Can Declines in Fertility During Floods Be Explained by Increased Demands on the Farm?

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Abstract: Projections of sea-level rise and coastal flooding place Bangladesh as one of the countries most vulnerable to climate change by the end of this century. These changes are expected to have widespread consequences, including for population dynamics. We build upon a growing economic demography literature to estimate the effect of flooding on fertility in rural Bangladesh, using satellite-based measures of flooding and vital registration data on the infant population (2003-2011). We additionally perform parallel analyses of the socio-economic effects of flooding to explore whether prevailing labor market opportunities during a flooding episode shape the decision to conceive. We find the odds of having a child under age 1 in a household declines 3 percent when the extent of flooding in a sub-district increases by one standard deviation. There are no differential effects on the sex ratio. Flood-induced declines in fertility coincide with increased labor force participation by men, but maternal health, fetal vulnerability at gestation and/or increased health risks post birth seem to play a larger role. Future research differentiating how climate change affects the opportunity cost of worker's time versus physiological factors related to human fertility is thus a key component to projecting the future stock of rural workers.

I. Introduction

Storms, torrential monsoon rains, and high tides in coastal areas contribute to rapid onset flooding events which can devastate agrarian households in developing countries (Gröger and Zylberberg, 2016; Taraz, 2017; Desmet et al., 2018). Future projections of sea-level rise and coastal flooding place Bangladesh as one of the leading countries vulnerable to climate change by the end of this century (Clark et al., 2016). Millions are predicted to be displaced in Bangladesh, when considering the population under threat of inundation exposure as a proxy for migration (Davis et al., 2018). The ubiquitous practice of using population as a means of measuring migration is driven by the paucity of global, granular data required to identify the migration-flooding nexus (Nicholls et al., 2011; Neumann et al., 2015). However, the magnitude of projected climate migrants using population as an outcome does not replicate when modeling migration using vital registration (Chen et al., 2017; Chen and Mueller, 2018), longitudinal (Gray and Mueller, 2012; Call et al., 2017), and call detail record (Lu et al., 2016) data. This raises the question whether the estimated relationship between population and natural disasters, in Bangladesh and elsewhere, incorporates aspects of climate-induced demographic change auxiliary to human mobility.

A growing economic literature sheds light on the relevance of environmental conditions on fertility rates (Lin, 2010; Mu and Zhang, 2011; Torche, 2011; Hernández-Julián, Mansour, and Peters, 2014). A paucity of studies has quantified the fertility effect of flooding (Davis, 2017). Furthermore, the fertility literature fails to account for the importance of behavioral mechanisms underlying conception decisions in the context of environmental change. In particular, the expansion of labor activities for adaptation purposes may be likely to change perceptions of the opportunity cost of one's time, and hence, decisions to conceive (Dimova et al., 2015; Mathenge and Tschirley, 2015; Mueller et al., 2020).

In this study, we merge satellite-based measures of flooding at the sub-district level with nationally representative household data on infant population (2003-2011) to evaluate the effect of monsoon flooding on fertility in Bangladesh. The standard approach to identifying the implications of a given natural disaster is to employ a difference-in-difference methodology (Mu and Zhang, 2011; Nobles, Frankenberg, and Thomas, 2015). While the technique permits identification of the effect of a particular flood, our estimation strategy allows for the generalization of impacts to a continuum of disasters of different magnitude and scale. Specifically, we estimate a fixed effect regression model which, in addition to conditioning on an objective measure of flooding exposure, controls for the role of cultural norms regarding optimal family size as well as temporal trends in fertility through the inclusion of division, year, and division by year fixed effects. A suite of household factors known to affect family size, such as demographic composition, education, religion, and wealth, are also incorporated to reduce the potential for omitted variable bias in influencing our results. Sensitivity analyses are performed to verify that the fertility effects are robust to the definition of a flooding event.

Next, we add parallel analyses on the socio-economic effects of flooding to explore whether prevailing labor market opportunities during a flooding episode shape the decision to conceive. Specifically, we use nationally representative socio-economic data (2005 and 2010) to explore whether gender-differentiated wages and/or employment opportunities in rural areas improve or worsen with the magnitude of a flood. We conclude with a mediation analysis to pinpoint which feature of the labor market affecting the opportunity costs of women's and/or men's time explains the observed fertility effects.

II. Conceptual Framework

There are several pathways in which a climatic event may affect the fertility of women in Bangladesh (Grace, 2017). Exposure to a flooding event can induce both biophysical and behavioral responses among men and women that affect the decision to conceive and jeopardize the viability of the fetus. In what follows, we briefly review the literature on the prenatal consequences of disasters to motivate the hypotheses we aim to test in the paper.

A. Conception

Classic economic models of fertility describe the choice of family size *n* to be based on maximizing household utility (Hotz, Klerman, and Willis, 1987). Household utility depends on the number children *n* and consumption of a staple good *x*, with choices constrained by a time-budget and a child production function as follows:

$$\max U(n, x, y; \theta) \text{ s.t. } w_f T + w_m T = x + w_f\left(T - l_f\right) + w_m(T - l_m) \text{ and } n = n(l_f, l_m; \rho)$$

where *w* denotes wages for females (*f*) and males (*m*), *T* represents the total time allocation, θ represents factors idiosyncratic to the household (e.g., preferences for children), and ρ represents a technology shifter in the production of children. For simplicity, the price of *x* is normalized to one, and we abstract from the labor-leisure decision. In the context of agricultural households, we could further augment the model by allowing for both household and wage labor activities, which are imperfect substitutes in the production of the staple good. The time-budget constraint could then be expressed as

$$w_f T + w_m T = x(t_f, t_m; \sigma) + w_f\left(T - l_f - t_f\right) + w_m(T - l_m - t_m)$$

where t is family labor and σ is a production technology parameter. We can then think of several mechanisms through which flooding may affect fertility (n) – market wages, and the production parameters σ and ρ. The former affects the shadow price of family labor through shocks to the agricultural production process, while the latter affects the shadow price of children through shocks to maternal and/or fetal health.

Empirical evidence corroborates that the opportunity cost of women's time should play a significant role in the decision to have a child, $\frac{\partial n}{\partial w^f}$ (Currie and Schwandt, 2014). For example, decreasing fertility trends have coincided with the expansion of education and the growing labor demand for workers due to massive structural change (Klasen, 2019). The garment and textile sectors, in particular, have created numerous opportunities for women to engage in the labor force in Bangladesh (Heath and Mobarak, 2015). At the same time, a significant percentage of women have managed to remain employed in the agricultural sector and diversify into self-employment in nonfarm enterprises as both activities allow women to work while rearing children (Klasen, 2019). This is particularly important among subsistence farming households where there may be a premium for children to ensure a future supply of workers on the farm.

Of relevance to our paper is how these aforementioned opportunity costs may change with exposure to a flooding event. There is a paucity of work that links the demand for women's labor to flooding anomalies. Therefore, hypothesizing whether a hazard will lower the opportunity cost of women's time, and increase their propensity to conceive an additional child is challenging. Climate anomalies, such as heat, have been shown to compromise labor and capital productivity (Heal and Park, 2013; Graff Zivin and Neidell, 2014) and drive firms to downsize (Zhang et al., 2018). Presumably, wages may decline due to flooding if firm behavior in wet conditions mimics firm behavior observed in hot conditions but the former relationship remains poorly understood. In the agricultural sector, studies have established more direct linkages between wages and floods in the country under investigation. Wages decline with flooding anomalies, however, the disruptions to the market are short-lived (Banerjee, 2007; Mueller and Quisumbing, 2011). This is attributable to the positive externalities from flooding. Specifically, riverine flooding enriches the nutrients of the soil causing delayed yield improvements (Banerjee, 2010). The flooding effect on yields can, in turn, generate an increased demand for work on the farm and decrease the supply of migrant workers, especially men, among rural households (Call et al., 2017; Chen and Mueller, Forthcoming). Together these findings suggest that, in households who rely on agriculture as their main livelihood, the decision to conceive is linked not only to market wages but also the technology parameter σ, which affects the shadow price of family labor.

It is worth noting that the psychology literature highlights the importance of social behavior in fertility decisions rather than the pricing channels emphasized in economic models (Davis, 2017). Following Hurricane Hugo, partners increased their sexual activity and, hence, such modifications to behavior contributed to the rise in fertility rates (Cohan and Cole, 2002). The authors of the study owe the behavioral response to the concept of partner attachment during a traumatic experience. In contrast, other studies have attributed these positive fertility effects to the need to replace the population facing greater mortality rates (Rodgers et al., 2005; Nobles et al., 2015). These social factors intrinsic to θ offer a rationale for increasing fertility rates in the wake of a disaster, where in spite of an increased demand for female (or male) labor, women opt to spend more time on leisure (rather than work) activities.

B. Gestation

The literature has since abstracted away from measuring the precise behavioral mechanism underlying fertility decisions (Becker and Lewis, 1973; Willis, 1973; Rosenzweig and Zhang, 2009), instead focusing on the well-identified physiological mechanisms during gestation, as captured by our technology parameter ρ. Reductions in the gestational age and birth weight of infants has been attributed to maternal stress evoked from experiencing a natural disaster (Torche, 2011) or religious fasting (Almond and Mazumder, 2011). The biological mechanism described by the authors stems from the increased production of cortisol, a stress-releasing hormone, which can lead to intrauterine growth restriction.

Other scholars have concentrated on providing an evidence base for an auxiliary biological mechanism proposed in evolutionary biology by Trivers and Willard (1973), hereafter referred to as Trivers-Willard. Trivers-Willard suggest differences in the sex ratio at birth are reflections of disparities in the parental condition. In particular, parents bearing more favorable socioeconomic, geographic, or environmental conditions are more likely to produce sons. Almond and Edlund (2007) offer one of the first tests of their hypothesis in human populations. They illustrate that parents with desirable socioeconomic characteristics are more likely to give birth to sons in the U.S.

The fetal origins hypothesis expands upon the idea of Trivers-Willard to note that disruptions in child health in the initial trimester can also lead to additional risks of disease, and hence increased mortality, at later stages in life (Barker, 1990). Hernandez-Julian, Mansour, and Peters (2014) examine whether birth and fertility outcomes conform with both the predictions of Trivers-Willard and Barker, by comparing the sex ratio and birth outcomes of infants around the time of the 1974 Bangladesh famine. Their identification strategy focuses on comparisons of the health outcomes of children exposed to the famine at gestation to those among siblings born during alternative periods. Their findings align closely with the notion of Trivers-Willard: women pregnant during the famine were less likely to have male children. In addition, they demonstrate that male infants exposed to malnutrition during the first trimester faced higher mortality rates compared to siblings in the family who were born outside of the famine period. Similar findings persist in the context of child exposure to risk in utero during civil conflict in Nepal (Valente, 2015) and earthquakes in Taiwan (Liu, Liu, and Tseng, 2015).

Mu and Zhang (2011) suggest son preference, in specific cultures, offers another rationale to natural selection for observed differences in sex ratios. First, exposure to famine at early stages of gestation augments risk of disability and illiteracy at a greater rate for rural women than men. Second, the effects are muted when distinguishing by whether the child is associated with a gender-neutral ethnic group. These two pieces corroborate that son preference is more likely to drive inequities in child birth and health outcomes in China than natural selection.

C. Hypotheses

The objective of the research is to determine whether fertility declines with flooding events in rural Bangladesh. The previous studies generate strong precedence for expected declines in fertility in the wake of natural disasters. We therefore posit rural households experience reductions in fertility when exposed to flooding. If one of the mechanisms underlying the decline relates to the natural selection channel implicit in Trivers-Willard, then we anticipate the declines will differ by child sex.[1]

We further propose to explore whether any declines in fertility can be explained by increases in the opportunity cost of men and women of child-bearing age (15-49) during floods. Given the positive externalities of flooding, we predict rural households will face an increase in the demand for employment in the agricultural sector. If women and men are pulled into working on the household's farm or on nearby farms for causal wage labor, then presumably they will have less leisure time for conception activities. Moreover, if flooding generates increased value in time spent on crop or fish production, then the tradeoff between women working or being pregnant will change as the return to their labor increases. As we lack data on birth records and, therefore the gestation period, we will be unable to rule out completely whether declines in fertility are driven entirely by the channel of focus versus other competing theories, such as increased health risks at gestation or post birth attributable to flooding.

To identify the possibility that opportunity costs are affecting the fertility decision at flooding, we propose to first evaluate gender-differentiated employment in terms of the number of male and female workers in the household and the average hours men and women report working. We then juxtapose these findings on labor outcomes with estimated relationships between flooding, crop revenue, and the expenditures for hired labor in agricultural and non-agricultural enterprises (proxies for the shadow wage of on-farm and off-farm production). In

[1] Differences in sex ratios may also be attributable to disaster-induced preferences for sons. For example, Abrejo, Shaikh, and Rizvi (2011) indicate that sex-selective abortion is prevalent in Bangladesh, despite legislation forbidding the procedure unless mothers face higher mortality risks. However, a recent report by the Population Council suggests that use of ultrasounds in Bangladesh for sex determination is limited, especially for the average rural household who lacks access to the services provided by government hospitals or private clinics (Talukder, Rob, and Noor, 2014).

what follows, we describe the sources of data and variables (Section III) and the Methodology (Section IV) to test our hypotheses.

III. Data

To estimate the effect of flooding on fertility, we link socio-economic data with a suite of environmental and climate measures. The data are matched at the sub-district (*upazila*) level; sub-districts in Bangladesh are the second lowest tier of local government. There are 491 sub-districts, which roughly represent the local labor and goods markets in Bangladesh and are comparable in size to U.S. counties.

A. Environmental Data

To measure flooding, we utilize remote sensing data from NASA's MODIS (Moderate Resolution Imaging Spectro-radiometer) satellite. Each pixel in an image captures an area of $500m^2$, and we examine images aggregated into 8-day composites that provide the best possible observation during the period. Inundation is represented by the Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), as in other studies in Bangladesh (Guiteras *et al.*, 2015; Chen *et al.*, 2017; Chen and Mueller, 2018). The MNDWI identifies water and non-water features based on differences in surface reflectance and has been shown to provide greater accuracy than other available band-ratio indices (Ji *et. al.*, 2009; Ogilvie *et. al.*, 2015). We consider a pixel to be inundated with water if it has an MNDWI value greater than 0.1. To translate pixel information to the sub-district (*upazila*) level, we use the difference in the maximum percentage of water pixels in the monsoon (July-Dec) versus the dry (Jan-Mar) season within a given year; this differencing helps to distinguish bodies of standing water from transitory flooding.

Remote sensing measures of flooding have several advantages. They have been shown to be more accurate than self-reported flood exposure or proxies based on rainfall (Guiteras *et. al.*, 2015). Satellite imagery is available at high spatial and temporal resolution, allowing us to exploit a broad range of variation across areas and over time. Satellite outages are also rare, making these data more consistent than *in situ* measures, as well as alleviating concerns about endogenous gauge or station placement. There are, of course, some limitations as well. Images may be obscured by cloud cover, especially during the monsoon season. Islam *et. al.* (2010) show that, in Bangladesh, the MODIS-based measure exhibits a high degree of correlation with more reliable measures which can only be constructed over smaller geographic and temporal scales. Remote-sensing based measures also cannot distinguish flooding depth and often fails to capture flash flooding. This makes it difficult to differentiate typical flooding activity from nuisance flooding, particularly because flooding is common in delta regions such as Bangladesh. To address this concern, we standardize these measures by the sub-district specific mean and standard deviation over the sample period. Figure 1 shows our standardized measure of flooding for the year 2002. As expected, flooding is more prevalent in the coastal zone, but there is substantial variation across sub-districts. We also observe high degrees of flooding in selected areas, even in an unexceptional year.

In addition to flooding, we control for a range of additional environmental factors that may be correlated with flooding and have direct effects on fertility. Measures of total annual precipitation are constructed at 0.25 x 0.25° resolution from NASA’s Tropical Rainfall Measuring Mission (TRMM). Correlations between TRMM and rain gauge data are very high, but extrapolation from TRMM daily measures can produce biased estimates for specific regions (dry vs. wet) during specific seasons (pre-monsoon vs. monsoon) (Tarek *et. al.*, 2017). We therefore focus on monthly precipitation values extracted from TRMM and aggregated up to annual measures, following Islam and Uyeda (2007). While *in situ* rainfall gauges are more accurate, this is true only within a small radius of the physical gauge. Outages and missing values are not uncommon and can also significantly affect measures of cumulative precipitation. Moreover, placement of gauges may be related to unobserved characteristics that also affect fertility directly.

To account for heat stress, we utilize data from the Bangladesh Meteorological Department's (BMD) 34 weather stations. These stations are placed throughout the country, with roughly one station per district (Figure A1). Hourly data on temperature and rainfall are collected, along with monthly information on bright sun exposure. From this data source, we create variables that have been demonstrated to affect yields in Asia, such as annual averages for minimum and maximum temperature and bright sun exposure (Welch et al., 2010). Missing observations are imputed using values obtained from the next closest station. All environmental measures are constructed as the average of values in the prior two years, to allow for effects in both the conception and gestation phase. Furthermore, all measures are standardized by the sub-district-specific mean and standard deviation to account for underlying differences in climate across regions.

B. Socio-Economic Data

We limit our attention to rural households, for whom flooding is likely to have the largest impact on livelihoods, and to households having at least one member in prime child-bearing age (15-49).

Fertility measures are taken from the Bangladesh Bureau of Statistics' Sample Vital Registration System (SVRS) for the years 2003-2011, inclusive. This survey is conducted annually to update inter-censal population statistics at the district (*zila*) level. Approximately 200,000 households (1 million individuals) are surveyed each year and, to achieve representation across rural, urban, and metropolitan areas, sampling is stratified by locality. The data include basic demographic characteristics, construction materials for the main dwelling, and use of improved sources of utilities and latrines. Chen and Mueller (2018) provide more details regarding the data collection process, sampling frame, and variables included in the SVRS.

Our primary outcome of interest is the presence of a child under the age of 1 in the household. We also analyze the sex ratio, or the number of female children (age <1) divided by the total number of children (age<1).[2] Because the survey is conducted annually with repeated cross-sections, these metrics proxy for births within the household during the previous calendar year. Unlike fertility histories, however, we lack data on the month of birth as well as more detailed information on stillbirths and early life mortality. Thus, our measures reflect a composite of fertility and infant mortality; we explore this issue in greater detail below.

To further examine the potential mechanisms that may be driving the flooding-fertility relationship, we utilize data from the Bangladesh Bureau of Statistics' 2005 and 2010 waves of the Household Income and Expenditure Survey. This survey provides detailed information on the income-generating activities of respondent households and is also nationally-representative at the district level. Our main outcomes of interest here pertain to household and market labor activities, as well as household agricultural production activities, which represent the largest source of demand for labor in rural areas (Bryan *et. al.*, 2014). Specifically, we examine total

[2] We assign a value of zero to households without a single birth during the last 12 months.

household revenue from all agricultural activities and from rice crops in particular, the expenditures for hired labor in agricultural and non-agricultural enterprises, and the number of wage laborers and average hours worked by gender.

Summary statistics are presented in Table 1. Over our sample period, 8.3% of households report having at least one child under the age of 1. This is a conservative proxy of the annual birth rate, given the presence of multiple women of child-bearing age in some households, as well as the incidence of infant mortality. Additionally, pregnancies that ended prematurely or with a stillbirth would not be included. The sex ratio also appears to be slightly skewed, as the proportion of households reporting a female child under the age of 1 is less than half that of the proportion reporting the presence of any infant.

IV. Methodology

Our primary empirical specification estimates the effect of flooding, accounting for concurrent environmental shocks as well as household characteristics related to risk tolerance and risk-coping behavior that would mitigate the impact of environmental shocks:

$$Y_{ijt} = \alpha + \beta F_{ijt-1,t-2} + \gamma W_{ijt-1,t-2} + \delta X_{ijt} + \mu_{kt} + \pi_t + \tau_k + \varepsilon_{ijt}, \qquad (1)$$

where F and W represent flooding and other weather factors (rainfall, min/max temperature, sun exposure), standardized for each sub-district and averaged over the prior two years. X represents household characteristics[3], and the remaining parameters represent fixed effects for division-

[3] In the SVRS data, household controls include sex, age, literacy, religion of the household head; number of household members and number of members in 7 age-sex categories (0-5, 6-14, 15-49, 50+ with males 15-49 as the omitted category), water source, fuel source, latrine type, and indicators for coastal and Northwest regions. In the HIES data, household controls include sex, age, education level, religion, marital status of the household head; number of household members and number of members in 7 age-sex categories (0-5, 6-14, 15-49, 50+ with males 15-49 as the omitted category), water source, fuel source, latrine type, roof and wall material, number of rooms and indicators for coastal and Northwest regions.

year, year, and division. As described above, our outcomes of interest *Y* include fertility in the previous year, represented by the presence of children under the age of 1 and the sex-ratio, as well as a variety of household production and labor/time allocation measures. All models are estimated using ordinary least squares, with one exception. A logit model is applied to estimate how flooding affects the household odds of having a child under age 1. Standard errors are clustered at the sub-district level.

In (1), we also explore alternate definitions of flooding *F* to compare the relative importance of the first and second lagged values. The main issue with the interpretation of the lagged flooding variables is that we are unable to identify the behavioral or biological channel in which flooding affects fertility without knowledge of the i) precise timing of birth, ii) gestation period, and iii) timing of household interview.

Here, we discuss the implications of iii). The vital registration monitors households on a continuous basis and does not provide details regarding the month in which the information was collected for each household. This is particularly important to determine the point at which flooding exposure affects fertility, whether it be through factors that affect conception (e.g., sexual activity, maternal stress), vulnerability at gestation (e.g., in the first trimester), or through increased mortality risk post birth (e.g. due to increased health risks caused by flooding for the child).

Figure 2 provides an illustration for how the interpretation of the one-year *t-1* and two-year *t-2* lagged variables varies greatly for two extreme cases, when the interview is performed in January or December in survey year *t*. For the infants ages 0 to 11 months that were recorded in the registry in December of year *t*, flooding exposure at gestation is isolated to the previous monsoon *t-1*. However, there may be behavioral mechanisms underlying the decision to conceive based on exposure in *t-1* and *t-2*. For the infants ages 0 to 11 months that were recorded in the registry in January of year *t*, flooding exposure at gestation occurs both in *t-1* and *t-2*. In contrast, behavioral mechanisms underlying the decision to conceive will be isolated to experiences during the monsoon in *t-2*. Furthermore, flooding effects on fertility in period *t*-1 also could be driven by increased rates of infant mortality post birth.

The sensitivity of timing of exposure and the interview month lead us to aggregate flooding exposure over the 24-month period in our preferred specification and precludes the ability to rule out the biological mechanisms that contribute to the observed fertility trends. We, thus, use the employment analysis to complement the fertility estimates in order to understand the merits of arguments posed by Currie and Schwandt (2014) in Bangladesh. Although we lack adequate data on employment and birth records to provide causal evidence for flooding-induced employment effects on fertility, we aim to bring an additional perspective to the fertility-environment literature on the role of labor market adjustments at the time of flooding on decisions to conceive.

V. Results

A. Fertility Effects of Flooding

To test our first hypothesis that flooding reduces fertility, we provide the estimates from a logit model which regresses the binary indicator for whether the household has a child under age 1 on the explanatory variables included in (1). In the first column of Table 2, we report the odds of having a child under age 1 in response to a one standard deviation change in flooding. The results indicate the odds of having a child under age 1 declines 3 percent when the share of pixels flooded in a sub-district increases by one standard deviation. The effect remains essentially unchanged when allowing for a quadratic relationship between flooding and fertility (column 2, Table 2).

The magnitude of the flooding effect slightly decreases when we substitute our preferred flooding variable in (1) with (i) a one-year lagged flooding variable, (ii) a two-year lagged flooding variable, and (iii) both (i) and (ii) in the same model (Table A1). However, precise estimates are only obtained when using (1).[4] The findings from the sensitivity analysis may highlight the importance of exposure at gestation on births. From Figure 2, it is clear that our ability to detect the increased risk of miscarriage in the first trimester is much higher in *t-1* It is also evident from Figure 2 that failing to incorporate flooding exposure at *t-2* would omit the added risk mothers faced who were interviewed in January and conceived during the months of September to November in *t-2*. We may be unlikely to detect the effect of flooding exposure at *t-2* on its own due to the small sample at risk at this period. However, accounting for cumulative exposure at gestation over a 24 month-period, our preferred specification of flooding, likely increases precision, by extending the sample at risk to account for this smaller segment of the population exposed at gestation during the monsoon of *t-2*.

We also evaluate whether the effects are robust to alternative samples (Table A2). First, the flooding impacts appear concentrated in rural areas, where livelihoods are likely more dependent on climate. For example, when we restrict the analysis to urban households, there is no statistically significant relationship between sub-district flooded extent and fertility. Second, having adequate temporal variation in the data is necessary to have sufficient power to detect a

[4] One potential concern with our fertility estimates may be that they are subject to sample selection bias. For example, able-bodied individuals may be more inclined to move from sub-districts that are heavily flooded to search for new economic opportunities and places of residence. The exodus of such a sample would bias the fertility-flooding relationship downward, if the remaining sample is at greater risk of having miscarriages for reasons such as being older or having poor health. Prior work assuages concerns over such bias, as there is now a robust body of evidence that shows a lack of causal flooding effect on internal and international migration patterns in Bangladesh (Gray and Mueller, 2012; Chen et al., 2017; Chen and Mueller, 2018; Chen and Mueller, Forthcoming).

significant fertility-flooding relationship. When we focus on the two years for which we have socio-economic data using fertility measures from the SVRS or HIES, we are unable to estimate a statistically meaningful relationship.

We also compare the flooding effect on fertility across households with different demographic and wealth characteristics. In particular, we explore whether there are heterogeneous effects by education (proxied by literacy status of the household head), religion, parity (number of children of the household head), age composition (share of household members aged 35 or older), and wealth (asset index)[5]. To allow for the fertility effects to vary by subsample, we modify (1) to include the aforementioned group-level indicators (*G*) as well as variables that interact the group level indicators with flooding:

$$Y_{ijt} = \alpha + (\beta + \beta^G)F_{ijt-1,t-2} + (\gamma + \gamma^G)W_{ijt-1,t-2} + \delta X_{ijt} + G_{ijt} + \mu_{kt} + \pi_t + \tau_k + \varepsilon_{ijt}. \quad (2)$$

The odds ratios estimated from (2) are displayed in Table 3. The fertility decline is slightly larger in magnitude for households with more children, households with fewer members aged 35 or older, Muslim households, and households with less wealth. With higher dependency ratios and fewer assets, these groups, with the exception of Muslims, also tend to be more economically vulnerable. Our findings therefore suggest that fertility may be another mechanism for risk-coping, and one used predominantly by poorer households. An alternative, equally-speculative interpretation is that more vulnerable households may be more likely to suffer adverse health effects that reduce observed fertility. Interestingly, there are no apparent differences in flooding-induced fertility declines by education. Although only 42% of households in our sample have a household head who is literate, this measure may be too coarse a proxy for education.

[5] We use a principal components analysis of survey indicators for household water and energy sources to formulate the household asset index (Filmer and Pritchett, 2001).

We, finally, investigate whether changes in fertility manifested into sex-ratio differences following Trivers-Willard (our second hypothesis). Turning to the last column in Table 2, the odds ratio on the flooding variable is close to one. In other words, there is no statistical support for the natural selection of female or male fetuses due to flooding anomalies.

B. Employment Mechanisms

We lastly explore whether the declines in fertility coincide with increases in the demand for labor on the farm (third hypothesis). Flooding anomalies incur deleterious consequences on rice revenue (column B, Table 4). However, total household revenue is relatively unaffected. These findings are consistent with earlier work which indicates that households avail from alternative coping strategies during the monsoon season, such as shifting from crop to fish production or delaying the crop production to take advantage of the benefits from the enriched soil (Banerjee 2010; Chen and Mueller, 2018).

Given the necessity to diversify household economic activities, do these coping strategies increase the demand for male and female family members to engage in income-generating activities, particularly those of child-bearing age (15-49 years old)? We first assess whether the number of men and women who reported to have worked at all increases with the exposure of a flood in Table 5. While the engagement of women in the labor force remains the same, we witness a greater number of men being active in the labor force with an increase in flooding. The coefficient estimate on flooded area in column A of Table 5 is 0.02, which suggests a one standard deviation increase in flooding causes a 2 percentage-point increase in the supply of male workers in the household. This increase in labor market activity is heavily concentrated in the agricultural sector (column B), and the much larger coefficient on flooding implies that not only are men entering the labor market, they are switching into the agricultural sector.

However, conditional on working, male members are spending less (not more) time working (column C, Table 5). This may indicate that each individual spends fewer hours in wage labor, or that new entrants tend to work fewer hours than those already in the labor market, or both. When evaluating the flooding effect on the total household expenditures on hired labor, the point estimate is very small in magnitude and statistically insignificant. Together, these results indicate that employers are hiring more workers, though perhaps for fewer hours each. Moreover, since the total cost of labor remains constant, wages are likely depressed following flooding events, consistent with Banerjee (2007) and Mueller and Quisumbing (2011). Adverse shocks to crop production push small farmers into the wage labor market, where they find limited opportunities and low wages. Also, consistent with Jayachandran (2006), we find little use of temporary migration in response to flooding. In Table 6 (columns A and C), flooding is shown to have no significant effect on the number of female and male family members reported to have worked in another district.

We finally examine whether factors affecting the production technology for children change with flooding exposure. Temporary migration is one factor, where changes in co-residence might limit opportunities for sexual activity and conception. However, as discussed above, we find no significant effect of flooding on the likelihood of working outside the district. Another possibility is that flooding has adverse effects on maternal health, which could reduce both the likelihood of conception and live births. We do not find strong evidence of this either; the number of individuals in a household reporting illness is not significantly affected by flooding, though the point estimate for men is sizable relative to the sample mean and significant at the 15% level.

C. Mediation Analysis

We have shown that flooding affects fertility, income, and labor market outcomes concurrently. To further explore whether changes in income-generating activities are mechanisms through which flooding affects fertility, we perform a mediation analysis.[6] This is done by adding income and labor market outcomes as regressors in our preferred fertility specification. Although these outcomes are clearly endogenous, including them in the fertility regression allows us to assess the empirical linkage between these factors. Of course, the estimates cannot be interpreted as causal effects. However, if the inclusion of these endogenous variables attenuates the estimated effect of flooding on fertility, we can infer that changes in labor force participation and income are mediating the flooding-fertility relationship.

Our application of this approach is complicated by the fact that the flooding-fertility relationship can only be detected with the greater temporal variation in the vital statistics (SVRS) data, while production and labor market activities are only available for the years in which the HIES is collected. Therefore, we generate out-of-sample predicted values as follows. First, we estimate a sub-district fixed effects (FE) regression for each labor and production market outcome L using the HIES:

$$L_{ijt} = \beta^{FE} F_{ijt-1,t-2} + \gamma^{FE} W_{ijt-1,t-2} + {\pi_t}^{FE} + \tau_j + \varepsilon_{ijt}. \qquad (3)$$

Because we lack detailed socio-economic data in the SVRS, we include only year fixed effects and the flooding and environmental variables in this specification. By doing so, we allow variation in outcomes due to differences in household characteristics to be subsumed into the sub-district fixed effect which will, in turn, help mitigate concerns about omitted household characteristics. Then, we combine these sub-district fixed effects (τ_j) with the parameter estimates from (1), the annual variation generated by the environmental variables, and

[6] This approach has been used in Emerick et. al. (2016), Heckman and Pinto (2015), and Maccini and Yang (2009).

household-specific variation generated by demographic composition to predict *L* for each household *i* in year *t* of the SVRS. We then add each predicted outcome into the fertility specification (1), sequentially.

In Table 7, we observe that controlling for the number of males working in agriculture has a negligible effect on the previously estimated flooding-fertility relationship. There is, however, a significant negative correlation between the number of workers and the likelihood of having an infant in the household. Additionally, we find little evidence of flood-induced changes in agricultural income mediating the flooding-fertility relationship, nor do we detect any statistically significant correlation between farm revenue and fertility. Taken together, our findings suggest that, although flooding changes income sources and labor market activity, the effects of on fertility are largely working through other channels.

VI. Conclusion

A key ingredient to economic growth is the possession of a stable work force over time. In several settings facing low rates of population growth, there is systematic evidence that changes in environmental conditions compromise fertility through increased fetal health risks at gestation (Lin, 2010; Mu and Zhang, 2011; Torche, 2011; Hernández-Julián, Mansour, and Peters, 2014). Most developing countries are unlikely to face a weakening of the labor force in the short term due to the persistent impacts of historical baby booms and, thus, the current youth bulge (Thurlow, 2015). However, developing countries, like Bangladesh, provide a laboratory setting to understand whether concerns over fertility declines, and the future work force, are justified given its constant threat of experiencing natural hazards under global climate change.

We use vital registration data to provide insights on the imminent loss of children (or at least delays in childbearing) due to increased flooding incidence. Our results indicate that the odds of having a child under age 1 declines 3 percent when the share of pixels flooded in a sub-district increases by one standard deviation. There are no differential effects on the sex ratio. Given the lack of detailed data on birth records and infant mortality over time, we are unable to pinpoint the precise biological or behavioral mechanism driving observed fertility trends. The main biological mechanisms revealed in the literature are the magnified vulnerability to fetal viability at gestation and the increased risk of infant mortality post birth. We evaluate the labor market effects of flooding to establish whether there is reason to believe that sexual activity or the decisions to conceive might change with the opportunity cost of the time of men and women during key child-bearing years (15 to 49 years old). Although declines in fertility coincide with "selling labor low" – reductions in crop revenue concurrent with increasing labor force participation, our mediation analysis suggests that this is not the primary mechanism through which flooding affects fertility. Rather, our findings suggest the need to develop an improved understanding of how climate change affects maternal, fetal, and child health via subsistence constraints. This has important implications for the future stock of rural workers and is an area warranting future research.

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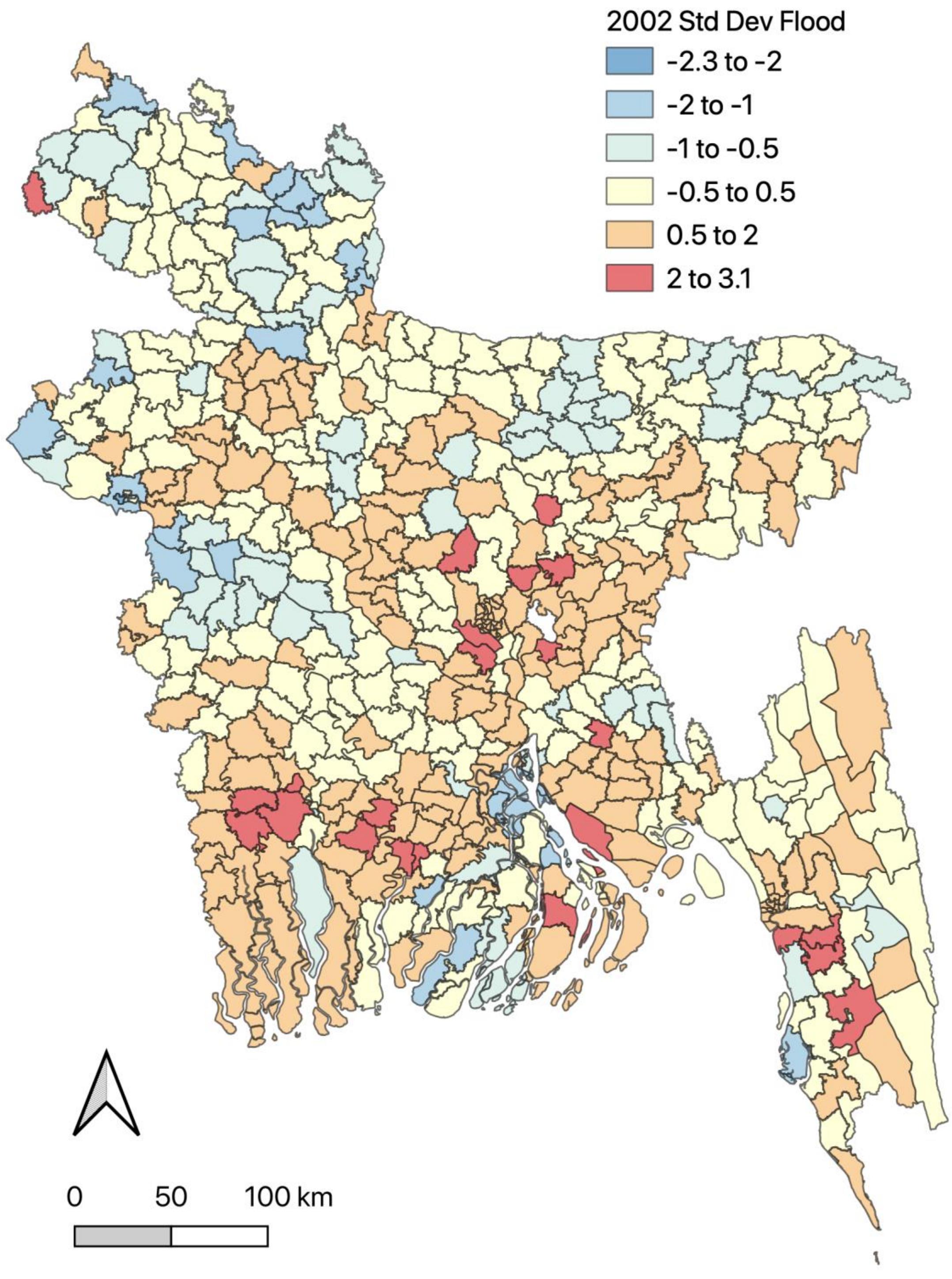

Figure 1. Sub-district Flooding, Standardized Measure, 2002.

	December interview in year t, Age in months												January interview in year t, Age in months											
	11	10	9	8	7	6	5	4	3	2	1	0	11	10	9	8	7	6	5	4	3	2	1	0
Month, year																								
Dec, t	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE												
Nov, t	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	GE												
Oct, t	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	GE	GE												
Sep, t	PE	PE	PE	PE	PE	PE	PE	PE	PE	GE	GE	GE												
Aug, t	PE	PE	PE	PE	PE	PE	PE	PE	GE	GE	GE	GE												
Jul, t	PE	PE	PE	PE	PE	PE	PE	GE	GE	GE	GE	GE												
Jun, t	PE	PE	PE	PE	PE	PE	GE	GE	GE	GE	GE	GE												
May, t	PE	PE	PE	PE	PE	GE	GE	GE	GE	GE	GE	GE												
Apr, t	PE	PE	PE	PE	GE	GE	GE	GE	GE	GE	GE	GE												
Mar, t	PE	PE	PE	GE	GE	GE	GE	GE	GE	GE	GE	GE												
Feb, t	PE	PE	GE	GE	GE	GE	GE	GE	GE	GE	GE	CE												
Jan, t	GE	GE	GE	GE	GE	GE	GE	GE	GE	GE	CE	CE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE
Dec, t-1	GE	GE	GE	GE	GE	GE	GE	GE	GE	CE	CE	CE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	GE
Nov, t-1	GE	GE	GE	GE	GE	GE	GE	GE	CE	CE	CE	CE	PE	PE	PE	PE	PE	PE	PE	PE	PE	PE	GE	GE
Oct, t-1	GE	GE	GE	GE	GE	GE	GE	CE	CE	CE	CE	CE	PE	PE	PE	PE	PE	PE	PE	PE	PE	GE	GE	GE
Sep, t-1	GE	GE	GE	GE	GE	GE	CE	CE	CE	CE	CE	CE	PE	PE	PE	PE	PE	PE	PE	PE	GE	GE	GE	GE
Aug, t-1	GE	GE	GE	GE	GE	CE	CE	CE	CE	CE	CE	CE	PE	PE	PE	PE	PE	PE	PE	GE	GE	GE	GE	GE
Jul, t-1	GE	GE	GE	GE	CE	CE	CE	CE	CE	CE	CE	CE	PE	PE	PE	PE	PE	PE	GE	GE	GE	GE	GE	GE
Jun, t-1	GE	GE	GE	CE	CE	CE	CE	CE	CE	CE	CE	CE	PE	PE	PE	PE	PE	GE	GE	GE	GE	GE	GE	GE
May, t-1	GE	GE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	PE	PE	PE	PE	GE	GE	GE	GE	GE	GE	GE	GE
Apr, t-1	GE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	PE	PE	PE	GE	GE	GE	GE	GE	GE	GE	GE	GE
Mar, t-1	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	PE	PE	GE	GE	GE	GE	GE	GE	GE	GE	GE	CE
Feb, t-1	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	GE	GE	GE	GE	GE	GE	GE	GE	CE	CE
Jan, t-1	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	GE	GE	GE	GE	GE	GE	GE	CE	CE	CE
Dec, t-2	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	GE	GE	GE	GE	GE	GE	CE	CE	CE	CE
Nov, t-2	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	GE	GE	GE	GE	GE	CE	CE	CE	CE	CE
Oct, t-2	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	GE	GE	GE	GE	CE	CE	CE	CE	CE	CE
Sep, t-2	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	GE	GE	GE	CE	CE	CE	CE	CE	CE	CE
Aug, t-2	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	GE	GE	CE	CE	CE	CE	CE	CE	CE	CE
Jul, t-2	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	GE	CE	CE	CE	CE	CE	CE	CE	CE	CE
Jun, t-2	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE	GE	GE	CE	CE	CE	CE	CE	CE	CE	CE	CE	CE

Notes:

CE	Exposure at conception (sexual activity, maternal stress, decision to conceive)
GE	Exposure at gestation (first trimester very important)
PE	Exposure after birth (health risks increase for child)

Figure 2. Phases of Fertility Cycle Affected by Monsoon Flooding

Table 1. Summary Statistics.

	N	Mean	Std. Dev.
Sample Vital Registration System			
Child, Age < 1	1,033,884	8.429%	0.278
Female Child, Age < 1	1,033,884	4.117%	0.199
Head is Literate	1,033,884	42.43%	0.494
Head is Muslim	1,033,884	88.15%	0.323
# Children of Hh Head	1,033,884	2.359	1.529
Proportion Hh Members > Age 35	1,033,884	0.300	0.213
Household Income and Expenditure Survey			
Agricultural Revenue (taka)	10,439	32,509	75,611
Rice Revenue (taka)	6,445	23,836	30,156
Expenditure, Non-Ag Labor (taka)	3,047	11,814	57,369
Expenditure, Ag Labor (taka)	9,463	2,139	5,549
# Male Workers	13,402	0.964	0.687
# Female Workers	13,402	0.106	0.333
# Male Ag Workers	13,402	0.437	0.496
# Female Ag Workers	13,402	0.035	0.184
Avg Hours Worked Last Year, Male	10,552	2,509	920
Avg Hours Worked Last Year, Female	1,325	1,892	1,000
# Males Worked Away	13,402	0.095	0.337
# Females Worked Away	13,402	0.007	0.092
# Males Sick	13,394	0.152	0.376
# Females Sick	13,394	0.212	0.428

Data from the Bangladesh Bureau of Statistics. SVRS includes years 2002-2011. HIES includes 2005 and 2010.

Table 2. Flooding-Fertility Relationship, Rural Households

	Child Under Age 1[a]		Sex Ratio[b]
Avg. Min. Temp.	0.985	0.985	1.000
	(-0.557)	(-0.549)	(-0.376)
Avg. Max. Temp.	0.982	0.982	1.000
	(-0.768)	(-0.749)	(-0.190)
Bright Sun	1.019	1.020	1.000
	(0.804)	(0.812)	(0.608)
Total Precipitation	1.011	1.011	1.000
	(0.472)	(0.469)	(0.115)
Flooded Area	0.970**	0.965**	0.999
	(-2.069)	(-2.048)	(-1.466)
Flooded Area Squared		1.009	
		(0.615)	
N	1,033,884	1,033,884	1,033,884

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005-2011, Bangladesh Bureau of Statistics. All environmental variables are the average of t-1 and t-2 values. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Includes controls for rainfall, min/max temperature, sun, demographic and wealth controls, region (coastal, northwest), year, division, and division by year fixed effects. Logit regression with effects reported as odds ratios. Standard errors clustered at sub-district level. t-statistics in parentheses. *** indicates significance at 1%, 5% (**) and 10% (*) levels. N=1,033,884

[a]Logit specification. Coefficients reported as odds ratios.

[b]Female birth/any birth. Zero if no births. OLS specification.

Table 3. Flooding-Fertility Relationship, Heterogeneous Effects

	A. Literacy	B. Parity	C. Age	D. Religion	E. Wealth
Avg. Min. Temp.	0.996	0.972	0.989	0.983	0.986
	(-0.145)	(-0.884)	(-0.383)	(-0.221)	(-0.476)
Avg. Max. Temp.	0.965	0.964	0.980	1.004	0.979
	(-1.408)	(-1.330)	(-0.794)	(0.0942)	(-0.889)
Bright Sun	1.019	1.020	0.999	1.043	1.020
	(0.669)	(0.722)	(-0.0518)	(1.185)	(0.731)
Total Precipitation	1.005	1.006	1.000	0.983	1.010
	(0.207)	(0.217)	(0.0154)	(-0.336)	(0.410)
Flooded Area	0.979	0.965*	0.961**	0.939*	0.969**
	(-1.255)	(-1.850)	(-2.489)	(-1.809)	(-2.063)
			Relative Effects		
	Head is Literate	Low Parity[a]	Older Members[a]	Head is Muslim	Higher Wealth[b]
Avg. Min. Temp.	0.979	1.028	0.987	1.004	0.995
	(-0.949)	(1.390)	(-0.655)	(0.0479)	(-0.150)
Avg. Max. Temp.	1.042**	1.035**	1.014	0.975	1.017
	(2.217)	(2.240)	(0.896)	(-0.624)	(0.653)
Bright Sun	1.001	0.998	1.072***	0.977	0.998
	(0.0546)	(-0.122)	(5.394)	(-0.691)	(-0.0841)
Total Precipitation	1.013	1.010	1.050***	1.032	1.001
	(0.648)	(0.569)	(3.167)	(0.635)	(0.0348)
Flooded Area	0.978	1.009	1.042**	1.036	1.007
	(-1.207)	(0.569)	(2.420)	(0.986)	(0.308)

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005-2011, Bangladesh Bureau of Statistics. All environmental variables are the average of t-1 and t-2 values. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Includes controls for rainfall, min/max temperature, sun, demographic and wealth controls, region (coastal, northwest), year, division, and division by year fixed effects. Logit regression with effects reported as odds ratios. Standard errors clustered at sub-district level. t-statistics in parentheses. *** indicates significance at 1%, 5% (**) and 10% (*) levels. N=1,033,884

[a]Defined relative to the median value for the sample.

[b]Defined relative to 80th percentile for the sample.

Table 4. Household Production Activities

	A. Total Hh Revenue[a]	B. Rice Revenue[a]	C. HH Exp, Ag. Labor[a]	D. Hh Exp, Non-Ag Labor[a]
Avg. Min. Temp.	-0.139**	-0.0648*	-0.275**	0.258
	(-2.400)	(-1.708)	(-2.140)	(1.510)
Avg. Max. Temp.	-0.0670	-0.210***	-0.169	0.141
	(-1.324)	(-5.681)	(-1.579)	(0.807)
Bright Sun	0.0411	0.0210	-0.0966	0.000773
	(0.982)	(0.771)	(-1.139)	(0.00693)
Total Precipitation	0.0613	-0.00496	0.0694	0.289*
	(1.309)	(-0.155)	(0.730)	(1.757)
Flooded Area	0.0199	-0.0617*	0.00281	-0.0466
	(0.369)	(-1.846)	(0.0263)	(-0.298)
N	10,439	6,445	9,463	3,047

Notes: Socio-economic data drawn from Household Income and Expenditure Surveys, 2005 and 2010, Bangladesh Bureau of Statistics. For each specification, the sample is limited to households engaged in the activity, including those reporting a zero value. All environmental variables are the average of t-1 and t-2 values. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Includes controls for rainfall, min/max temperature, sun, demographic and wealth controls, region (coastal, northwest), year, division, and division by year fixed effects. Standard errors clustered at sub-district level. t-statistics in parentheses. *** indicates significance at 1%, 5% (**) and 10% (*) levels.

Table 5. Household Labor Allocation, by Gender

	Males			Females		
	A. # of Workers	B. # of Ag Workers	C. Avg. Hours Worked[a]	D. # of Workers	E. # of Ag Workers	F. Avg. Hours Worked[a]
Avg. Min. Temp.	-0.0231***	-0.0128	-0.00881	-0.0156**	-0.00992**	0.0347
	(-3.169)	(-0.832)	(-0.661)	(-1.967)	(-2.138)	(0.720)
Avg. Max. Temp.	-0.00822	-0.0284**	0.00230	-0.00415	-0.00283	-0.00721
	(-1.152)	(-2.068)	(0.156)	(-0.573)	(-0.599)	(-0.147)
Bright Sun	0.000588	0.0181*	-0.0175*	-0.00730	-0.000671	0.0154
	(0.0989)	(1.862)	(-1.730)	(-1.311)	(-0.235)	(0.462)
Total Precipitation	0.0102	-0.00103	0.00846	0.00344	-0.00160	0.0219
	(1.442)	(-0.0728)	(0.583)	(0.529)	(-0.403)	(0.508)
Flooded Area	0.0173**	0.0390***	-0.0329**	0.00314	0.00685	-0.0478
	(2.060)	(3.079)	(-2.425)	(0.435)	(1.309)	(-0.929)
N	13,402	13,402	10,552	13,402	13,402	1,325

Notes: Socio-economic data drawn from Household Income and Expenditure Surveys, 2005 and 2010, Bangladesh Bureau of Statistics. All environmental variables are the average of t-1 and t-2 values. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Includes controls for rainfall, min/max temperature, sun, demographic and wealth controls, region (coastal, northwest), year, division, and division by year fixed effects. Standard errors clustered at sub-district level. t-statistics in parentheses. *** indicates significance at 1%, 5% (**) and 10% (*) levels.

[a]Limited to individuals engaged in the labor market including those reporting a zero value.

Table 6. Alternate Time Allocation Measures

	Males		Females	
	A. # Work Out of District	B. # with Illness	C. # Work Out of District	D. # with Illness
Avg. Min. Temp.	-0.00775	-0.0113*	-0.00102	-0.0237**
	(-0.720)	(-1.723)	(-0.405)	(-2.541)
Avg. Max. Temp.	-8.48e-05	0.000999	-0.00258	0.00586
	(-0.00852)	(0.145)	(-1.533)	(0.626)
Bright Sun	-0.00228	-0.00112	0.000141	-0.00266
	(-0.284)	(-0.219)	(0.116)	(-0.390)
Total Precipitation	0.000346	0.0106	0.00220	1.69e-05
	(0.0394)	(1.489)	(1.290)	(0.00218)
Flooded Area	-0.00585	0.0135	0.00155	-0.000263
	(-0.701)	(1.611)	(1.000)	(-0.0259)
N	13,402	13,394	13,402	13,394

Notes: Socio-economic data drawn from Household Income and Expenditure Surveys, 2005 and 2010, Bangladesh Bureau of Statistics. All environmental variables are the average of t-1 and t-2 values. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Includes controls for rainfall, min/max temperature, sun, demographic and wealth controls, region (coastal, northwest), year, division, and division by year fixed effects. Standard errors clustered at sub-district level. t-statistics in parentheses. *** indicates significance at 1%, 5% (**) and 10% (*) levels.

Table 7. Mediation Analysis of Flooding-Fertility Mechanisms.

	A.	B.	C.
Flooded Area	0.968**	0.970*	0.970*
	(-2.131)	(-1.917)	(-1.937)
# Male Ag. Workers[a]	0.872*	0.854***	0.880*
	(-1.954)	(-2.265)	(-1.657)
Rice Revenue[a,b]		1.009	1.015
		(0.298)	(0.468)
Total Hh Ag. Revenue[a,b]			0.979
			(-0.807)

Notes: Socio-economic data drawn from Household Income and Expenditure Surveys, 2005 and 2010, Bangladesh Bureau of Statistics. Flooded area is the fraction of water pixels in the upazila, averaged over t-1 and t-2, drawn from NASA's MODIS satellite. Includes controls for rainfall, min/max temperature, sun, demographic and wealth controls, region (coastal, northwest), year, division, and division by year fixed effects. Standard errors clustered at sub-district level. Standard errors bootstrapped with 500 replications. t-statistics in parentheses. *** indicates significance at 1%, 5% (**) and 10% (*) levels.

[a]Predicted value.

[b]Log value

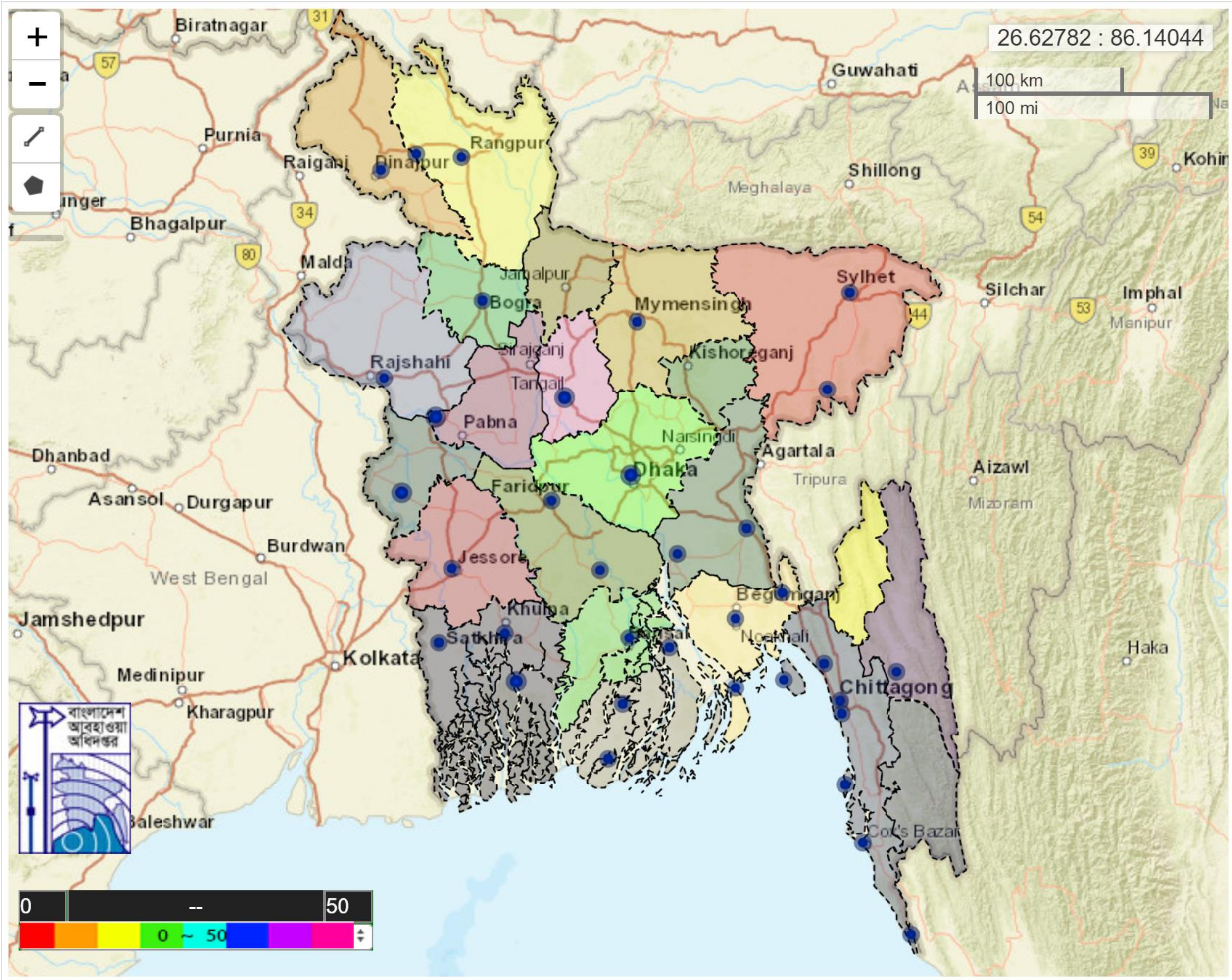

Figure A1. Bangladesh Meteorological Department Weather Stations.
Source: Bangladesh Meteorological Department, http://www.bmd.gov.bd.

Table A1. Flooding-Fertility Relationship, Alternate Specifications

	A.	B.	C. Two Lags	
	1 Year Lag	2 Year Lag	1 Year	2 Year
Avg. Min. Temp.	0.989	0.981	1.032	0.953
	(-0.433)	(-0.674)	(0.958)	(-1.332)
Avg. Max. Temp.	0.989	0.973	1.035	0.946**
	(-0.512)	(-1.135)	(1.313)	(-2.016)
Bright Sun	1.014	1.021	0.998	1.025
	(0.702)	(0.971)	(-0.139)	(1.414)
Total Precipitation	1.013	1.002	1.015	0.990
	(0.635)	(0.0954)	(0.675)	(-0.472)
Flooded Area	0.983*	0.987	0.982	0.985
	(-1.786)	(-1.338)	(-1.572)	(-1.409)

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005-2011, Bangladesh Bureau of Statistics. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Includes controls for rainfall, min/max temperature, sun, demographic and wealth controls, region (coastal, northwest), year, division, and division by year fixed effects. Logit regression with effects reported as odds ratios. Standard errors clustered at sub-district level. t-statistics in parentheses. *** indicates significance at 1%, 5% (**) and 10% (*) levels. N=1,033,884

Table A2. Flooding-Fertility Relationship, Alternate Samples

	A. Urban Households	B. 2005 & 2010 Only	C. HIES
Avg. Min. Temp.	0.990	1.029	1.130**
	(-0.279)	(0.721)	(2.226)
Avg. Max. Temp.	1.013	0.941*	1.040
	(0.369)	(-1.645)	(0.787)
Bright Sun	0.986	1.025	1.048
	(-0.713)	(0.777)	(1.234)
Total Precipitation	0.948	0.993	1.184***
	(-1.122)	(-0.200)	(3.531)
Flooded Area	1.024	0.984	1.079
	(1.414)	(-0.531)	(1.301)
N	590,419	268,529	13,402

Notes: Socio-economic data drawn from Sample Vital Registration System, 2005-2011, Bangladesh Bureau of Statistics. All environmental variables are the average of t-1 and t-2 values. Inundated area is the fraction of water pixels in the upazila, drawn from NASA's MODIS satellite. Includes controls for rainfall, min/max temperature, sun, demographic and wealth controls, region (coastal, northwest), year, division, and division by year fixed effects. Logit regression with effects reported as odds ratios. Standard errors clustered at sub-district level. t-statistics in parentheses. *** indicates significance at 1%, 5% (**) and 10% (*) levels.