

Furthner, D., Ehrenmueller, M., Lanzersdorfer, R., Halmerbauer, G., Schmitt, K. and Biebl, A., 2018. Education, school type and screen time were associated with overweight and obesity in 2930 adolescents. *Acta Paediatrica*, *107*(3), pp.517-522.

Fuwa, N. 2006. The net impact of the female secondary stipend program in Bangladesh. *Available at SSRN 879245*.

Garcia-Hombrados, J., 2022. Child marriage and infant mortality: causal evidence from Ethiopia. *Journal of Population Economics*, *35*(3), pp.1163-1223.

Gluckman, P.D., Hanson, M.A. and Pinal, C., 2005. The developmental origins of adult disease. *Maternal & child nutrition*, *1*(3), pp.130-141.

Godfrey, K.M. and Barker, D.J., 2001. Fetal programming and adult health. *Public health nutrition*, *4*(2b), pp.611-624.

Goel, D., 2013. *Impact of Water Related Natural Disasters on Children's Health in Bangladesh* (Doctoral dissertation, Georgetown University).

Goldfield, G.S., Cameron, J.D., Murray, M., Maras, D., Wilson, A.L., Phillips, P., Kenny, G.P., Hadjiyannakis, S., Alberga, A.S., Tulloch, H. and Doucette, S., 2015. Screen time is independently associated with health-related quality of life in overweight and obese adolescents. *Acta Paediatrica*, *104*(10), pp.e448-e454.

Goudet, S.M., Faiz, S., Bogin, B.A. and Griffiths, P.L., 2011. Pregnant women's and community health workers' perceptions of root causes of malnutrition among infants and young children in the slums of Dhaka, Bangladesh. *American journal of public health*, *101*(7), pp.1225-1233.

Grabner, M., 2009. The causal effect of education on Obesity: Evidence from compulsory schooling laws. *Available at SSRN 1505075*.

Gregorio, J.D. and Lee, J.W., 2002. Education and income inequality: new evidence from cross-country data. *Review of income and wealth*, *48*(3), pp.395-416.

Grépin, K. A., and Bharadwaj, P. 2015. Maternal education and child mortality in Zimbabwe. *Journal of Health Economics, 44,* 97-117.

Grimes, D.A. and Shields, W.C., 2005. Family planning for obese women: challenges and opportunities. *Contraception*, *72*(1), pp.1-4.

Grossman, M. 2006. Education and nonmarket outcomes. *Handbook of the Economics of Education*, *1,* 577-633.

Gupta, R., Kaul, V., Agrawal, A., Guptha, S. and Gupta, V.P., 2010. Cardiovascular risk according to educational status in India. *Preventive medicine*, *51*(5), pp.408-411.

Hahn, Y., Islam, A., Nuzhat, K., Smyth, R., and Yang, H. S. 2018a. Education, marriage, and fertility: Long-term evidence from a female stipend program in Bangladesh. *Economic Development and Cultural Change, 66(2),* 383-415.

Hahn, Y., Islam, A., Nuzhat, K., Smyth, R., and Yang, H. S. 2018a. Education, marriage, and fertility: Long-term evidence from a female stipend program in Bangladesh. *Economic Development and Cultural Change, 66(2),* 383-415.

Hahn, Y., Nuzhat, K., and Yang, H. S. 2018b. The effect of female education on marital matches and child health in Bangladesh. *Journal of Population Economics, 31(3),* 915-936.
Hahn, Y., Nuzhat, K., and Yang, H. S. 2018b. The effect of female education on marital matches and child health in Bangladesh. *Journal of Population Economics, 31(3),* 915-936.
Halder, A.K. and Kabir, M., 2008. Inequalities in infant immunization coverage in Bangladesh. *Health Services Insights*, *1*, pp.HSI-S927.

Hands, B.P., Chivers, P.T., Parker, H.E., Beilin, L., Kendall, G. and Larkin, D., 2011. The associations between physical activity, screen time and weight from 6 to 14 yrs: the Raine Study. *Journal of Science and Medicine in Sport*, *14*(5), pp.397-403.

Haq, A. and Md, S., 2023. The impact of extreme weather events on fertility preference and gender preference in Bangladesh. *Frontiers in Environmental Science*, *11*, p.1095460.

Haque, A. and Jahan, S., 2016. Regional impact of cyclone sidr in Bangladesh: A multi-sector analysis. *International Journal of Disaster Risk Science*, *7*, pp.312-327.

Hasan, M.M., 2014. Climate change induced marginality: Households' vulnerability in the meal consumption frequencies.

Hernández-Julián, R., Mansour, H. and Peters, C., 2014. The effects of intrauterine malnutrition on birth and fertility outcomes: evidence from the 1974 Bangladesh famine. *Demography, 51(5),* pp.1775-1796.

Hierink, F., Rodrigues, N., Muñiz, M., Panciera, R. and Ray, N., 2020. Modelling geographical accessibility to support disaster response and rehabilitation of a healthcare system: an impact analysis of Cyclones Idai and Kenneth in Mozambique. *BMJ open*, *10*(11), p.e039138.

Hoddinott, J. and Kinsey, B., 2001. Child growth in the time of drought. *Oxford Bulletin of Economics and statistics*, *63*(4), pp.409-436.

Holt, V.L., Scholes, D., Wicklund, K.G. and Cushing-Haugen, K.L., 2005. Body mass index, weight, and oral contraceptive failure risk. *Obstetrics & Gynecology*, *105*(6), pp.1492-1493.

Hong, S. Y., and Sarr, L. R. 2012. Long-term impacts of the free tuition and female stipend programs on education attainment, age of marriage, and married women's labor market participation of in Bangladesh. *Working Paper.*

Hoque, M.E., Khokan, M.R. and Bari, W., 2014. Impact of stature on non-communicable diseases: evidence based on Bangladesh Demographic and Health Survey, 2011 data. *BMC Public Health*, *14*(1), pp.1-8.

Hossain, M.Z., Islam, M.T., Sakai, T. and Ishida, M., 2008. Impact of tropical cyclones on rural infrastructures in Bangladesh. *Agricultural Engineering International: CIGR Journal*.

Hossain, S., Biswas, R.K. and Hossain, M.A., 2021. Body mass index of women in Bangladesh: comparing multiple linear regression and quantile regression. *Journal of Biosocial Science*, *53*(2), pp.247-265.

Howitt, C., Hambleton, I.R., Rose, A.M., Hennis, A., Samuels, T.A., George, K.S. and Unwin, N., 2015. Social distribution of diabetes, hypertension and related risk factors in Barbados: a cross-sectional study. *BMJ open*, *5*(12), p.e008869.

Hsiang, S.M. and Jina, A.S., 2014. *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones* (No. w20352). National Bureau of Economic Research.

Hsiang, S.M. and Narita, D., 2012. Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics*, *3*(02), p.1250011.

ICF. 1993-94–2017-18. Demographic and Health Surveys (Bangladesh) 1993-1994, 1996-1997, 1999-2000, 2004, 2007, 2011, 2014, 2017-2018. Funded by USAID. Rockville, MD: ICF.

ICF. 1996-97–2017-18. Demographic and Health Surveys (Bangladesh) 1996-1997, 1999-2000, 2004, 2007, 2011, 2014, 2017-2018. Funded by USAID. Rockville, MD: ICF.

Inoue, S., Sugiyama, T., Takamiya, T., Oka, K., Owen, N. and Shimomitsu, T., 2012. Television viewing time is associated with overweight/obesity among older adults, independent of meeting physical activity and health guidelines. *Journal of Epidemiology*, *22*(1), pp.50-56.

Islam, A., and Nguyen, C. 2018. Do networks matter after a natural disaster? A study of resource sharing within an informal network after Cyclone Aila. *Journal of Environmental Economics and Management*, *90*, 249e268. https://doi.org/10.1016/j.jeem.2018.06.007

Islam, A.Z., Mondal, M.N.I., Khatun, M.L., Rahman, M.M., Islam, M.R., Mostofa, M.G. and Hoque, M.N., 2016. Prevalence and determinants of contraceptive use among employed and unemployed women in Bangladesh. *International Journal of MCH and AIDS*, *5*(2), p.92.

Islam, M.A., Paull, D.J., Griffin, A.L. and Murshed, S., 2021. Spatio-temporal assessment of social resilience to tropical cyclones in coastal Bangladesh. *Geomatics, Natural Hazards and Risk*, *12*(1), pp.279-309.

Islam, M.M. and Ahmed, S., 2017. Effects of natural disaster on food availability, accessibility and consumption in household level of coastal villages. *Journal of Geography & Natural Disasters*, *7*(3), pp.1-6.

Islam, M.Q., 2020. Children's vulnerability to natural disasters: Evidence from natural experiments in Bangladesh. *World Development Perspectives*, *19*, p.100228.

Islam, M.S., Salam, M.A., Biswas, J.K. and Kabir, M.S., 2012. Aila impact on the livelihood of the coastal people of Bangladesh. *Bangladesh Rice Research Institute*, *Gazipur-1701*, *Bangladesh*.

Islam, R., Walkerden, G. and Amati, M., 2017. Households' experience of local government during recovery from cyclones in coastal Bangladesh: resilience, equity, and corruption. *Natural Hazards*, *85*, pp.361-378.

Jahan, U.T., Mahmud, S., Dutta, M.K., Deb, A., Dhali, B.H. and Islam, M.S., 2022. Antenatal Care Practice and Reasons for Spontaneous Vaginal Delivery at Homein Rural Bangladesh: A Synopsis. *IAHS Medical Journal*, *5*(2), pp.62-66.

Jakariya, M., Ahmed, M.F. and Sikder, M.T., 2016. Vulnerability analysis of the cyclone Aila affected community in the South-West Belt of Bangladesh. *J Health Environ Res*, *2*(2), pp.5-12.

Jamil, K., Bhuiya, A., Streatfield, K. and Chakrabarty, N., 1999. The immunization programme in Bangladesh: impressive gains in coverage, but gaps remain. *Health Policy and Planning*, *14*(1), pp.49-58.

Kabir, A., Ali, R., Islam, M.S., Kawsar, L.A. and Islam, M.A., 2009. A comparison of regional variations of fertility in Bangladesh. *International quarterly of community health education*, *29*(3), pp.275-291.

Kabir, R. and Khan, H.T., 2017. Study on the health status of coastal people in Bangladesh after cyclone Sidr and Aila. *European Scientific Journal*, *13*(15), pp.10-21.

Kabir, R., 2014. *The impacts of cyclones Sidr and Aila on the health of the coastal people of Bangladesh* (Doctoral dissertation, Middlesex University).

Kabir, R., Khan, H.T., Ball, E. and Caldwell, K., 2016. Climate change impact: the experience of the coastal areas of Bangladesh affected by cyclones Sidr and Aila. *Journal of environmental and public health*, *2016*. DOI: 10.1155/2016/9654753

Kamal, S.M., 2011. Socio-economic determinants of age at first marriage of the ethnic tribal women in Bangladesh. *Asian Population Studies*, *7*(1), pp.69-84.

Karbownik, K. and Wray, A., 2019. Long-run consequences of exposure to natural disasters. *Journal of Labor Economics*, *37*(3), pp.949-1007.

Karim, A., 2018. The household response to persistent natural disasters: Evidence from Bangladesh. *World Development*, *103*, pp.40-59.

Keats, A. 2018. Women's schooling, fertility, and child health outcomes: Evidence from Uganda's free primary education program. *Journal of Development Economics*, *135*, 142-159.

Kemptner, D., Jürges, H. and Reinhold, S., 2011. Changes in compulsory schooling and the causal effect of education on health: Evidence from Germany. *Journal of health economics, 30*(2), pp.340-354.

Khandker, S. R., Samad, H. A., Fuwa, N., and Hayashi, R. 2021. The Female Secondary Stipend and Assistance Program in Bangladesh: What Did It Accomplish? *ADB South Asia Working Paper Series* (SAWP 81).

Khandker, S. R., Samad, H. A., Fuwa, N., and Hayashi, R. 2021. The Female Secondary Stipend and Assistance Program in Bangladesh: What Did It Accomplish? *ADB South Asia Working Paper Series* (SAWP 81).

Khandker, S., Pitt, M., and Fuwa, N. 2003. *Subsidy to Promote Girls' Secondary Education: The Female Stipend Program in Bangladesh (MRPA Paper No. 23688).* University Library of Munich, Germany.

Kling, J., Liebman, J., and Katz, L. (2007), "Experimental Analysis of Neighborhood

Kugler, A.D. and Kumar, S., 2017. Preference for boys, family size, and educational attainment in India. *Demography*, *54*(3), pp.835-859.

Kuh, D., Ben-Shlomo, Y., Lynch, J., Hallqvist, J. and Power, C., 2003. Life course epidemiology. *Journal of epidemiology and community health*, *57*(10), p.778.

Kulatunga, U., Wedawatta, G., Amaratunga, D. and Haigh, R., 2014. Evaluation of vulnerability factors for cyclones: the case of Patuakhali, Bangladesh. *International journal of disaster risk reduction*, *9*, pp.204-211.

Le, K. and Nguyen, M., 2022. Droughts and child health in Bangladesh. *Plos one*, *17*(3), p.e0265617. https://doi.org/10.1016/j.worlddev.2017.10.026

Lenzen, M., Malik, A., Kenway, S., Daniels, P., Lam, K.L. and Geschke, A., 2019. Economic damage and spillovers from a tropical cyclone. *Natural Hazards and Earth System Sciences*, *19*(1), pp.137-151.

Lépine, A., Restuccio, M. and Strobl, E., 2021. Can we mitigate the effect of natural disasters on child health? Evidence from the Indian Ocean tsunami in Indonesia. *Health economics*, *30*(2), pp.432-452.

Liang, X., 1996. Bangladesh: Female secondary school assistance. *Human Development Department, World Bank*, pp.1-16.

Liao, L.Z., Chen, Z.C., Li, W.D., Zhuang, X.D. and Liao, X.X., 2021. Causal effect of education on type 2 diabetes: A network Mendelian randomization study. *World Journal of Diabetes*, *12*(3), p.261.

Lin, Y., Liu, F. and Xu, P., 2021. Long-term effects of early-life exposure to tropical cyclones. *China Economic Review*, *69*, p.101662.

Liu, H. and Guo, G., 2015. Lifetime socioeconomic status, historical context, and genetic inheritance in shaping body mass in middle and late adulthood. *American sociological review*, *80*(4), pp.705-737.

Lumey, L.H., Stein, A.D. and Susser, E., 2011. Prenatal famine and adult health. *Annual review of public health*, *32*, pp.237-262.

Maccini, S. and Yang, D., 2009. Under the weather: Health, schooling, and economic consequences of early-life rainfall. *American Economic Review*, *99*(3), pp.1006-1026.

MacKinnon, J.G., Nielsen, M.Ø. and Webb, M.D., 2022. Cluster-robust inference: A guide to empirical practice. *Journal of Econometrics*.

MacKinnon, J.G., Nielsen, M.Ø. and Webb, M.D., 2022. Cluster-robust inference: A guide to empirical practice. *Journal of Econometrics*.

Mahmud, S., 2003. Female secondary school stipend programme in Bangladesh. *United Background paper prepared for the Education for All Global Monitoring Report*, *4*.

Majumder, N. and Ram, F., 2015. Explaining the role of proximate determinants on fertility decline among poor and non-poor in Asian countries. *PloS one*, *10*(2), p.e0115441.

Malak, M.A., Sajib, A.M., Quader, M.A. and Anjum, H., 2020. "We are feeling older than our age": Vulnerability and adaptive strategies of aging people to cyclones in coastal Bangladesh. *International Journal of Disaster Risk Reduction*, *48*, p.101595.

Marttinen, R., Vernikoff, L., Phillips, S. and Fletcher, N., 2017. Physical activity, screen time, and obesity. *Californian Journal of Health Promotion*, *15*(1), pp.27-35.

Maruf, F.A. and Udoji, N.V., 2015. Prevalence and socio-demographic determinants of overweight and obesity in a Nigerian population. *Journal of epidemiology*, *25*(7), pp.475-481.

Matin, N. and Taher, M., 2001. The changing emphasis of disasters in Bangladesh NGOs. *Disasters*, *25*(3), pp.227-239.

Matovelo, D., Ndaki, P., Yohani, V., Laisser, R., Bakalemwa, R., Ndaboine, E., Masatu, Z., Mwaikambo, M., Brenner, J.L. and Wilson, W.M., 2021. Why don't illiterate women in rural, Northern Tanzania, access maternal healthcare?. *BMC pregnancy and childbirth*, *21*, pp.1-11.

Mazumder, B., Rosales-Rueda, M.F. and Triyana, M., 2023. Social Interventions, Health, and Well-Being: The Long-Term and Intergenerational Effects of a School Construction Program. *Journal of Human Resources*, *58*(4), pp.1097-1140.

McCrary, J., and Royer, H. 2011. The effect of female education on fertility and infant health: evidence from school entry policies using exact date of birth. *American Economic Review*, *101*(1), 158-95.

McGavock, T., 2021. Here waits the bride? The effect of Ethiopia's child marriage law. *Journal of Development Economics*, *149*, p.102580.

Millimet, D.L. and Wang, L., 2011. Is the quantity-quality tradeoff a tradeoff for all, none, or some?. *Economic Development and Cultural Change*, *60*(1), pp.155-195.

Nahar, M.Z. and Zahangir, M.S., 2019. Determinants of fertility in Bangladesh: Evidence from the 2014 demographic and health survey. *International quarterly of community health education*, *40*(1), pp.29-38.

NASA POWER. 2008-2017. NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program. Available at: https://power.larc.nasa.gov/data-access-viewer/

National Scientific Council on the Developing Child. 2020. *Connecting the brain to the Rest of the Body: Early Childhood Development and Lifelong Health Are Deeply Intertwined Working Paper No. 15*. Retrieved from www.developingchild.harvard.edu.

Ng, M., Fleming, T., Robinson, M., Thomson, B., Graetz, N., Margono, C., Mullany, E.C., Biryukov, S., Abbafati, C., Abera, S.F. and Abraham, J.P., 2014. Global, regional, and national prevalence of overweight and obesity in children and adults during 1980–2013: a systematic analysis for the Global Burden of Disease Study 2013. *The lancet*, *384*(9945), pp.766-781.

Nonvignon, J. and Novignon, J., 2014. Trend and determinants of contraceptive use among women of reproductive age in Ghana. *African Population Studies*, pp.956-967.

Nowak-Szczepanska, N., Gomula, A., Chakraborty, R. and Koziel, S., 2021. Nutritional and weight status of Indian mother-child dyads experienced by a natural disaster. *Maternal & Child Nutrition*, *17*(3), p.e13164.

Nyqvist, M.B. and Jayachandran, S., 2017. Mothers care more, but fathers decide: Educating parents about child health in Uganda. *American Economic Review*, *107*(5), pp.496-500.

O'Donnell, O., Van Doorslaer, E. and Rosati, F.C., 2002. Child labour and health: Evidence and research issues. *Understanding Children's Work Programme Working Paper*.

Onarheim, K.H., Iversen, J.H. and Bloom, D.E., 2016. Economic benefits of investing in women's health: a systematic review. *PloS one*, *11*(3), p.e0150120.

Özer, M., Fidrmuc, J., and Eryurt, M. A. 2018. Maternal education and childhood immunization in Turkey. *Health Economics*, *27(8)*, 1218-1229.

Paul, S.K., Paul, B.K. and Routray, J.K., 2012. Post-Cyclone Sidr nutritional status of women and children in coastal Bangladesh: an empirical study. *Natural hazards*, *64*, pp.19-36.

Perova, N.V., Davis, C.E., Tao, S., Pajak, A., Stein, Y., Broda, G.B., Li, Y. and Tyroler, H.A., 2001. Multi-country comparison of plasma lipid relationship to years of schooling in men and women. *International journal of epidemiology*, *30*(2), pp.371-379.

Pitanga, F.J., Alves, C.F., Pamponet, M.L. and Medina, M.G., 2016. Screen time as discriminator for overweight, obesity and abdominal obesity in adolescents. *Revista Brasileira de Cineantropometria & Desempenho Humano*, *18*, pp.539-547.

Pouliou, T. and Elliott, S.J., 2010. Individual and socio-environmental determinants of overweight and Obesity in Urban Canada. *Health & place*, *16*(2), pp.389-398.

Powdthavee, N., 2010. Does education reduce the risk of hypertension? Estimating the biomarker effect of compulsory schooling in England. *Journal of Human Capital*, *4*(2), pp.173-202.

Procedures That Control the False Discovery Rate," *Biometrika*, 93, 491–507.

Psacharopoulos, G., 1985. Returns to education: A further international update and implications. *Journal of Human resources*, pp.583-604.

Pun, K., Villa, K. and Fontenla, M., 2022. The impact of Nepal's earthquake on the health status of rural children. *Review of Development Economics*.

Qian, N., 2008. Missing women and the price of tea in China: The effect of sex-specific earnings on sex imbalance. *The Quarterly journal of economics*, *123*(3), pp.1251-1285.

Rabbani, M.G., Rahman, A.A., Shoef, I.J. and Khan, Z.M., 2015. Climate change and food security in vulnerable coastal zones of Bangladesh. *Food security and risk reduction in Bangladesh*, pp.173-185.

Rahman, M.M., Arif, M.S.I., Hossain, M.T., Almohamad, H., Al Dughairi, A.A., Al-Mutiry, M. and Abdo, H.G., 2023. Households' vulnerability assessment: empirical evidence from cyclone-prone area of Bangladesh. *Geoscience letters*, *10*(1), pp.1-21.

Rahman, M.O. and Bennish, M., 1993. Health related response to natural disasters: The case of the Bangladesh cyclone of 1991. *Social Science & Medicine*, *36*(7), pp.903-914.

Raine, K.D., 2004. Obesity and overweight in Canada: a population health perspective. *Canadian Institute for Health Information, Canadian Population Health Initiative*.

Raynor, J., Wesson, K., and Keynes, M. 2006. The girls' stipend program in Bangladesh. *Journal of Education for International Development*, *2*(2), 1-12.

Raynor, J., Wesson, K., and Keynes, M. 2006. The girls' stipend program in Bangladesh. *Journal of Education for International Development*, *2*(2), 1-12.

Reddy, K.S., Prabhakaran, D., Jeemon, P., Thankappan, K.R., Joshi, P., Chaturvedi, V., Ramakrishnan, L. and Ahmed, F., 2007. Educational status and cardiovascular risk profile in Indians. *Proceedings of the National Academy of Sciences*, *104*(41), pp.16263-16268.

Rehbein, F., Psych, G., Kleimann, M., Mediasci, G. and Mößle, T., 2010. Prevalence and risk factors of video game dependency in adolescence: results of a German nationwide survey. *Cyberpsychology, behavior, and social networking*, *13*(3), pp.269-277.

Reinhold, S. and Jürges, H., 2010. Secondary school fees and the causal effect of schooling on health behavior. *Health Economics*, *19*(8), pp.994-1001.

Rodriguez-Llanes, J.M., Ranjan-Dash, S., Mukhopadhyay, A. and Guha-Sapir, D., 2016. Flood-exposure is associated with higher prevalence of child undernutrition in rural eastern India. *International Journal of Environmental Research and Public Health*, *13*(2), p.210.

Roy, S.K., Jahan, K., Alam, N., Rois, R., Ferdaus, A., Israt, S. and Karim, M.R., 2021. Perceived stress, eating behavior, and overweight and obesity among urban adolescents. *Journal of Health, Population and Nutrition*, *40*(1), p.54.

Russell, L.T., Coleman, M. and Ganong, L., 2018. Conceptualizing family structure in a social determinants of health framework. *Journal of Family Theory & Review*, *10*(4), pp.735-748.

Saha, S.K., 2017. Cyclone Aila, livelihood stress, and migration: empirical evidence from coastal Bangladesh. *Disasters*, *41*(3), pp.505-526.

Sara, R., and Priyanka, S. (2022). Long-term effects of an education stipend program on domestic violence: Evidence from Bangladesh. *Available at SSRN*.

Sarkar, P. K., kumar Sarker, N., Doulah, S., and Bari, T. I. A. 2015. Expanded programme on immunization in Bangladesh: a success story. *Bangladesh Journal of Child Health*, *39*(2), 93-98.

Sarker, A. R., Akram, R., Ali, N., and Sultana, M. 2019. Coverage and factors associated with full immunisation among children aged 12–59 months in Bangladesh: insights from the nationwide cross-sectional demographic and health survey. *BMJ open, 9(7),* e028020.

Schurmann, A. T. 2009. Review of the Bangladesh female secondary school stipend project using a social exclusion framework. *Journal of Health, Population, and Nutrition, 27(4)*, 505.

Schurmann, A. T. 2009. Review of the Bangladesh female secondary school stipend project using a social exclusion framework. *Journal of Health, Population, and Nutrition, 27(4),* 505.

Sen, A. 1981. Ingredients of famine analysis: availability and entitlements. *The Quarterly Journal of Economics*, *96*(3), 433-464.

Singh, R.B., Sharma, J.P., Rastogi, V., Niaz, M.A., Ghosh, S., Beegom, R. and Janus, E.D., 1997. Social class and coronary disease in a rural population of north India: The Indian Social Class and Heart Survey. *European heart journal*, *18*(4), pp.588-595.

Sobal, J., 2011. The sociology of obesity. In J. H. Cawley (Ed.), *The Oxford handbook of the social science of obesity* (pp. 105–119). New York, NY: Oxford University Press.

Streatfield, P.K. and Karar, Z.A., 2008. Population challenges for Bangladesh in the coming decades. *Journal of health, population, and nutrition*, *26*(3), p.261.

Strömberg, D., 2007. Natural disasters, economic development, and humanitarian aid. *Journal of Economic perspectives*, *21*(3), pp.199-222.

Sukhi, T.J., 2014. *NGO's role in Cyclone Disaster management of Bangladesh: focusing cyclone Sidr in Patuakhali* (Doctoral dissertation, University of Dhaka).

Tansel, A. and Karaoglan, D., 2016. The causal effect of education on Health Behaviors: Evidence from Turkey. *Available at SSRN 2798089*.

Tasdik Hasan, M., Adhikary, G., Mahmood, S., Papri, N., Shihab, H.M., Kasujja, R., Ahmed, H.U., Azad, A.K. and Nasreen, M., 2020. Exploring mental health needs and services among affected population in a cyclone affected area in costal Bangladesh: a qualitative case study. *International journal of mental health systems*, *14,* pp.1-9.

Thomas, D., 1990. Intra-household resource allocation: An inferential approach. *Journal of Human Resources*, pp.635-664.

Thomas, D., 1994. Like father, like son; like mother, like daughter: Parental resources and child height. *Journal of Human Resources*, pp.950-988.

Thomas, D., Strauss, J. and Henriques, M.H., 1991. How does mother's education affect child height? *Journal of Human Resources*, 183-211.

Tillmann, T., Vaucher, J., Okbay, A., Pikhart, H., Peasey, A., Kubinova, R., Pajak, A., Tamosiunas, A., Malyutina, S., Hartwig, F.P. and Fischer, K., 2017. Education and coronary heart disease: mendelian randomisation study. *bmj*, *358*.

Tucker, L.A. and Bagwell, M., 1991. Television viewing and obesity in adult females. *American Journal of Public Health*, *81*(7), pp.908-911.

UNICEF 2021. Leaving no child behind: scaling up investment in immunization to protect against disease. United Nations Children's Fund (UNICEF) June 2021

Van Aalst, M.K., 2006. The impacts of climate change on the risk of natural disasters. *Disasters*, *30*(1), pp.5-18.

Victora, C.G., Adair, L., Fall, C., Hallal, P.C., Martorell, R., Richter, L. and Sachdev, H.S., 2008. Maternal and child undernutrition: consequences for adult health and human capital. *The lancet*, *371*(9609), pp.340-357.

Wang, S.S., Lu, A.X., Cao, L.L., Ran, X.F., Wang, Y.Q., Liu, C. and Yan, C.H., 2022. Effects of prenatal exposure to persistent organic pollutants on neonatal Outcomes: A mother-child cohort (Shanghai, China). *Environmental Research*, *203*, p.111767.

Webbink, D., Martin, N.G. and Visscher, P.M., 2010. Does education reduce the probability of being overweight?. *Journal of Health Economics*, *29*(1), pp.29-38.

Welton, M., Vélez Vega, C.M., Murphy, C.B., Rosario, Z., Torres, H., Russell, E., Brown, P., Huerta-Montanez, G., Watkins, D., Meeker, J.D. and Alshawabkeh, A., 2020. Impact of hurricanes Irma and Maria on Puerto Rico maternal and child health research programs. *Maternal and child health journal*, *24*, pp.22-29.

WHO and UNICEF. 2018. The extension of the 2025 Maternal, Infant and Young Child nutrition targets to 2030. Discussion paper.

World Health Organization (WHO) 2017. WHO South-East Asia: Expanded Programme on Immunization (EPI) REGIONAL FACT SHEET 2017. *World Heal Organ* 2017, 6:1–98.

World Health Organization, 2009. *Women and health: today's evidence tomorrow's agenda*. World Health Organization.

World Health Organization, 2017. *The Partnership for Maternal, Newborn and Child Health 2016 annual report: coming of age in a time of transition* (No. WHO/FWC/NMC/17.1). World Health Organization.

World Health Organization, 2021. *Facts about overweight and obesity: Fact sheets*. World Health Organization. https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight

World Health Organization. 2006. WHO child growth standards: length/height-for-age, weight-for-age, weight-for-length, weight -for-height and body mass index-for-age: methods and development. World Health Organization. https://apps.who.int/iris/handle/10665/43413

World Health Organization. 2008. WHO child growth standards: training course on child growth assessment. World Health Organization.

World Risk Report. 2011-2022. *Focus: natural disasters.* Prepared by United Nations University and The Nature Conservancy. Available at: www.WorldRiskReport.org

Wu, H. (2022). The Effect of Maternal Education on Child Mortality in Bangladesh. *Population and Development Review*.

Wu, H. 2022. The Effect of Maternal Education on Child Mortality in Bangladesh. *Population and Development Review*, *48*, 475-503.

Wyatt, S.B., Winters, K.P. and Dubbert, P.M., 2006. Overweight and obesity: prevalence, consequences, and causes of a growing public health problem. *The American journal of the medical sciences*, *331*(4), pp.166-174.

Xie, S. and Mo, T., 2014. The impact of education on health in China. *China Economic Review*, *29*, pp.1-18.

Xu, S., Shonchoy, A. S., and Fujii, T. 2022. Assessing gender parity in intrahousehold allocation of educational resources: Evidence from Bangladesh. *World Development*, *151*, 105730.

Yin, H., Wu, Q., Cui, Y., Hao, Y., Liu, C., Li, Y., Liang, L., Wang, L. and Tao, Y., 2017. Socioeconomic status and prevalence of chronic non-communicable diseases in Chinese women: a structural equation modelling approach. *BMJ open*, *7*(8), p.e014402.

Zaman, M.M., Bhuiyan, M.R., Karim, M., Rahman, M., Akanda, A.W. and Fernando, T., 2015. Clustering of noncommunicable diseases risk factors in Bangladeshi adults: An analysis of STEPS survey 2013. *BMC public health*, *15*(1), pp.1-9.

Zhang, S. 2012. *Mother's education and infant health: Evidence from closure of high schools in China*. Cornell University working paper.

Zheng, J., Han, W., Jiang, B., Ma, W. and Zhang, Y., 2017. Infectious diseases and tropical cyclones in Southeast China. *International journal of environmental research and public health*, *14*(5), p.494.

Zhou, Y., 2019. The Impact of Transportation Disadvantage on Healthcare Access. *All Dissertations. 2520.*

Zhou, Z. and Zhang, L., 2021. Destructive destruction or creative destruction? Unraveling the effects of tropical cyclones on economic growth. *Economic Analysis and Policy*, *70*, pp.380-393.

APPENDIX A: SUPPLEMENTARY TABLES AND FIGURES FOR CHAPTER 1

Table A1. Sample Selection Criteria for Main Analysis Samples.

Panel A: Maternal Education Sample	
BDHS Individual Recode Files, 1993-94 to 2017-18	107,579
Drop if Muslim is missing	107,572
Drop if schooling is missing	107,488
Restrict to women age>=16 years	105,451
Restrict to maternal birth cohorts 1975-1998	58,707
Panel B: Child Immunizations Sample	
BDHS Children's Recode Files, 1993-94 to 2017-18	55,351
Drop if Muslim is missing	55,345
Restrict to children aged 12-59 months	38,400
Drop if maternal schooling is missing	38,361
Restrict to women age>=16 years	38,255
Restrict to maternal birth cohorts 1975-1998	28,765
Drop if immunization is missing	25,465

Table A2. Difference-in-Differences Estimates for Individual Vaccine Doses.

	(1) BCG Vaccine	(2) DPT1 Vaccine	(3) DPT2 Vaccine	(4) DPT3 Vaccine	(5) Poliomyelitis1 Vaccine	(6) Poliomyelitis2 Vaccine	(7) Poliomyelitis3 Vaccine	(8) Measles Vaccine
Fully Exposed × Rural	0.0131**	0.0219***	0.0307***	0.0318***	0.0128**	0.0324***	0.0360***	0.0271**
	(0.029)	(0.004)	(0.003)	(0.007)	(0.015)	(0.001)	(0.000)	(0.012)
	[0.036]	[0.015]	[0.015]	[0.018]	[0.025]	[0.008]	[0.001]	[0.023]
Partially Exposed × Rural	-0.00683	0.000907	-0.00844	-0.0239	0.00182	-0.00225	-0.00691	-0.0185
	(0.400)	(0.878)	(0.164)	(0.173)	(0.838)	(0.752)	(0.528)	(0.297)
	[0.365]	[0.491]	[0.161]	[0.161]	[0.491]	[0.476]	[0.384]	[0.276]
Covariates								
Observations	25,619	25,611	25,606	25,606	25,618	25,571	25,571	25,537
Dep. Var. Mean	0.962	0.957	0.933	0.893	0.967	0.938	0.893	0.863

Notes: The sample includes children under 5 born to women born between 1975 and 1998. The dependent variable in each column indicates whether the child received the BCG/ DPT1/ DPT2/ DPT3/OPV 1/ OPV 2/, OPV 3/ Measles vaccine. BCG=Bacillus Calmette-Guérin; DPT= Diphtheria-Pertussis-Tetanus; OPV= Oral Polio Vaccine. Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts (reference group) are born between 1975 and 1979. Covariates include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. P-values are reported in parentheses. Benjamini et al. (2006) sharpened q-values are computed over all 16 hypotheses (8 outcomes and 2 treatments) following Anderson (2008) and are shown in square brackets. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels based on p-values.

Source: Bangladesh Demographic and Health Surveys, 1996-1997 through 2017-2018.

Table A3. Event Study Estimates of the Impact of FSSSP on Education.

	(1) Years of Schooling	(2) Secondary or Higher Education
Birth Year 1975 × Rural	0.036	-0.001
	[-40.72, 13.21]	[-1.900, 1.811]
Birth Year 1976 × Rural	0.277	0.012
	[-7.708, 105.9]	[-1.844, 16.15]
Birth Year 1977 × Rural	0.080	0.004
	[-13.78, 14.64]	[-9.562, 2.156]
Birth Year 1978 × Rural	0.098	0.003
	[-24.41, 40.86]	[-2.551, 6.118]
Birth Year 1980 × Rural	0.449	0.054
	[-24.41, 50.28]	[-3.105, 5.130]
Birth Year 1981 × Rural	0.729	0.064
	[-26.85, 29.83]	[-2.727, 4.022]
Birth Year 1982 × Rural	0.575	0.052
	[-21.02, 27.36]	[-2.386, 3.138]
Birth Year 1983 × Rural	0.920	0.104
	[-17.94, 18.09]	[-2.111, 2.331]
Birth Year 1984 × Rural	1.006	0.087
	[-17.37, 35.88]	[-1.800, 4.046]
Birth Year 1985 × Rural	1.120	0.102
	[-18.91, 32.65]	[-1.808, 4.010]
Birth Year 1986 × Rural	1.248	0.130
	[-16.63, 30.45]	[-1.747, 3.846]
Birth Year 1987 × Rural	1.190	0.145
	[-23.21, 21.07]	[-2.359, 2.709]
Birth Year 1988 × Rural	1.276	0.131
	[-22.12, 23.34]	[-1.950, 3.346]
Birth Year 1989 × Rural	1.233	0.131
	[-23.83, 19.82]	[-2.246, 2.729]
Birth Year 1990 × Rural	1.451	0.150
	[-26.06, 22.44]	[-2.330, 3.103]
Birth Year 1991 × Rural	1.722	0.173
	[-25.32, 22.62]	[-2.522, 2.878]
Birth Year 1992 × Rural	1.281	0.134
	[-28.73, 23.64]	[-2.667, 3.191]
Birth Year 1993 × Rural	1.565	0.156
	[-31.10, 24.55]	[-3.165, 3.437]
Birth Year 1994 × Rural	2.003	0.222
	[-26.64, 34.11]	[-3.071, 3.636]
Birth Year 1995 × Rural	2.305	0.225
	[-35.36, 23.66]	[-3.045, 3.387]
Birth Year 1996 × Rural	2.133	0.222
	[-30.47, 38.98]	[-3.174, 4.562]
Birth Year 1997 × Rural	2.140	0.234

Table A3 (Continued)

	[-36.19, 39.89]	[-3.606, 5.428]
Birth Year 1998 × Rural	2.502	0.222
	[-47.49, 54.90]	[-4.771, 7.688]
Observations	58,707	58,707
Dep. Var. Mean	5.560	0.505

Notes: The sample includes women born between 1975 and 1998 (reference birth year is 1979). All regressions include a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.

Source: Bangladesh Demographic and Health Surveys, 1993-94 through 2017-18.

Table A4. Event Study Estimates of the Impact of FSSSP on Child Immunizations.

	(1) Full Immunization	(2) Any Immunization
Birth Year 1975 × Rural	0.00388	-0.00243
	[-4.944, 3.662]	[-1.136, 1.131]
Birth Year 1976 × Rural	-0.00174	-0.00246
	[-1.589, 2.305]	[-1.267, 1.281]
Birth Year 1977 × Rural	-0.00624	0.00434
	[-4.236, 4.793]	[-1.656, 2.933]
Birth Year 1978 × Rural	-0.00159	-0.0103
	[-6.523, 3.956]	[-2.712, 2.879]
Birth Year 1980 × Rural	-0.0332	-0.0132
	[-2.298, 3.621]	[-1.657, 2.074]
Birth Year 1981 × Rural	-0.00451	-0.000816
	[-3.300, 2.851]	[-1.585, 1.288]
Birth Year 1982 × Rural	-0.0422	0.0126
	[-2.235, 2.550]	[-1.073, 1.157]
Birth Year 1983 × Rural	-0.000423	0.00361
	[-2.391, 2.715]	[-1.237, 1.444]
Birth Year 1984 × Rural	0.0129	0.00348
	[-1.671, 2.754]	[-1.152, 1.269]
Birth Year 1985 × Rural	0.0628	0.0281
	[-1.571, 2.469]	[-1.056, 1.386]
Birth Year 1986 × Rural	0.0226	0.00873
	[-1.868, 2.712]	[-0.994, 1.345]
Birth Year 1987 × Rural	0.0174	-0.00306
	[-2.173, 2.822]	[-1.166, 1.185]
Birth Year 1988 × Rural	0.00574	0.00349
	[-2.310, 2.553]	[-1.068, 1.179]
Birth Year 1989 × Rural	0.0129	0.0150
	[-2.189, 2.427]	[-1.119, 1.223]
Birth Year 1990 × Rural	0.0553	0.00836
	[-2.412, 3.195]	[-1.288, 1.405]
Birth Year 1991 × Rural	0.0243	0.00900
	[-1.983, 2.790]	[-1.086, 1.469]
Birth Year 1992 × Rural	0.00161	0.00824
	[-2.216, 3.336]	[-1.156, 1.513]
Birth Year 1993 × Rural	0.0212	0.000876
	[-2.663, 4.201]	[-1.621, 1.947]
Birth Year 1994 × Rural	0.0509	-0.00445
	[-2.951, 4.024]	[-1.468, 1.899]
Birth Year 1995 × Rural	0.0939	0.0180
	[-3.391, 4.500]	[-1.836, 2.052]
Birth Year 1996 × Rural	0.0232	0.0161
	[-4.252, 5.020]	[-1.810, 2.530]
Birth Year 1997 × Rural	-0.0301	0.0297

Table A4 (Continued)

	[-4.553, 6.076]	[-2.471, 3.180]
Birth Year 1998 × Rural	0.0814	0.0326
	[-5.051, 6.325]	[-2.633, 3.455]
Observations	25,465	25,465
Dep. Var. Mean	0.827	0.971

Notes: The sample includes children under 5 born to women born between 1975 and 1998 (reference birth year is 1979). All regressions include a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

Table A5. Difference-in-Differences Estimates of the Impact of FSSSP on Motherhood.

	(1) Ever Became a Mother (Age>24)	(2) Ever Became a Mother (Age>24)
Fully Exposed × Rural	0.008	0.008
	[-0.00639, 0.0228]	[-0.00639, 0.0228]
Partially Exposed × Rural	-0.005	-0.005
	[-0.0174, 0.00664]	[-0.0174, 0.00664]
Covariates		X
Observations	31,528	31,528
Dep. Var. Mean	0.963	0.963

Notes: The sample includes women born between 1975 and 1998 and older than 24 at the time of the survey. Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts (reference group) are born between 1975 and 1979. Covariates include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.

Source: Bangladesh Demographic and Health Surveys, 1993-94 through 2017-18.

Table A6. Difference-in-Differences Estimates of the Impact of FSSSP on Maternal Education (Child Sample).

	(1)	(2)	(3)	(4)
	Years of Schooling		Secondary or Higher Education	
Fully Exposed × Rural	1.324***	1.146***	0.139***	0.121***
	[1.006, 1.611]	[0.843, 1.436]	[0.102, 0.178]	[0.0825, 0.156]
Partially Exposed × Rural	0.614***	0.486**	0.0651***	0.0516**
	[0.257, 0.868]	[0.195, 0.736]	[0.0213, 0.101]	[0.0203, 0.0834]
Covariates		×		×
Observations	28,765	28,765	28,765	28,765
Dep. Var. Mean	5.432	5.432	0.493	0.493

Notes: The sample includes women born between 1975 and 1998. Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts (reference group) are born between 1975 and 1979. Covariates include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels, respectively and 95% confidence intervals are in square brackets.
Source: Bangladesh Demographic and Health Surveys, 1993-94 through 2017-18.

Table A7. Effect of FSSSP on Summary Indexes.

	(1) Education - Avg Std Z-score	(2) Immunizations - Avg Std Z-score	(3) High Income - Avg Std Z-score	(4) Low fertility - Avg Std Z-score	(5) High autonomy - Avg Std Z-score	(6) High media usage - Avg Std Z-score	(7) High health inputs - Avg Std Z-score
Fully Exposed ×Rural	0.268***	0.0817***	0.0983***	0.153***	0.102***	0.181***	0.179***
	(0.000)	(0.001)	(0.003)	(0.000)	(0.002)	(0.000)	(0.000)
	[0.001]	[0.003]	[0.004]	[0.001]	[0.004]	[0.001]	[0.001]
Partially Exposed × Rural	0.114**	-0.0236	0.0201	0.0651**	0.0266	0.0644	0.125**
	(0.011)	(0.406)	(0.457)	(0.020)	(0.333)	(0.120)	(0.027)
	[0.01]	[0.143]	[0.151]	[0.016]	[0.125]	[0.046]	[0.02]
Observations	28,765	25,465	28,423	28,407	16,935	28,728	28,196
Dep. Var. Mean	0.392	0.129	0.012	0.179	0.097	-0.055	0.053

Notes: The sample includes women born between 1975 and 1998 in Column 1 and children under 5 born to women born between 1975 and 1998 in Columns 2-7. Fully exposed cohorts are born between 1983 and 1998, partially exposed cohorts are born between 1980 and 1982, and unexposed cohorts (reference group) are born between 1975 and 1979. Covariates include a binary indicator for rural residence, a binary indicator for Muslim, maternal birth year fixed effects, survey wave fixed effects, and division fixed effects. Standard errors are clustered at the mother and maternal year of birth levels using a two-way Wild cluster bootstrap approach. P-values are reported in parentheses. Benjamini et al. (2006) sharpened q-values are computed over all 14 hypotheses (7 outcomes and 2 treatments) following Anderson (2008) and are shown in square brackets. ***, ** and * represent statistical significance at 0.01, 0.05, and 0.1 levels based on p-values.

Source: Bangladesh Demographic and Health Surveys, 1993-1994 through 2017-2018 (Column 1).
Bangladesh Demographic and Health Surveys, 1996-1997 through 2017-2018 (Columns 2-7).

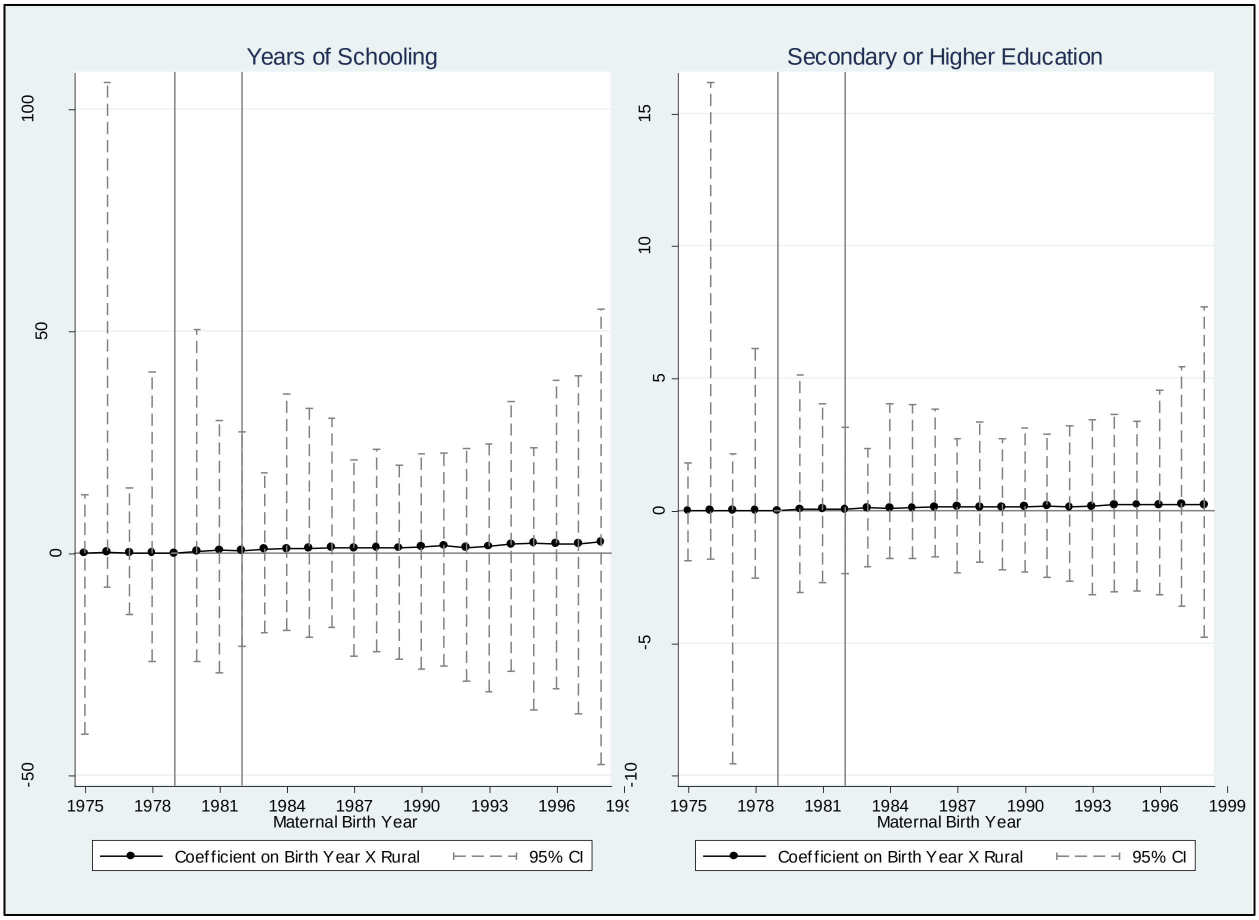

Figure A1. Event Study Graphs for Maternal Education.
Notes: Graphs present interaction coefficients from an event study regression of maternal education on interactions between a rural dummy and maternal birth year fixed effects, a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. The sample includes cohorts born between 1975 and 1998 (reference birth year 1979).
Source: Bangladesh Demographic and Health Surveys, 1993-94 through 2017-18.

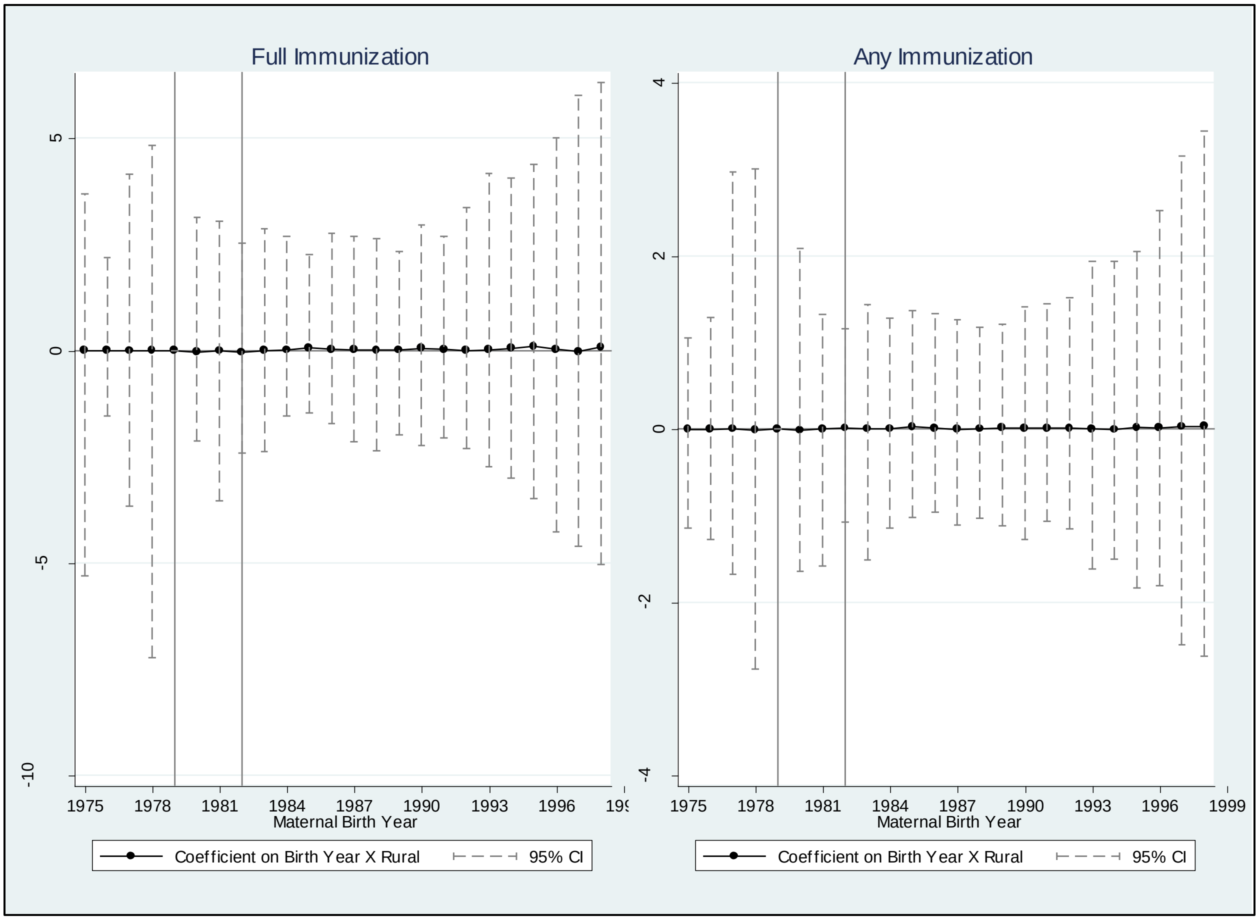

Figure A2. Event Study Graphs for Child Immunizations.
Notes: Graphs present interaction coefficients from an event study regression of maternal education on interactions between a rural dummy and maternal birth year fixed effects, a binary indicator for rural, maternal birth year fixed effects, a binary indicator for Muslim, survey wave fixed effects, and division fixed effects. The sample includes cohorts born between 1975 and 1998 (reference birth year 1979). Full immunization indicates that the child has received all eight doses of WHO recommended vaccines. Any immunization indicates that the child has received at least one of the eight recommended vaccine doses.
Source: Bangladesh Demographic and Health Surveys, 1996-97 through 2017-18.

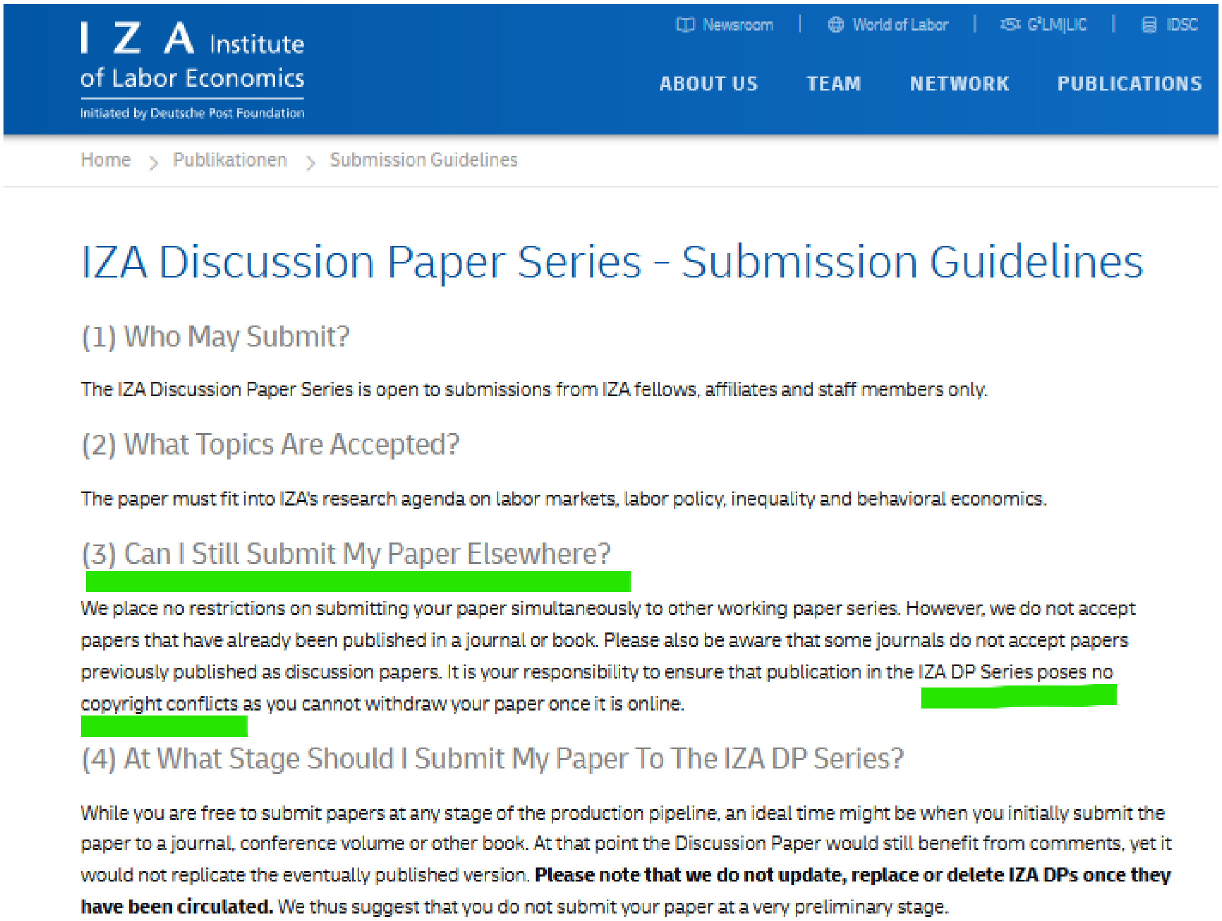
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Figure A3. Copyright.

APPENDIX B: SUPPLEMENTARY TABLES AND FIGURES FOR CHAPTER 2

Table B1. Event Study Estimations.

	Education (in years)	Education (Secondary or higher)	Women's obesity
	(1)	(2)	(3)
Birth Year 1975 × Rural	.5400	.0749	.0114
	[−38.57, 39.37]	[−4.861, 4.391]	[−1.58, 1.952]
Birth Year 1976 × Rural	.7543	.1105	.0282
	[−43.95, 51.36]	[−5.058, 5.587]	[−1.276, 2.068]
Birth Year 1977 × Rural	.3918	.0732	-.0093
	[−41.64, 34.23]	[−5.792, 4.745]	[−2.558, 2.397]
Birth Year 1978 × Rural	.5044	.0756	.0080
	[−50.37, 63.17]	[−4.788, 7.573]	[−1.941, 2.735]
Birth Year 1980 X Rural	1.1554	.1227	.0463
	[−39.47, 46.93]	[−5.997, 5.355]	[−1.868, 2.402]
Birth Year 1981 × Rural	1.4913	.1645	.0351
	[−33.64, 36.42]	[−4.112, 4.966]	[−1.842, 2.117]
Birth Year 1982 × Rural	.7798	.0755	.0202
	[−29.48, 44.57]	[−4.991, 7.053]	[−1.443, 1.954]
Birth Year 1983 × Rural	1.6328	.1847	.0285
	[−37.31, 52.46]	[−4.723, 6.979]	[−1.955, 2.651]
Birth Year 1984 × Rural	1.4156	.1506	.0399
	[−44.86, 54.13]	[−7.858, 9.141]	[−2.062, 2.417]
Birth Year 1985 × Rural	1.7081	.1864	.0366
	[−38.02, 45.66]	[−5.452, 6.178]	[−1.619, 1.945]
Birth Year 1986 × Rural	1.9421	.2260	.0365
	[−41.93, 59.72]	[−5.715, 8.142]	[−2.059, 2.766]
Birth Year 1987 × Rural	2.0795	.2471	.0472
	[−34.47, 57.61]	[−3.748, 5.718]	[−1.819, 2.446]
Birth Year 1988 × Rural	1.7603	.2049	.0552
	[−33.44, 42.2]	[−5.055, 6.731]	[−1.98, 2.531]
Birth Year 1989 × Rural	2.1685	.2584	.0128
	[−28.09, 36.19]	[−3.646, 5.821]	[−1.352, 2.157]
Birth Year 1990 × Rural	1.9971	.2583	.0500
	[−24.65, 32.18]	[−2.679, 4.363]	[−1.271, 2.327]
Birth Year 1991 × Rural	2.5532	.2794	.0603
	[−48.63, 53.6]	[−5.702, 6.374]	[−2.079, 2.983]
Birth Year 1992 × Rural	1.9499	.2408	.0773
	[−31.78, 48.76]	[−3.845, 6.652]	[−1.443, 2.711]

Table B1 (Continued)

Birth Year 1993 × Rural	2.1046	.2356	.0668
	[−19.58, 20.02]	[−3.292, 2.503]	[−1.341, 1.704]
Birth Year 1994 × Rural	2.5340	.3109	.0359
	[−28.58, 39.8]	[−3.834, 4.405]	[−1.472, 1.632]
Birth Year 1995 × Rural	2.9628	.3228	.0784
	[−28.51, 32.86]	[−3.642, 4.06]	[−1.878, 2.51]
Birth Year 1996 × Rural	3.3284	.3623	.0794
	[−36.21, 57.67]	[−4.72, 7.133]	[−1.922, 2.448]
Birth Year 1997 × Rural	2.2426	.2232	.0317
	[−29.97, 33.72]	[−5.079, 5.376]	[−2.083, 2.352]
Birth Year 1998 × Rural	3.4083	.3434	.0469
	[−74.24, 102.5]	[−10.64, 15.41]	[−3.475, 3.629]
Observations	18,664	18,664	18,664
Dep. var. mean	5.4782	.4972	.0512

Notes: Our sample consists of females born from 1975 to 1998 (in comparison to 1979). Regressions incorporate birth year (1975-1988) × rural fixed effects, binary indicator (rural residence, Muslim), and fixed effects (female birth year, survey wave, and division). We applied standard errors clustered at the female birth year level by applying a one-way Wild cluster bootstrap method. ***, **, and * correspond to 1%, 5%, and 10% levels of statistical significance, and 95% CIs are in square brackets.
Source: BDHS, 2011 and 2017-18.

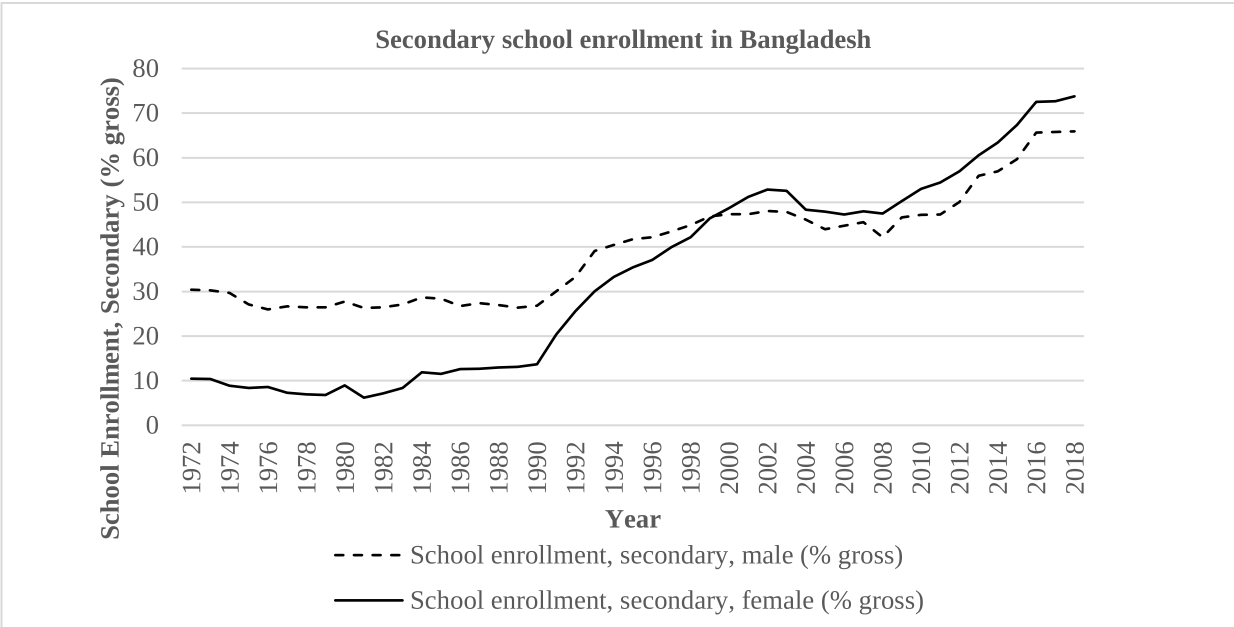

Figure B1. Gender Differences in School Enrollment in Bangladesh.
Notes: Secondary education enrollment by gender, 1972-2018 (females- solid line; males- dashed line). The gross enrollment rate = grades 6-10 students/ people age group (ages 11-15).
Source: Bangladesh Bureau of Educational Information and Statistics (BANBEIS), 2018.

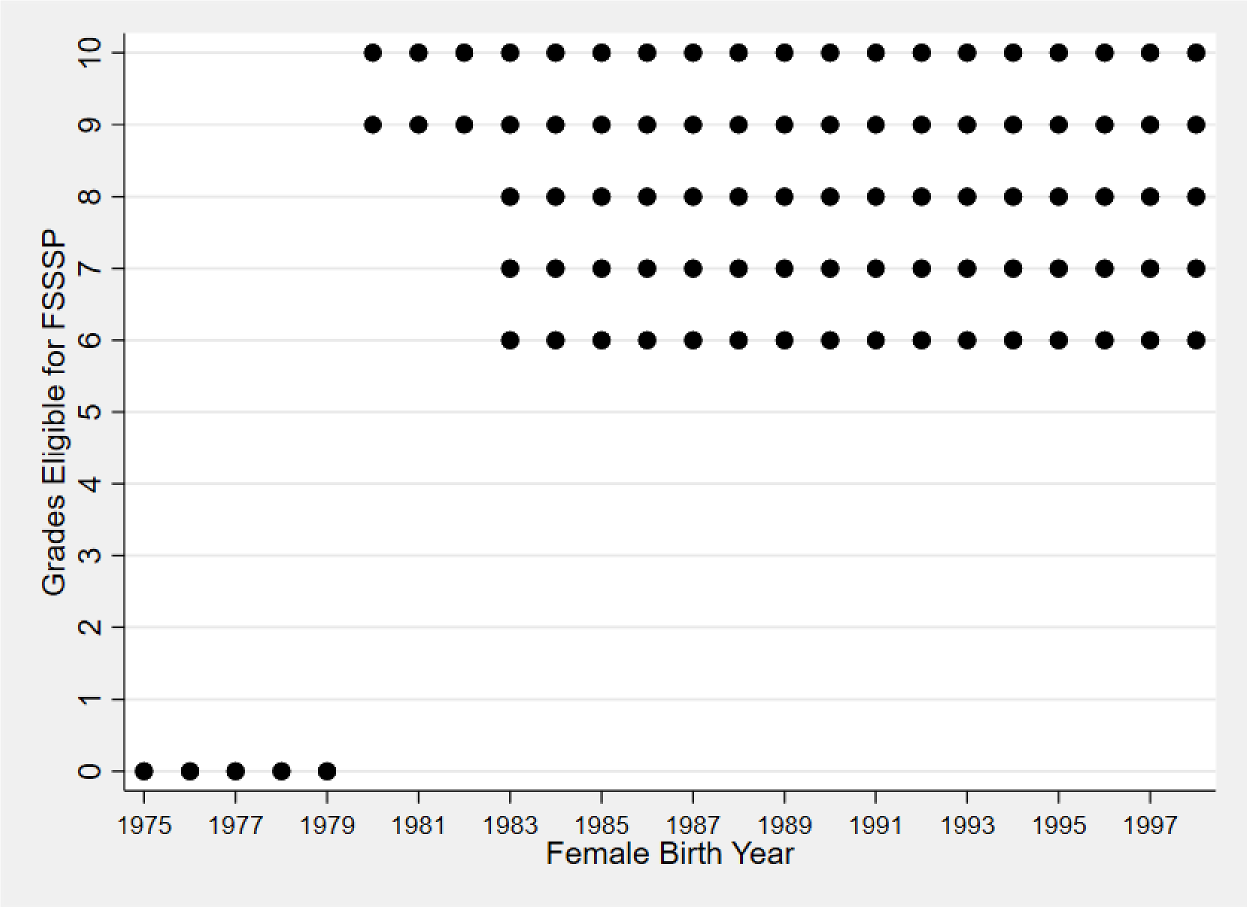

Figure B2. FSSSP Exposure by Birth Cohort.
Notes: For exposure to FSSSP in 1994 (Full exposure - females' birth year from 1983 to 1998 [qualified: 5 years of stipend]; partial exposure - females' birth year from 1980 to 1982 [qualified: 2 years of stipend]; and non-exposure - females' birth year from 1975 to 1979 [not qualified: 0 years of stipend]).

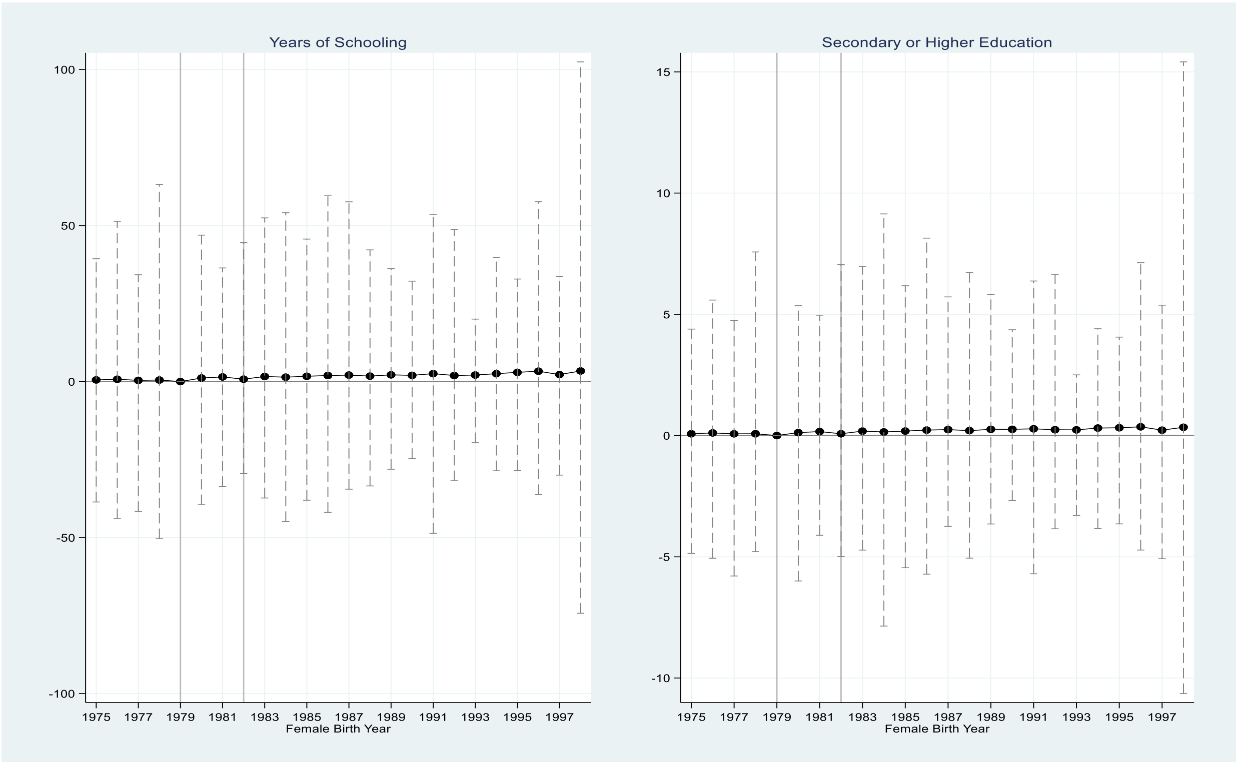

Figure B3. Event Study Graphs of Education with Confidence Interval.
Notes: Graphs show Birth Year (1975-1998) × Rural fixed effects, binary indicator (rural residence, Muslim), and fixed effects (female birth year, survey wave, and division). Our sample consists of females birth year from 1975 to 1998 (in comparison to 1979).
Source: BDHS, 2011 and 2017-18.

Figure B4. Event Study Graphs of Women's Obesity with Confidence Interval.
Notes: The graph shows birth year (1975-1988) × rural fixed effects, binary indicator (rural residence, Muslim), and fixed effects (female birth year, survey wave, and division). Our sample consists of females birth year from 1975 to 1998 (in comparison to 1979).
Source: BDHS, 2011 and 2017-18.

APPENDIX C: SUPPLEMENTARY TABLES AND FIGURES FOR CHAPTER 3

Table C1. Flood-affected Districts in Bangladesh, 2008 through 2017.

Year of flood	Affected districts
2008	Dhaka, Faridpur, Manikganj, Munshiganj, Shariatpur. Tangail, Bogura,Gaibandha, Kurigram, Jamalpur, Sirajganj,Lalmonirhat
2010	Faridpur, Madaripur, Manikganj, Munshiganj, Rajbari, Shariatpur, Gaibandha, Jamalpur, Sirajganj, Lalmonirhat, Nilphamari, Moulvibazar, Sherpur, Sylhet
2011	Chittagong, Cox's Bazar, Bandarban, Jessore, Khulna, Tangail, Gaibandha, Jamalpur, Sirajganj, Faridpur, Gopalganj, Kushtia, Madaripur, Manikganj, Munshiganj, Rajbari, Shariatpur, Kishoreganj, Brahmmanbaria, Netrokona, Habiganj, Moulvibazar, Sherpur, Sunamganj, Sylhet
2012	Chittagong, Cox's Bazar, Bandarban, Faridpur, Manikganj, Munshiganj, Rajbari, Shariatpur, Narayanganj, Tangail, Jessore, Khulna, Satkhira, Bogura, Gaibandha, Kurigram, Nilphamari, Naogaon, Lalmonirhat, Rangpur, Jamalpur, Sirajganj, Netrokona, Habiganj, Moulvibazar, Sherpur, Sunamganj, Sylhet
2013	Faridpur, Manikganj, Munshiganj, Shariatpur, Rajbari, Narayanganj, Tangail, Jessore, Khulna, Satkhira, Chapai-Nawabgonj, Rajshahi, Kushtia, Magura, Panchagr, Thakurgain, Dinajpur, Noagaon, Bogura, Gaibandha, Kurigram, Lalmonirhat, Rangpur, Jamalpur, Sirajganj, Netrokona, Habiganj, Moulvibazar, Sherpur, Sunamganj, Sylhet
2014	Faridpur, Manikganj, Munshiganj, Shariatpur, Tangail, Bogura, Gaibandha, Kurigram, Nilphamari, Lalmonirhat, Rangpur, Jamalpur, Sirajganj,Netrokona, Habiganj, Moulvibazar, Sherpur, Sunamganj, Sylhet
2015	Faridpur, Manikganj, Munshiganj, Shariatpur, Tangail, Bogura, Gaibandha, Kurigram, Natore, Lalmonirhat, Rangpur, Jamalpur, Sirajganj, Narayanganj, Jessore, Khulna, Satkhira, Netrokona, Habiganj, Sherpur, Sunamganj, Sylhet
2016	Chittagong, Faridpur, Manikganj, Munshiganj, Rajbari, Shariatpur, Tangail, Bogura, Gaibandha, Kurigram, Natore, Lalmonirhat, Rangpur, Jamalpur, Sirajganj, Narayanganj, Netrokona, Habiganj, Sherpur, Sunamganj, Sylhet),
2017	Chittagong, Manikganj, Rajbari, Tangail, Bogura, Gaibandha, Nilphamari, Natore, Lalmonirhat, Pabna, Rangpur, Jamalpur, Sirajganj, Narayanganj, Jessore, Netrokona, Moulvibazar, Sherpur, Sunamganj, Sylhet

Table C2. Impact of Childhood Wind Exposure to Tropical Storms on Child Health.

	Panel A: Anthropometrics measure z-scores					
	HAZ score		WHZ score		WAZ score	
	(1)	(2)	(3)	(4)	(5)	(6)
Wind exposure	-.020***	-.020***	.007	.007	-.006	-.006
	(.006)	(.006)	(.005)	(.005)	(.004)	(.004)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	-1.512	-1.512	-.689	-.689	-1.350	-1.350
	Panel B: Anthropometrics measure nutritional indicators					
	Likelihood of stunting		Likelihood of wasting		Likelihood of underweight	
	(1)	(2)	(3)	(4)	(5)	(6)
Wind exposure	.005***	.005***	-.002*	-.002*	.001	.001
	(.002)	(.002)	(.001)	(.001)	(.002)	(.002)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	.344	.344	.099	.098	.269	.269
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×		×

Notes: The sample includes under-five children born between 2008 and 2019. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

Table C3. Impact of Childhood Wind Exposure to Tropical Storms on Child Health — Neonatal and Postnatal Analysis.

	Panel A: Anthropometrics measure z-scores					
	HAZ score		WHZ score		WAZ score	
	(1)	(2)	(3)	(4)	(5)	(6)
Neonatal wind exposure	-.018	-.017	.0001	.001	-.012	-.011
	(.011)	(.011)	(.011)	(.011)	(.010)	(.010)
Postnatal wind exposure	-.016**	-.015*	.003	.004	-.008	-.007
	(.008)	(.008)	(.008)	(.008)	(.007)	(.007)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	-1.511	-1.511	-.689	-.689	-1.350	-1.350
	Panel B: Anthropometrics measure nutritional indicators					
	Likelihood of stunting		Likelihood of wasting		Likelihood of underweight	
	(1)	(2)	(3)	(4)	(5)	(6)
Neonatal wind exposure	.006*	.006*	.0004	.0003	.004	.004
	(.003)	(.003)	(.002)	(.002)	(.004)	(.004)
Postnatal wind exposure	.006**	.006**	-.001	-.001	.003	.002
	(.002)	(.002)	(.002)	(.002)	(.003)	(.003)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	.344	.344	.099	.098	.269	.269
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×		×

Notes: The sample includes under-five children born between 2008 and 2019. Neonatal and postnatal[45] wind exposure represents the first four weeks or one month of a baby with wind exposure to tropical storms and the first eight weeks or two months of a baby with wind exposure to tropical storms. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

[45] For example, tropical storm RASMI dissipated in October 2008. Children exposed to tropical storms during the neonatal period if children born in October 2008, and children exposed to tropical storms during the postnatal period if children born between October and November 2008, respectively.

Table C4. Impact of Wind Exposure to Prenatal (in-utero) and Childhood — Single Regression Analysis.

	Panel A: Anthropometrics measure z-scores					
	HAZ score		WHZ score		WAZ score	
	(1)	(2)	(3)	(4)	(5)	(6)
Prenatal wind	-.023***	-.022***	-.014***	-.010***	-.016***	-.014***
exposure	(.004)	(.004)	(.003)	(.003)	(.003)	(.003)
Neonatal wind	.014	.014	.008	.003	.005	.004
exposure	(.015)	(.015)	(.013)	(.013)	(.013)	(.013)
Postnatal wind	-.023**	-.022**	-.002	.001	-.010	-.008
exposure	(.011)	(.011)	(.009)	(.009)	(.008)	(.008)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	-1.511	-1.511	-.689	-.689	-1.350	-1.350
	Panel B: Anthropometrics measure nutritional indicators					
	Likelihood of stunting		Likelihood of wasting		Likelihood of underweight	
	(1)	(2)	(3)	(4)	(5)	(6)
Prenatal wind	.005***	.005***	.002**	.002**	.004***	.004***
exposure	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Neonatal wind	-.003	-.003	.001	.001	-.0003	.0001
exposure	(.005)	(.005)	(.003)	(.003)	(.005)	(.005)
Postnatal wind	.007**	.007**	-.002	-.002	.002	.002
exposure	(.003)	(.003)	(.002)	(.002)	(.003)	(.003)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	.344	.344	.099	.098	.269	.269
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×		×

Notes: The sample includes under-five children born between 2008 and 2019. Prenatal wind exposure represents 9 months uterine period[46] with wind exposure to tropical storms. Neonatal and postnatal[47] wind exposure represents the first four weeks or one month of a baby with wind exposure to tropical storms and the first eight weeks or two months of a baby with wind exposure to tropical storms. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.
Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

[46] For example, tropical storm RASMI dissipated in October 2008. Mothers exposed to tropical storms during the prenatal period of their children born between February and October 2008.
[47] For example, tropical storm RASMI dissipated in October 2008. Children exposed to tropical storms during neonatal period if children born in October 2008 and children exposed to tropical storms during postnatal period if children born between October and November 2008, respectively.

Table C5. Impact of Whole-life Tropical Storms Exposure on Child Health.

	Panel A: Anthropometrics measure z-scores					
	HAZ score		WHZ score		WAZ score	
	(1)	(2)	(3)	(4)	(5)	(6)
Whole life tropical storms exposure	-.507***	-.422***	-.236***	.021 (.055)	-.374***	-.216***
	(.046)	(.065)	(.039)		(.024)	(.048)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	-1.511	-1.511	-.689	-.689	-1.350	-1.350
	Panel B: Anthropometrics measure nutritional indicators					
	Likelihood of stunting		Likelihood of wasting		Likelihood of underweight	
	(1)	(2)	(3)	(4)	(5)	(6)
Whole life tropical storms Exposure	.132***	.110***	-.007	-.031***	.101***	.049***
	(.013)	(.022)	(.007)	(.010)	(.008)	(.017)
Observations	41,193	41,193	41,193	41,193	41,193	41,193
Dep.Var.Mean	.344	.344	.098	.098	.269	.269
District FE	×	×	×	×	×	×
Childbirth year FE	×	×	×	×	×	×
Covariates		×		×		×

Notes: The sample includes under-five children born between 2008 and 2019. Covariates include a binary indicator Muslim (a reference to other religions), household members, and child age in years. ***, **, and * represent statistical significance at 0.01, 0.05, and 0.1 levels. Standard errors are clustered at the district level.

Source: Multiple Indicators Cluster Survey (MICS), Bangladesh 2012-2013 and 2019. NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program.

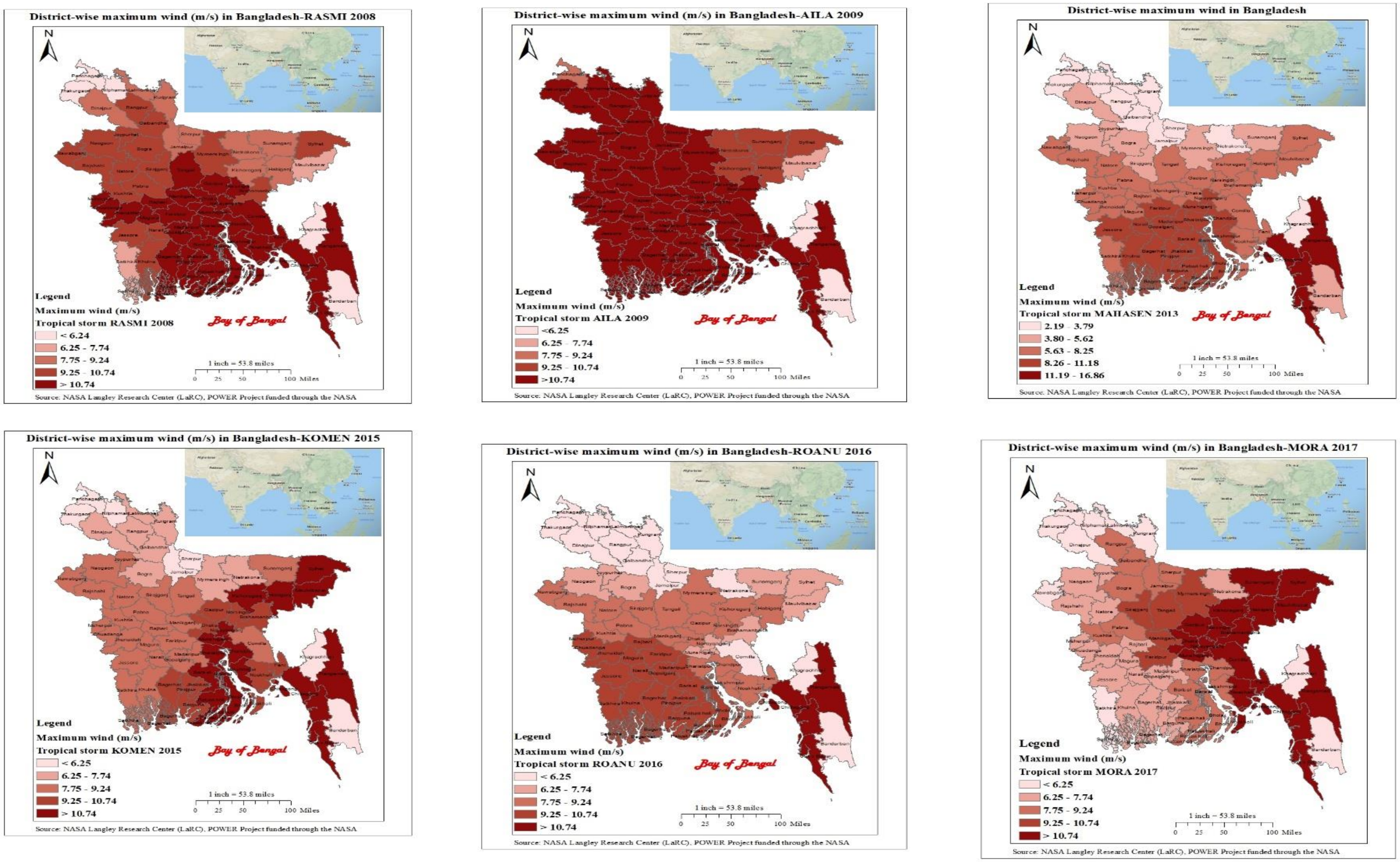

Figure C1. District-wise Maximum Wind During Tropical Storms Over Bangladesh, 2008 through 2017.
Notes: The figure is created using ArcMap. Maximum wind (m/s) of each tropical storm's maximum wind (m/s). The base map layer is from the Database of Global Administrative Areas and downloadable @ https://gadm.org/download_country.html.
Source: NASA Langley Research Center (LaRC), POWER Project funded through the NASA Earth Science/Applied Science Program