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Weather Shock, Agricultural Productivity and Infant Health: A Tale of Environmental Injustice*

Soumya Pal [†]

Abstract

We study how income shock affect due to weather shock causally impacts the birth outcomes. We selected households depended directly on agriculture due to their extreme vulnerability to temperature and rainfall shocks. We find large efficiency loss attributed to weather shock for major food crops to the extent of 20%. However, we find that access to technology provides resilience against weather shock, therefore, causing the heterogeneity in vulnerability across farming households. Based on it, we designed the agriculture-household model, which predicts that health outcomes of child is dependent on income shock due to change in weather conditions. We tested the hypothesis by introducing weather shock in the cropping season before the conception of child to eliminate the confounding effect of direct impact due to extreme weather conditions. We find that weather shocks in cropping season, increases the likelihood of child mortality, low birth weight, and birth size. We further find that access to technology, financial tools, and economic security net reduces the impact of income loss due to weather shock. Our results suggests that access to resilient capabilities leads to heterogeneous impact across farmer households causing environmental injustice. Further, our findings provide insights into the policy design for long term shift in weather patterns due to climate change and stresses on the inequality in resilience against extreme weather events

JEL Codes: Q1, Q5, I1, I3, D1

Keywords: Environmental Justice, Weather Shock, Farm Income, Child Mortality

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1 Introduction

Fetal Origin hypothesis identifies income shock as an important component for the maternal health and birth outcomes, especially in the settings of low income (Almond & Currie, 2011). Multiple studies documented the dependence of birth outcomes on economic status of the household, in the context of positive and negative income shocks (Camacho, 2008; Amarante et al., 2016). Extreme weather shocks are considered as an important determinant for income loss across climate vulnerable production units (Dell et al., 2014, Somanathan et al., 2021) and health outcomes of newborns (Deschênes et al., 2009). However, limited empirical research examined the impact of income shock due to extreme weather conditions at the fetal origin (Maccini & Yang, 2009; Hsiang & Jina, 2014). Our paper shows that income loss due to weather shocks can deteriorate the fetal conditions resulting into poor birth outcome. We isolated the confounding effects of direct impact of extreme climate on health of newborns by assigning the shock at cropping season preceding the conception of child. We further highlighted the importance of agriculture technology, financial tools and economic safety nets as capability enhancing factors against extreme weather conditions. Inferring from the outcomes, we establish differential impacts due to variation in access to resilient factors against income and weather shock, henceforth, contributing to the vast literature of environmental justice in development economics (Banzhaf et al., 2019)

In particular, we investigate the impact of income shock due to extreme weather conditions amongst the household dependent on agriculture as the primary source of income. We selected the farming household due to their maximum vulnerability to the weather shocks in terms of income loss (Nordhaus, 2013). Further, our focus on the rural settings of India is motivated by the concentration of excessive child mortality in the region (Deaton, 2008; Drèze et al., 2020). Rural regions of India are primarily dependent on agriculture for income which further determines the expenditure on child health care (Jensen, 2000). With poorer health infrastructure in amalgamation with low economic security net, any shock to agriculture income can deteriorate the birth outcomes. Henceforth, investigation on the indirect linkage between weather shocks and child health stipulates to be crucial. Furthermore, in the context of global rise in temperature, it is essential to identify the impact of weather shocks and measure the difference in the vulnerability.

How do weather shock impacts the production of major food crops? How does it transmit to income shock leading to health outcomes of newborn? Does access to agriculture technology reduces the impact? To study these questions we develop an equilibrium model based on Agriculture-Household model. When the income of the household and share of consumption depends on the agriculture production (due to subsistence farming practices), the shock to production affect the expenditure on essential commodities like health of children. Hence, in equilibrium, expenditure on consumption and health including leisure time affects due to reduction in income due to weather shock. Because of the limited access to other income sources and inefficiency in market (markups as wedges between Marginal cost and price of inputs), any loss in production, with prices of output held fixed, the expenditure on maternal health can reduce ¹. This may lead to poorer birth outcomes, causing higher likelihood

¹With loss in income, the income pie reduces for household, hence, shifting the expenditure towards essential goods. Health expenditures generally take toll due to lesser priority on health outcomes (Duflo, 2000; Rosenzweig, 1990). Rosenzweig's health care expenditure model explains the mechanism of

of child mortality. Therefore, in equilibrium, weather shocks in the cropping season preceding the conception of child and the birth outcomes are related, proceeding in the same direction. Henceforth, any loss in production, with limited other income sources and poor public health care services can reduce the likelihood of "good" birth outcomes.

To test the implications of our model, we examine the effects of rainfall and temperature shocks, on the efficiency loss in the production of major food crops. We also estimated the impact of adoption of resilient agriculture technologies as inputs on reducing the impacts of extreme weather on production. We combine rainfall and temperature data provided by NASA-GIS, USA, with the ICRISAT macros data to estimate the loss in efficiency attributable to extreme weather. Our data expands between year 1970 to 2011 across 640 districts of India. We adjusted for new district formation in the last three decades by restricting to merge across 1970 district boundaries. Henceforth, to estimate the implications of income loss due to weather shock on the birth outcomes, we combined the rainfall and temperature data at the district level with DHS-India data. We used the information on child mortality, birth weight and birth size for all the births occurred between 2010-16. We defined rainfall and temperature shock as values less than 20th percentile or more than 80th percentile. Our definition of weather shock is consistent with the previous works in impact of extreme weather conditions (Deschênes & Greenstone, 2011; Corno et al., 2020). Our main results indicate that, as predicted, extreme weather events reduces the efficiency of major crop's production. For rice production, the extent of efficiency loss is 20.2% , whereas for wheat and maize the loss is 18.3% and 24.2%. Further, we estimated the extent of loss in productivity of wheat and rice due to extreme weather conditions during the respective months of cropping. We find that excessively high temperature during the transplantation month for rice , that is, July, reduces the productivity by 10.7%, and excessively high rainfall during the sowing period, that is, May and June, reduces the productivity by the margin of 12.7% and 6.7% respectively. Similarly, for wheat, higher temperature during sowing months, that is, October and November, reduces the productivity by 6-7% and lower rainfall in the harvest season reduces the productivity by 16%, henceforth reducing the farmer's income. However, the effects are not uniform as the districts with access to technologies like irrigation and High Yielding Variety seeds reduces the impact as they provide resilience against extreme rainfall and temperature.

After establishing that extreme weather events, impacts the agriculture productivity and efficiency, we examine an important implication of such phenomenon: poor birth outcomes in agriculture based household. We examined the indirect impact of extreme weather events on birth outcomes by matching the weather conditions in the crop season preceding the conception of child. This eliminates the direct impact of extreme weather events on fetal growth and causally estimate the impact of income loss. We find that occurrence of extreme weather events, causing the income loss, leads to increase in the child mortality in the range of 1.04% to 1.5% (depending upon the shocks, such as extreme rainfall or extreme temperature). To understand the mechanism of increased child mortality, we estimated the impact on birth size and weight, signaling the fetal growth. We find that the birth weight and size is influenced by the extremely High-Low temeperature and rainfall in the cropping season preceding the conception. We eliminate any confounding effects occurring due to spatial heterogene-

income shock to compromise at child's and maternal health

ity and overall economic development of the state by introducing suitable fixed effects in the econometric model.

We further studied the heterogeneity in impacts across households, differentiating with respect to access to technology as inputs, financial tools, and economic safety nets. First, with access to technology like irrigation, the impact of extremely low rainfall, reduces the child mortality by 3%. Second, households with access to safety net scheme like Below Poverty Line (BPL) card reduces the child mortality in interaction with extreme weather events by 1.8% to 3.38%. We also investigated the role of television as resilience technology as it plays an important role in knowledge dissemination about choice of crops, inputs, and weather events; also known as Extension Services in Agriculture (Krishna & Naik, 2020). We find that access to television do reduces the likelihood of child mortality caused due to income shock caused by extreme weather events. This result established the existence of environmental injustice as the access to resources makes one group lesser vulnerable compared to others for the same weather shocks. Additionally, these results can be interpreted as the economic mechanism causing the impacts. First, we show that access to simple technology like irrigation can reduce the likelihood of child mortality, as it reduces the crop loss by reducing the negative impact of weather on its productivity and efficiency. Second, access to free ration/food scheme (or any lump sum transfer to household) allows household to smoothen the consumption, ex post income shock. It allows household to continue the optimal care for mother during the maternity period. These mechanisms also highlights the role of policy intervention to protect the vulnerable group as weather shocks becomes more frequent due to climate change.

Our paper is related with three main strands of the literature of the economics. First, how income shock determines the fetal origin (Van den Berg et al., 2006; Rosenzweig & Wolpin, 1986) and weather shocks causing the income loss (Deschênes & Greenstone, 2011; Nordhaus, 2011; Rosenzweig & Udry, 2014), especially in developing countries (Gupta et al., 2021; Costinot et al., 2016). There is only limited evidence about how income loss due to weather shocks affect the health outcomes in the household (Maccini & Yang, 2009). The existing literature suggests that weather shocks can directly impact the fetal health, however evidence are scarce on the indirect effect. We contribute to this literature by showing that, where agriculture is the primary source of income, weather shocks can result in substantial loss to birth outcomes, including child mortality, low birth weight, and size. These findings suggest that changing weather conditions can shock the household ability to spend on maternal health, due to income loss, causing distress in birth outcomes.

Second, this paper fits within the broad body of research in environmental justice which focuses on the vulnerability to weather shocks and climate-based disaster originating from social and economic inequality. Much of these studies focused on inequality in exposure to air pollution and disparity in the benefits from regulations (Sadd et al., 1999; Bento et al., 2015). A growing part of the literature has explored the influence of weather shocks in forced migration across globe and livelihood loss associated with it (Deschênes & Moretti, 2009; Kubik & Maurel, 2016). Additionally, studies shown that economic activities like mining and hazardous industry have differential impacts based on the spatial distribution of population based on economic and social status (Viscusi & Hamilton, 1999; Martinez-Alier, 2001). In this paper, we show that weather shocks can significantly affect the agriculture-based households with minimal resources as inputs in production. The differential in impact is an example of how differential

access to climate-resilient technologies, caused due to severe income inequality, can affect the livelihood. Additionally, our findings show that availability of public-facilities and economic security net can smoothen the consumption of household, vulnerable to weather shocks. Hence, understanding the role of weather resilient factors can contribute to policy for achieving environmental justice: for example, our framework suggests that access to technology for farmers, free food, and extension services like communication can minimize the impact of weather shocks on the consumption and health outcomes. Our findings could not explore other climate adaptive tools like crop insurance, storage rooms, transportation, and subsidies for technology due to limited information. However, our findings emphasize on the role of adaptation capabilities and environmental injustice due to income inequality between farmers.

Third, our results contribute to the large economic literature that investigates the role of income shock to the household on health outcomes. Expenditure on maternal and child health are sensitive to income of the household, specially the poorer households (Bhalotra, 2007; Osendarp et al., 2021) . Henceforth, despite the ineffective social security policies in developing country setup, it creates a safety net against the economic downturn due to income shock, preventing poor health outcomes (Lagarde et al., 2007; Handa et al., 2016) . Additionally, adoption of modern technology in agriculture, reduces the vulnerability against weather shocks, hence, reducing the negative income shock (Emerick et al., 2016). However, the access to technology is restricted to income of the household in absence of subsidy to inputs, hence expanding the vulnerability to a larger number of households in the developing country setup. We show that income constraint reduces the adoption of technology, leading to higher losses in agriculture production. Households facing tremendous loss, reduces the consumption of food crop, leisure time, and health outcomes of income. We studied two period model, where the income is gained at time before the conception of child, therefore, eliminating the direct impact. The phenomenon has a long run implications for farm-based household due to increasing frequency of weather shocks in amalgamation with poor infrastructure and slow pace of diffusion in agri-based technology in India and other developing countries.

The remainder of paper proceeds as follows. Section 2 provides background information on vulnerability of agriculture sector to weather shocks, negative income shock, differential access to adaptation technologies, impact on child health, and environmental justice in India. Section 3 illustrates the model. Section 4 describes the multiple datasets used in the analysis, and Section 5 explains the empirical strategy. Sections 6 and 7 show the main empirical results and provides robustness checks. Section 8 brings additional results to explain the mechanisms. Section 9 concludes.

2 Background

In this section, we discuss the consequences of weather shocks on agriculture around the world, with special focus on developing country’s setup. Additionally provide insights into the differential impacts due to variation in the capability to minimize the shock.

2.1 *Weather shock and Agriculture Productivity*

Studies in economics find agriculture to be the most sensitive to weather shock and impacts the livelihood of a large section of population, mostly dependent on agriculture in developing countries. This may lead to a potential threat to national food security and hard push towards poverty line. Literature in environmental economics, finds significant loss to major crops due to extreme temperature and rainfall in India and other developing countries. The extend of loss ranges between 3% to 5%, especially for food crops like wheat and rice (Gupta, 2017; Stern, 2006). Global projections by Stern Review and IPCC report finds that crop loss will lead to severe hunger, particularly in the developing countries. However, the projections and impact assessment for weather shocks are bound to uncertainty due to econometric complexities arising from non-linear nature of mathematical relationship. Further, the sensitivity of impact is dependent on the choice of fixed effects, therefore, causing additional complexity. Recent literature on econometric strategy finds mixed result for impact of weather shock on productivity of food crops, driven by choice of fixed effects and region of study (Deschênes et al., 2009 ; Nordhaus, 1994; Gupta et al., 2017). Henceforth, the estimation of impact of small term weather shocks and long term climate change remains a puzzle, however, there is an agreement on the impacts on economic growth, specially agricultural sector (Shukla et al., 2019; Dell et al., 2009). We contribute to this literature by measuring the efficiency loss in production attributed to short term weather shocks, particularly, for rice, wheat, and maize. We assumed simplistic Cobb-Douglas production function and utilized the stochastic frontier model with gamma distribution, as suggested by Greene, 1998 which allowed higher flexibility in terms of parameters (Greene, 1998). We further studied the impact of weather shock to each months in the cropping season, therefore, identified the vulnerable stages in the crop growth. Our econometric strategy combined the framework of Ricardian (Nordhaus et al., 1994) and fixed effect panel model (Deschênes et al., 2009). Our approach to evaluate the impact of weather shocks on agriculture productivity provides a new framework, which allows for monthly evaluation and better prediction for inefficiency.

2.2 *Differential mitigation capabilities and extent of income shock*

Mitigation strategies plays key role in reducing the impact of weather shock, such as technology (Carter, 1997), trade (Costinot et al., 2016), and crop-switching (Blanc et al., 2017). For technology, carbon fertilization is proved to be effective in increasing the yields of major food crops, specially, rice, wheat, and soybean (Nordhaus, 2013). Trade models studied the adaptation to long-term weather shocks using the framework of Ricardian model. The Ricardian trade model stated that each region should specialize in the production activities which are most suited to their environment, and engage in trade to fulfill the requirements of other goods. Long term weather shocks may shift the productivity of some crops to selected regions of the world, hence adoption of efficient bilateral and multi-lateral trade can reduce the overall food shortage. However, the differentiability to adopt can induce inequality in the impact of weather shocks. This phenomenon is studied in the economic literature utilizing the framework of environmental justice. It states that the socio-economically weaker sections

of society are more vulnerable to the wrath of extreme weather conditions. From the perspective of Macro-impact, developing and under-developed countries faces higher losses in the event of weather shock due to minimal availability of resources. We extended the notion of environmental justice by studying the household-level variation in impacts, utilizing the inherent income inequality amongst the farmers (Reardon et al., 2000; Himanshu et al., 2013). We studied the adaptation capabilities as function of access to modern agriculture technology like irrigation, financial tools like saving accounts in banks, and economic security nets. Variation in access to resilient factors generate gradient in the income shock, leading to heterogeneous consumption smoothening. Henceforth, we designed theoretical model to understand the impact on health outcomes of newborns in farm-based households. Empirical results suggest that farm-households with minimal resources are significantly more vulnerable to income shock, caused due to loss in production, attributed to weather shock. Our work extended the notion of environmental justice to indirect impacts amongst the most vulnerable groups.

3 The Model

In this section, we defined the statistics to measure the weather shock. Further we develop a simple equilibrium model to study how weather shock culminate to health outcomes of newborns via income loss. We show under what assumptions, access to technology and social security net, reduces the impact, hence leading to inequality for income shock.

3.1 Metrics for weather shock

We utilized the framework of weather measurement by *Deryugina & Hsiang* where it is described as joint probability distribution over a number of climate variables. We defined the state of weather as multivariate distribution, denoted by the vector X :

$$X = \{temperature, rainfall, humidity\}$$

where X is extracted randomly from a multivariate distribution function $f_x()$. Hence, we defined weather outcome as probabilistic metric, however, attached no parametric distribution to it. The parametric functional distribution is not required as we aim to introduce a metric for weather shock, non-parametrically.

We defined the weather shock as the statistical distance. The statistical distance measures the difference between the average weather outcomes to realized weather. Farther the distance, the extent of extremity increases. Unlike Euclidean measure of distance, statistical distance adjusts for the variation and co-variation between variables in a multivariate problem. Hence, we used the Mahalanobis distance (Mahalanobis, 1936), as the metric, to measure the weather shock. It is a scale invariant metric, which measures the distance between a point, say $x \in R^3$, origination from the multivariate distribution $f_x()$, and the mean of the distribution (μ). The distance is adjusted for variation in each random component, by adjusting with variance-covariance matrix,

Ω . The statistical distance, defined as, Λ ,

$$\Lambda(X, \mu) = \sqrt{(X - \mu)^T \Omega^{-1} (X - \mu)}$$

where Λ^2 measures the distance of weather outcome (set of components) from the mean. Since, mean weather patterns varies by months and location, we add superscript $\{i, t\}$ to denote month (t) and location (i). Henceforth, we will use Λ_{it} to denote the extent of weather shock and utilize in the household-level equilibrium model.

3.2 Setup for Agriculture-Household Model

There is a unit mass of households with agriculture as primary source of income and expects child-birth. Maternal and child health-care expenditure depends on the income attributed to profits from cropping season corresponding to period of child conception. Each household decides the share of expenditure on market consumption, subsistence consumption, leisure, and maternal-child health-care. We design the equilibrium with two different specifications; first, Cobb-Douglas utility with Cobb-Douglas technology function, second, CES utility and technology function.

Specifications for Scenario 1,

Preferences- Households have non-constant return to scale Cobb-Douglas utility, depend upon subsistence consumption (c), market consumption (m), newborn health outcomes (h), and leisure (l).

$$U(.) = c^{\gamma_1} m^{\gamma_2} h^{\gamma_3} l^{\gamma_4}$$

Income- Household earn income from agriculture production (y) adjusted for subsistence consumption and cost of production (K), lump sum transfer (τ), and wages (W) from non-household labor supply (z).

$$I = P_y(y - c) - K + \tau + Wz$$

Production Function- Households produce food crops assuming Cobb-Douglas non-constant returns to scale function. Input demands include land (θ), technology from other sectors (x_j), where j denotes sector, and labor (L). Production function is specified with productivity gain from each input and vulnerability to weather shock (λ).

$$y = \left(\frac{A_\theta \theta}{\lambda^{\alpha_\theta}}\right)^{\beta_1} \left(\frac{A_L L}{\lambda^{\alpha_L}}\right)^{\beta_2} \prod_j^N \left(\frac{A_j x_j}{\lambda^{\alpha_j}}\right)^{\beta_j}$$

Cost- We assume inefficient markets, therefore, introduce markups (μ_s), with the prices of inputs.

$$K = r\theta(1 + \mu_\theta) + WL(1 + \mu_L) + \sum_{j=1}^N P_j(1 + \mu_j)x_j$$

²Assuming the multivariate distribution to be Multivariate Normal, then Λ follows a special gamma distribution, known as Chi-Square distribution. However, we are measuring it without assigning any distribution to weather, as it restricts the estimation.

3.3 Optimal choice of inputs under weather conditions

Optimal allocation for inputs are based on the price, resilience against weather shock and the extent of weather shock³. On solving the partial equilibrium for profit maximization, we get the allocation as (Proof in Appendix)

$$\begin{aligned}x_j^* &= \beta_j P_i y_i / P_j (1 + \mu_j) \\ \theta^* &= \beta_1 P_i y_i / r (1 + \mu_\theta) \\ L^* &= \beta_2 P_i y_i / W (1 + \mu_L)\end{aligned}$$

The allocation in the imperfect market states that higher markups on the technology, land, and labor influences the choice of inputs, for a given amount of output. Outputs are influenced by the productivity adjusted for weather conditions and sensitivity towards it, hence any change in the λ will induce producers/farmers to adopt better technologies. However, higher prices will inhibit the adoption of weather-resistant inputs, causing differential loss of productivity. Henceforth, under the circumstances, farmer may exit the market or face reduced profits. Additionally, by increasing the price, a farmer may reduce losses, however, differential impact across farmers will not allow the price rise. The profit equation states dependence on weather shock, higher shocks, reduces profit, however differentially, depends on access to resilient inputs.

$$\pi = P_y \left[\frac{A_\theta}{\lambda^{\alpha_\theta}} \frac{A_L}{\lambda^{\alpha_L}} \prod \frac{A_j}{\lambda^{\alpha_j}} \right]^{1/\beta_1 + \beta_2 + \sum \beta_j} - K$$

Further cost minimization problem finds that unit cost of produce depends on the weather shock, where the unit cost is expressed as (Proof in the Appendix),

$$K = A^{-1} (1 + \mu) \lambda^{\alpha_L + \alpha_\theta + \sum \alpha_j} r^{\beta_1} W^{\beta_2} \prod P_j^{\beta_j}$$

where A is geometric mean of individual input's productivity and μ is geometric mean of markups charged by input providers.

Proposition 1- Signification deviation from mean weather conditions reduces the overall productivity. The effects vary according to the accumulated capital of farmers and the markups charged by the input suppliers. Cost of production increases following the power law, with respect to extreme weather conditions and sensitivity of inputs.

Proof: See Appendix

The goal of the proposition is to show whether adverse weather conditions affect the profits of farmers or increases the overall cost of producing equal amount of outputs. In particular, adaptability to extreme conditions depends on the accumulated wealth, hence small holder farmers will bear the maximum cost of weather shocks. It predicts that cost of the production will increase as extreme rainfall and temperature will force farmers to adopt high-end technologies with minimal vulnerability. However, the price of technology and imperfect markets will be a major barrier for wider acceptance. Further, it finds that labor requirements will also increase as their productivity is compromised amidst the extreme weather conditions (Somanathan et al., 2021).

³The α s are the sensitivity of each unit of inputs to weather shocks, defined through Mahalanobis distance λ . Zero sensitivity signifies nil vulnerability to weather shock, the values vary between $[0, \infty]$

3.4 Extreme Weather, Income Shock, and Newborn Health Outcomes

Post establishing the income loss due to weather shock, we switch to household utility's maximization. The optimal allocation yield an important relationship between health outcomes and loss in agriculture due to weather shock. This also establishes the importance of weather resistant technologies to reduce the impact. However, agri-household models assume that consumption is not completely dependent on the agriculture output due to access to labor markets beyond household farms. Generalized results, with strong correlations between consumption and production, provides simultaneity, which results in higher complexity to estimate the parameters. We are following the generalized approach where perfect labor and input market is not assumed. Previously, we introduced markups to model the imperfect market.

The utility maximization yielded relationship between child health outcomes and indirect impact of weather shock via income loss, can be specified as:

$$H = \gamma_3[P_y y + W(l - z) + \tau/P_h(1 - \gamma_1)]$$

Comparative Statics for Health outcome states the relationship between change in health of child with respect to change in agriculture output. Additionally, health outcomes are also function of wages and outside household labor supply.

$$\frac{\partial h}{\partial \lambda} = \frac{\partial h}{\partial y} \frac{\partial y}{\partial \lambda}$$

Proposition 2- The health outcome of newborn is indirectly related to weather shock through production loss in season preceding the conception of child.

Proof- Detailed Proof in Appendix

This proposition predicts the impact on child health due to production loss in cropping season before the conception of child. Choice of duration for production shock is very critical, as the, weather shock during pregnancy can result in direct effect to the fetal growth, hence, difficult to isolate the indirect effect. This proposition also states that access to weather resistant inputs play key role in smoothening the expenditure on maternal and fetal health, however, from *Proposition 1*, we proved that cost of production also increases. Hence access to perfect market for output is important to compensate for the increased input cost. It presents a trade-off between loss in production and higher input cost in the context of weather shock. In developing countries like India, access to output, input and , labor markets is not equally distributed amongst the farmers (Manjula, 2021). Further, the health state function emphasize on the lump sum transfer (τ) to the farmers. Access to financial tools like banking services reduces the inefficiency in the transfer, hence, improving the overall economic state of the household, specially, during the income shock occurring due to loss in production. Further we investigate the equilibrium with CES utility and Production function. Detail proof in Appendix.

Utility function

$$U = (\gamma_1 c^{\sigma/(\sigma-1)} + \gamma_2 M^{\sigma/(\sigma-1)} + \gamma_3 h^{\sigma/(\sigma-1)} + \gamma_4 l^{\sigma/(\sigma-1)})^{\sigma-1/\sigma}$$

And, Production function,

$$y = (\sum \beta_j x_j^{\eta/\eta-1} + \beta_1 \theta^{\eta/\eta-1} + \beta_2 L^{\eta/\eta-1})^{\eta-1/\eta}$$

4 Data and Descriptive Statistics

In this section, we describe the sources of data that we exploit to test the main predictions of our model in the context of India. All data sets used in the analysis are summarized in the Appendix B.

4.1 Agriculture Productivity data

In order to establish loss in efficiency in production of major food crops due to extreme rainfall and temperature, we utilized the panel data consisting of information on production of major crops at the district level. The panel data is provided by International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), spanning for five decades between 1966-2011. The data set is known as ICRISAT-Macros, where the detailed information on crop production, prices, inputs usage, labor demand, and wages are provided at the district level. This data adjusts for the changing boundaries of districts in the five decades by superimposing the collected data on the 1960 district level map. This provided continuous and comparable data, resulting into a balanced panel. Rainfall and Temperature data is merged to the ICRISAT-Macros at the district level for the period between 1966-2011. We utilized the information on production for three major food crops, that is, wheat, rice, and maize for estimating the inefficiency associated with weather conditions in each month of cropping season.

4.2 Birth Outcome data

Our main data source is the Demographic and Health Survey (DHS). DHS are nationally representative, household level surveys, carried out in the developing countries. For analysis in India, we utilized the National Family Health Survey-IV for 2015-16 available at district level. It provides information for birth outcomes and child mortality for 650 districts, born between 2010 to 2016. Due to absence of geo-coded data, we merge the rainfall and temperature shock at the district level.

In the survey, the information on woman's pregnancy history and child mortality is collected retrospectively during the woman's interview: women are asked to recall age at birth, month, and year of child birth. Additionally, the survey collects information on birth size and weight. Birth size is based on the memory whereas birth weight is collected from the birth cards, provided in the institutional birth. Hence, information on birth weight is biased towards those families who can afford birth at clinic or hospital. We adjusted for the bias in the model specification, discussed in details in the subsequent sections. Further, information on women is restricted to the age group 15-49, which is the fertility age group for woman. The birth history of women is restricted to ever married sample, which may lead to bias, but we expect not to cause significant bias. Trends in child mortality vary in the time period 2010-16, which is adjusted in the model specification.

Prior empirical evidence has indicated that income shock is associated with child mortality and poor health outcomes of newborn (Case et al., 2002; Roseinzeig & Schultz, 1983; Lindo, 2011). More generally, income shock to the household may reduce the consumption of food, health expenditure, and leisure time attributed to the budget

constrain. This increases the dependency on the lump-sum transfer and public provision of health infrastructure in the region. We aim to understand the mechanism of income shock associated with weather shock. Since, agriculture-based households are most vulnerable to weather shock, with respect to income loss. We focus on the regions producing food crops as it determines the subsistence of level consumption. Finally, our sample consists of 11,422 births across food crop producing districts. We estimated the infant mortality across the agriculture household based on the possession of land size. Higher mortality is observed in the farming households with land size less than 1 acre. The mean birth weight and size is higher in small and marginal farmers ⁴.

4.3 Weather Data and Construction of Weather Shocks

To examine how household economic conditions attributed to the weather shock affect the child mortality, where we follow an approach that is widely used in the environmental economics (Deschênes et al., 2009). We used local variation in the rainfall and temperature as a proxy for weather conditions. Extreme rainfall and temperature is an exogenous event that has meaningful effects on the productivity of crops, which affects the budget constraint of household dependent on agriculture. Droughts, floods, and heat waves destroy the crops, specially, to those who do not have access to climate resilient technology and other financial tools. Non-access to savings and crop insurance constraints the budget of household.

To construct a measure of extreme weather events, we use rainfall and temperature data produced by the National Aeronautics and Space Administration (NASA)- GIS. The data contains meteorology and solar related parameters enumerated from monitoring and innovation energy system. The system provides access to daily average data which is geo-coded. The resolution for data for a specific site is 0.5*0.5 degree. The meteorological data being provided by the assimilation models. It utilizes the observations from Modern Era Retrospective-Analysis for Research and Application (MERRA-2) and GEOS 5.12.4. We extracted the data using R-studio. We designed an algorithm utilizing the spatial tools provided in the R-library. Due to lack of geo-coded data in the DHS-India, we merge the data at the district boundaries level.

The existing economic literature implements a wide variety of methodologies to construct measures of rainfall and temperature shocks. Here, we adapt an approach used by Deschênes et al., 2009 and define extreme rainfall and temperature for each district as observations above or below the 10th percentile. We average the daily weather observations at the month level as the birth information is provided at month-year level in the DHS. The definition of extreme weather utilized in the paper is appropriate for the research objectives. First, our rainfall and temperature shock, has significant impact on crop yields. Second, the measure of weather shocks is extreme observations of temperature and rainfall, defined using the local conditions for each district. These events are likely to influence the crop productivity, hence reducing the income of the agri-based households. Utilizing the distribution of temperature and rainfall at the district level, all districts are likely to experience equal probability and considered as i.i.d. Although, each district is equally likely to have experienced weather events in

⁴Categorization of farmers is based on the possession of land size. Classification is suggested by Government of India

a given month-year, rainfall and temperature varies over time, so our identification comes from timing of shocks. However, weather events influence the birth outcomes directly. To eliminate the direct impacts, we merged the weather shock at the cropping season preceding the conception of birth. Here, we indirectly measure the weather shock causing income loss causing the poor birth outcomes.

5 Empirical Strategy

We adopted twofold empirical strategy. First, we estimated the efficiency loss in the production due to extreme temperature and rainfall. Thereafter, we determine the role of climate resistant technologies in reducing the impact of weather shocks on major food crop's productivity. Second, post establishing the impact of extreme weather on crop productivity, we examined the indirect impact of weather shocks on the birth outcomes of agri-based households, via the income loss. We discuss our econometric specification below. We also discuss the threat to identification strategy in estimating the causal relationship between weather shocks (resulting in income loss) to poor birth outcomes. Additionally, we explored the roles of selected technology inputs, financial services and economic safety net in compensating for the income loss.

5.1 Specification for measurement of efficiency loss

To measure the extent of inefficiency attributed to weather conditions, we utilized stochastic frontier model which measures the productivity gap. The stochastic frontier model is based on the premise that no production unit can achieve the maximum technological frontier and the deviation from it is attributed to the inefficiencies associated with each unit (Greene, 1990; Belotti et al., 2013). In our specification, we are interested in the extent of inefficiencies caused by the weather conditions. We conducted separate assessment for each crop and measured the inefficiency with respect to the rainfall and temperature in each month on respective cropping season. Our empirical model is a Cobb-Douglas Production function with controls for state level variation and state-specific trends in productivity. The model specification is as follows:

$$\log y_{it} = \beta_1 \theta_{it} + \beta_2 L_{it} + v_{it} - u_{it}$$

where the $\log y_{it}$ is log transformation of production at district i at time t , θ_{it} and L_{it} are log transformation of land and labor force in the agriculture sector. u_{it} is the technical inefficiency which is expressed as the linear function of extreme rainfall and temperature. The functional specification is :

$$u_{it} = \delta z_{it} + \omega_{it}$$

Here z_{it} corresponds to the incident of extreme rainfall and temperature observed at each month of cropping season. ω_{it} is the random variable distributed as truncated normal with zero mean and variance σ^2 .

We adopted single stage Maximum Likelihood Estimation following the framework utilized by Mastromarco & Ghosh, 2009. This approach corrects for the flaws in the two stage MLE framework.

5.2 Specification for estimating the interaction effect of extreme climate and technology diffusion

We adopted the "New Approach" suggested by Deschênes et al., 2007. This approach improves upon the Hedonic model suggested by Nordhaus et al., 1994, which specified the model as cross-section which constrained the time variability in weather conditions. This new approach can be specified as:

$$\log y_{jst} = \alpha + \sum_1^N \beta_i W_{jsti} + \sum_1^N \pi_i W_{jsti} * Irrig_{jst} + \sum_1^N \pi_i W_{jsti} * HYV_{jst} + \delta_j + \phi_{st} + \epsilon_{jst}$$

The subscript j, s, t, i represents jth district, sth state, t year and ith month. The outcome variable y_{jst} is production per unit land allocated in district j , state s and year t . W_{jsti} represents Temperature and Precipitation. Temperature variable was constructed by generating tertiles for each district, where the 1st and 3rd tertile is low and high temperature. For precipitation, low and high is defined as less than -1σ and more than 1σ respectively for each district. $Irrig_{jst}$ and HYV_{jst} represent fraction of total cultivated land irrigated and using HYV seeds respectively. δ_j and ϕ_{st} are district and state-by-year fixed effect. Our interest of parameters are β_i s and π_i s. Choice of Months (N) is based on season for Kharif and Rabi crops in India.

The econometric specification includes key fixed effects which controls for the time and space related changes in the production mechanism, which may confound the main results. First, it includes district level fixed effects which absorbs the time-invariant district-specific determinants of productivity for a given food crop. Second, it also includes year indicators that control for the average annual changes in all districts with respect to time. We also tested the model with state-year fixed effects to eliminate any policy level changes which may influence the gradient of productivity. Third, we included time variation in the occurrence of extreme rainfall and temperature which enables the model to predict the effect of long-term changes in weather pattern. Further, we improve upon the new approach by including month-level variation in weather patterns and interaction with technologies which provides resilience to the crops. Inclusion of month-level variation in extreme temperature and rainfall enabled us to estimate the impact at various stages in cropping season. We identified the key months which affect the output. It suggested the mechanism about how weather shock functions with respect to agriculture productivity. We were also interested in understanding the role of technologies as a weather-resistant inputs. The interaction terms yielded the requirement for technology diffusion as a measure for long-term resistance against climate change.

5.3 Specification for estimating the indirect impact of weather shock on the birth outcomes

The duration of interest is the cropping season before the conception of child, the time when the farmer gains income from the sales of food based and crops and save a

share for future consumption. This income determines the farmer’s ability to spend on maternal and child health-care needs during the pregnancy period in absence of efficient labor market and lump-sum transfer to household. In our analysis we study both these cases and estimate the health function of child following up on the Rosenzweig, 1983 model.

We convert our data into birth-year panel format. Hence, a household with n births in k years, contributes nk observations to the sample: one observation for each birth until the period of data collection. We merge these data with our rainfall and temperature data in a manner that it coincides with the cropping season before the conception of birth. For example, if a child is conceived in the month of November in 2012, the temperature and rainfall information are related to the months of Kharif crop, that is, from May to October as it is the cropping season preceding the conception. The choice of duration for introducing income shock is based on idea that weather shock can compromise the budget constraint of farmers in India, who are primarily dependent on the production of food crops for income.

Utilizing on the birth-year panel data, we estimated the probability of infant mortality for a child i born in household h in time period t at district d situated in state s . The econometric specification is as follows:

$$H_{iphtds} = \sum_{j=1}^2 \beta_j T_{jd(t-1)s} + \sum_{k=1}^2 \Delta_k R_{jd(t-1)s} + \Omega_h + \omega_p + Trends_s + \epsilon_{iphtds}$$

The dependent variable H_{iphtds} is the binary coded variable where 1 signifies death of the child born at t and zero otherwise. Since we are interested in the infant mortality, our focus is on deaths happened before 12 months of age. The variables $T_{jd(t-1)s}$ and $R_{jd(t-1)s}$ are the multiple category variables stating the distance from mean temperature and rainfall for the district d . Ω_h is the household fixed effects which controls for the household invariant characteristics such as religion, caste, and assets. ω_p is parents related fixed effects controls for idiosyncratic characteristics of parents, specially, mother’s health status and care during pregnancy and post-pregnancy. $Trends_s$ is the trend variable, controlling for overall growth in the health related outcomes in the state s . We estimated the regression with standard errors clustered at the district-year level to allow for serial correlation in the error term, and show robustness (Abadie et al., 2017).

With the estimation of weather shock at district level for a given cropping season, the hazard to infant survival is identified within-location and within-year-of-conception. The key identifying assumptions is that weather shock will in the period before conception will indirectly affect the health outcomes of newborn via income loss. The exogenous nature of weather shocks are very important as they enabled causality. There are many unobservables that can influence the birth outcomes. The inclusion of Trends variable strengthened the estimates as it controls for all state-level policy in regards to weather shocks may confound the results.

Further to understand the mechanism, we utilized the similar econometric approach to estimate the impact on birth weight and size. Birth weights are only reported for those who delivered in a hospital or clinic, no data for in-house delivery, which required correction for selection bias. We adopted two-stage Heckman model, where in first stage we predicted the inverse mills ratio and multiplied in the second stage, to adjust for the selection bias. Last, we interacted the main econometric specifications with resilient technology inputs and social security program to understand the variation in hazard with respect to access.

5.4 Threat to Identification

A potential threat to our identification is the direct effect of weather shocks on maternal and child health. To eliminate the direct effect, we introduced the weather shock before conception of child. This may cause additional issues as the income gained in the cropping season during the pregnancy is not considered in the econometric strategy. However, we introduced the weather shock at the cropping season 6 months before birth to account for income missed out in the robustness check, but the direct effect in this framework cannot be eliminated. Further, we merged the weather shock in the current location, which could be detrimental as the mother might be residing in different location during child birth. Meanwhile, the evidence suggests that father's income is important determinants of birth outcome and survival. Further, a farmer can allocate the land to different crops in a cropping season. Unavailability of information on land share allocation compelled us to assume the uniformity in crop plantation. We corrected for the crop selection by selecting the districts where a particular food crop is grown. However, food crops like rice, wheat, and maize are grown all across India as they constitute the main staple food. Our identification is also subject to threat from household labor force distribution including the leisure. Since, time utilization information is not provided in the data, we proxy it with occupation status of the households. We selected households dependent on agriculture for income. We also controlled for the employment status of the mother, however, the workforce participation rate for women in rural India is minuscule and concentrated mostly in the household with marginal farmers.

6 Empirical Results

Our results examine the loss of efficiency attributed to the extreme weather events in the cropping season, role of technology in reducing the crop damage and how it transfers to the agri-culture based households as income loss. Further, we emphasize on the indirect effect by estimating the infant mortality function in India.

6.1 Efficiency loss attributed to weather conditions

Table 2 reports our first set of results: the loss in efficiency due to weather conditions for major food crops. We report the the summary statistics for inefficiency separately for rice (Column 1), wheat (Column 2), and Maize (Column 3). Consistent with our model regarding the production function and literature on impact of weather shock on crop production, extreme rainfall and temperature during the months of cropping season for each food crop resulted in significant loss to the efficiency. In case of rice production, mean efficiency loss attributed to weather shock is 20.2% with maximum loss observed at 98.4%. Higher efficiency loss is found for maize, which is, 24.%. Compared to the major food crops, the efficiency loss is minimal for wheat. We also obtained positive coefficients for extremely high temperature and rainfall during the months of transplantation and harvesting for rice. However, for wheat, the negative coefficients are observed for extremely high temperature during plantation and extremely low rainfall at harvest period. For maize, the negative coefficients are

reported for extremely low temperature and high rainfall during the months of winter. Unlike rice and wheat, maize is grown throughout the year in India. These results are the foundation for subsequent sections, where we discuss about the interaction effect with weather resistant inputs and impact on birth outcomes due to income loss for farming households.

6.2 Productivity loss and interaction effect

Tables 3a-3d report the impact of extreme temperature and rainfall during the months of cropping season for rice and wheat respectively. Further, we explored the interaction effects with weather resilient inputs, Irrigation and HYV seeds. The regression results control for district level controls and state-year controls as suggested by the new approach. Main results are reported in the column 3 for all Tables 3a-3d as they have the appropriate specifications. For rice productivity, high temperatures during the month of July, August, and September (Growth and Harvest period) reduces the productivity by 10.7%, 6.02% , and 12.5%. However, on interaction with share of irrigated land and usage of HYV seeds, the impact either reduces to statistically insignificant or increases the productivity, with exception with low temperature, as irrigation cannot provide resilience to it. For wheat, high temperature during the month of October, November, and March decreases the productivity by 5.96%, 6.84%, and 6.55%. Interaction with irrigation nullify the impact, however, with HYV seeds, low temperature the impact remains intact. Lower temperature reduces the productivity, although, statistical significance is slim.

Table 3b and 3d report the impact on rice and wheat productivity due to rainfall shock. For rice, excessive rainfall in May reduce the productivity by 12.7 %, whereas, low rainfall in the harvest months of August and September, destroys the crop and productivity shrinks by 11.9% and 14.6%. Interaction with Irrigation shows that during low rainfall, it increases the productivity by 10.5%, hence enabling farmers to adapt during the transplantation period. Similar results are found during the harvest month when the precipitation level is low. For wheat productivity, lower rainfall in the months of December and March, that is, growth and harvest period, lowers the productivity by the margin of 18.5% and 16.1% respectively. Access to irrigation facilities and HYV seeds nullify the impact of extreme weather shocks, however, none of them are effective against the excessive rainfall or flood situation.

6.3 Indirect impact of adverse weather conditions on child mortality

A dramatic consequence of loss in productivity and efficiency in food crop production is infant mortality in the farming households, which is arguably one of the important risks in India's health-care conditions (Deaton, 2008). In addition to its maternal and child health consequences, infant mortality is associated with long-term trauma and excessive fertility in the developing countries settings (Büchi, 2007; Murthi, 1995). These effects multiply in the absence of adaptation capabilities, henceforth, causing differential impacts. In our sample, 45.29 births results in mortality before completion of one year in the marginal farmer's household, whereas the mortality rate is 36.57 amongst large farmers. Documenting the indirect impact of loss in production due to

weather shocks is important as our findings are likely to have long term consequences on the maternal and child health of vulnerable households, especially in context of climate change.

We study the impact of extreme rainfall and temperature occurrence on the birth survival of the household. We eliminated the direct impact of extreme weather on birth outcomes by inducing the weather shock before the conception of child. We also document the differential impacts across the farming households with respect to adaptation capabilities and access to social security net. We understand that extreme weather events can impact the non-farming households in the rural India, hence, we studied the overall impact on rural infant survival, to show excessive risk for farm-based households. Table 4 reports the impact of Extremely low and high temperature and rainfall on child mortality. In Model 3 which has the best econometric specification, shows that extremely low and high temperature increases the likelihood of child mortality by 1.19% and 1.04%. Further, extremely high precipitation leads to higher likelihood of child mortality by 1.48%. Impact assessment on overall rural area, we find, statistically weaker association with extreme weather events.

7 Mechanisms: Adverse Birth Outcomes and Heterogeneity in adaptation across farming households

In this section, we study the underlying mechanisms of our main results, hence whether weather shocks affects the fetal growth, causing adverse birth outcomes leading to higher child mortality. We do so by examining the impact of weather shocks during pre-conception period on likelihood of low birth weights and size. Additionally, we examined the heterogeneity in the impacts across differently capable households. This exercise is relevant to highlight the average effects that we have documented so far mask a substantial amount of heterogeneity across farm-based households, with some group exhibiting significantly larger responses to extreme temperature and rainfall. Ergo, we underline the environmental injustice in the context of developing country setup.

7.1 Impact on birth outcomes

Table 4a and 4b reports the consequences of extreme rainfall and temperature on birth weights and size. Exploiting the information on birth weight and size in the pregnancy history of women, we find significant increase in the risk of low birth weight and size in the region. Column three of table 4a reports the causal relationship, stating that, both extremely low and high temperature during the cropping season preceding the conception of child, increases the risk of low birth weight by 4.75% and 2.56%. Similarly, with extremely high precipitation, the impact increases the likelihood of low birth weight by 4.29%. The results shows the increased risk for fetal undergrowth, hence, increasing the likelihood of mortality. We utilized the *fetal origin hypothesis* to design the mechanism for understanding the excessive mortality. Our results follows from the theoretical model which finds loss in income either through loss in production

or increased cost of input baskets. Fixed real prices of food crops in market disables the farmers to revise the price to absorb the income shock, hence inefficient markets burdens the farm-based households (Ray, 2005).

7.2 Heterogeneity in impacts by household adaptation capabilities

In our model, resilient technologies as input and social security program are adaptation pathway for households affected by extreme weather events. Empirically, we have tested our model by interacting the weather events with access to input technology and food security program to understand the heterogeneity as a mechanism to explain the excessive child mortality attributed to weather shocks. Further we discuss the role of each capability enhancing tool on the basis of coefficients reported in table 5.

7.2.1 Irrigation

We utilized the information on acres of land irrigated collected for each farm-based household during the survey. We converted it into fraction of total area irrigated and interacted with the extreme temperature and rainfall in the econometric model. We show that households with higher fraction of land irrigated reduces the likelihood of child mortality in the extreme weather events. We find that in cases of Extremely low temperature, high temperature and high rainfall shrinks the likelihood of child mortality by 3.8%, 3.9%, and 4.5%. Access to irrigated land implies that additional water preserves the crop in extreme temperatures. In case of extremely high rainfall, one possible explanation is that higher share of irrigation implies higher income which may act as an resilient factor against flash floods. Higher wealth enables access to maternal and child health care and, smoothen the migration to ensure safety (Hirovonen, 2016).

7.2.2 Access to formal credit markets and savings

Other adaptation factor is the development of local area banking services as it provided household options for saving and credit, which can smoothen the health expenditure on maternal and child health care during the income shock. One example is the positive impact of nationalization of banks in India, causing reduction in poverty, especially in rural areas. We utilize the information on whether the household owns a savings account in a formal bank. Access to savings account enables credit and other insurance services. We define the access to banking services as dummy variable, where 1 identifies households with savings account. We show that interaction of savings account with extreme temperature and rainfall reduces the likelihood of child mortality by 3.7%, 2.4% , and 3.9%. The results also highlights the burden on the households who do not have access to banking services as they are susceptible to excessive mortality attributed to weather shock to productivity.

7.2.3 Consumption Smoothing through price-discounted food ration

An implication of our theoretical model is that the lump-sum transfers to the household increases the health outcomes of newborns. India's program on providing food products to the households at cheaper rate compared to market prices is aimed to reduce hunger in the country. The program requires household to be below poverty line, however, mis-allocation of program resulted in beneficiaries from richer households as well, especially in rural areas (Bardhan & Mookherjee, 2011). The importance of provision for cheaper food is illustrated by our paper. We used the information on possession of BPL cards, which is the eligibility criteria to be a potential beneficiary. We find that access to BPL cards reduces the child mortality in the household under all the four extreme weather conditions. It establishes the role of lump-sum transfer as predicted by our model.

7.2.4 Safety net against health shocks

Households are vulnerable to health related shocks where access to health insurance can smoothen the consumption and reduces the burden on budget (Morduch, 1995). We tested the role of health insurance in reducing the impact of income shock due to extreme weather. We did not find any significant advantage to those enrolled in insurance policy, however, interaction with extreme low rainfall reduce the child mortality. The results are not significant, violating the prediction of model, may be explained from low diffusion rate of health insurance in India.

7.2.5 Communication as extension services to reduce impact of weather shocks

Extension services such as communication about optimal agriculture strategies enables the farmer to plan the production process (Aker, 2011). Effective knowledge dissemination plays a key role in improving the productivity in agriculture sector. Ergo, access to communication tools such as television results in advantage for farmers, specially with frequent weather shocks, as it enables the production process. We tested the hypothesis by interaction of access to television with extreme weather conditions. We find that child mortality reduces with all extreme weather conditions by a significant margin. We assumed that household had access to television during the weather shocks as the information is not collected retrospectively.

8 Conclusions

The findings presented in the paper indicate that in developing countries where farmers depends on the predictability of weather conditions for realizing maximum productivity, weather shocks can lead to significant income shock resulting into health hazard of newborns. It also establishes the role of climate resilient inputs, development of banking services, and social security net (or lump sum transfer) in reducing the income shock, hence, resulting in heterogeneous effects across farm-based households. The heterogeneity also highlights the risk of environmental injustice with imperfect goods

and labor markets amalgamated with poor maternal and child health care facilities. We believe these results can speak directly to the recent developments in the literature of climate change economics: our findings suggest that extreme weather conditions shrinks the income capacity of farmers, leading to lesser expenditure on maternal and health care, therefore causing poor health outcome for child. We find that access to multiple resilience factors can protect the household from short-term impacts. Hence, it underlines the importance of diffusion of technology and other economic services, as it alarmingly causing heterogeneity in impacts. Our results shows that not all household are equally susceptible to weather shocks, therefore, results in selected poverty for significantly large populations. Across the globe, people witness the impact of climate change in forms of drought, flash floods or cyclones. As the impact intensifies further, more households will slip into the poverty trap, causing massive health hazard in the form of excessive child mortality. Universal access to crop-insurance, afford-ability of climate inputs, and improvement in the goods and labor market with respect to efficiency is critical to protect the households from major income shocks due to frequent adverse weather events. An interesting avenue for future research lies in understanding the long-term impacts of uncertain weather conditions by introducing dynamic equilibrium model. Our findings highlight the transmission of weather shocks to income and extending upto child survival in the vulnerable households. Therefore, assessment of long term impacts is essential as we are heading towards the 2 degree warming mark based on the Intergovernmental Panel for Climate Change reports. In sum, designing successful policies to enable farmers to mitigate the impact of weather shocks and its heterogeneity- a goal that has received increasing attention at the global politics and grassroots movements- requires understanding of the economic mechanisms and the role of technology in minimizing the negative effect. More generally, our findings point to the importance of policy to mitigate the impact of climate change as the weather shocks are occurring more frequently.

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9 Appendix: Omitted Proofs

In this we document the profit maximization, cost minimization and household utility maximization for Cobb-Douglas and CES utility function.

A.1: Proof of the Proposition 1

A.1.1 Cobb Douglas Technology with variable returns to scale

$$\max \pi = P_y \left(\frac{A_\theta \theta}{\lambda^{\alpha_\theta}} \right)^{\beta_1} \left(\frac{A_L L}{\lambda^{\alpha_L}} \right)^{\beta_2} \prod_j^N \left(\frac{A_j x_j}{\lambda^{\alpha_j}} \right)^{\beta_j} - (r\theta(1 + \mu_\theta) + WL(1 + \mu_L) + \sum_{j=1}^N P_j(1 + \mu_j)x_j) \quad \dots \text{equation(1)}$$

Differentiating equation (1) with respect to θ , L , and x_j , we get,

$$\begin{aligned} P_y \frac{\beta_1}{x_j} y &= P_j(1 + \mu_j) \\ P_y \frac{\beta_1}{\theta} y &= r(1 + \mu_\theta) \\ P_y \frac{\beta_2}{L} y &= P_j(1 + \mu_L) \end{aligned}$$

Replacing the values in production function, the profit function yields,

$$P_y \left[\frac{A_\theta}{\lambda^{\alpha_\theta}} \frac{A_L}{\lambda^{\alpha_L}} \prod \frac{A_j}{\lambda^{\alpha_j}} \right]^{1/\beta_1 + \beta_2 + \sum \beta_j} - K$$

Cost Minimization

For unit output y , we solve the equilibrium to compute the cost equation

$$\min K = r\theta(1 + \mu_\theta) + WL(1 + \mu_L) + \sum_{j=1}^N P_j(1 + \mu_j)x_j - \zeta(P_y y - P_y)$$

Differentiating with respect to θ , L , and x_j ,

$$\begin{aligned} \frac{r\theta\lambda^{\alpha_\theta}(1+\mu_\theta)}{A_\theta\beta_1} &= \zeta P_y y \dots 1 \\ \frac{P_j x_j \lambda^{\alpha_j}(1+\mu_j)}{A_j\beta_j} &= \zeta P_y y \dots 2 \\ \frac{WL\lambda^{\alpha_L}(1+\mu_L)}{A_L\beta_2} &= \zeta P_y y \dots 3 \end{aligned}$$

Solving θ and x_j in terms of L and replacing in $y = 1$,

$$L = \left(\frac{\lambda^{\alpha_L}}{A_L} \right)^{\beta_1} \left(\frac{\lambda^{\alpha_\theta}}{A_\theta} \right)^{\beta_2} \prod \left(\frac{\lambda^{\alpha_j}}{A_j} \right)^{\beta_j} \left(\frac{r(1 + \mu_L)}{W(1 + \mu_L)} \frac{\beta_2}{\beta_1} \right)^{\beta_1} \prod \left(\frac{\beta_j W(1 + \mu_L)}{\beta_2 P_j(1 + \mu_j)} \right)^{\beta_j}$$

Replacing the value of L in 3, we get the Price equation, hence K ,

$$P_y = \left(\frac{\lambda^{\alpha_L} W(1 + \mu_L)}{A_L} \right)^{\beta_2} \frac{\lambda^{\alpha_L} r(1 + \mu_L)}{A_L} \prod \frac{\lambda^{\alpha_j} P_j(1 + \mu_j)}{A_j} \right)^{\beta_j}$$

A.1.2 Constant Elasticity of Substitution (CES) Technology

$$\max \pi = P_y (\sum \beta_j (\frac{A_j x_j}{\lambda^{\alpha_j}})^{\eta-1/\eta} + \beta_1 (\frac{A_\theta \theta}{\lambda^\theta})^{\eta-1/\eta} + \beta_2 (\frac{A_L L}{\lambda^{\alpha_L}})^{\eta-1/\eta})^{\eta/(1-\eta)} - \sum P_j x_j (1 + \mu_j) - WL(1 + \mu_L) - r\theta(1 + \mu_\theta)$$

Differentiating with respect to θ , L , and x_j ,

$$\begin{aligned} x_j &= (\frac{P_y \beta_j}{P_j(1+\mu_j)})^\eta y^{\eta/\eta-1} (\frac{A_j}{\lambda^{\alpha_j}})^{\eta-1} \\ \theta &= (\frac{P_y \beta_1}{r(1+\mu_\theta)})^\eta y^{\eta/\eta-1} (\frac{A_\theta}{\lambda^\theta})^{\eta-1} \\ L &= (\frac{P_y \beta_2}{W(1+\mu_L)})^\eta y^{\eta/\eta-1} (\frac{A_L}{\lambda^{\alpha_L}})^{\eta-1} \end{aligned}$$

Replacing the values in production function y ,

$$y = (\sum \beta_j^\eta (\frac{P_j(1+\mu_j)\lambda^{\alpha_j}}{A_j})^{1-\eta} + \beta_1^\eta (\frac{W(1+\mu_L)\lambda^{\alpha_L}}{A_L})^{1-\eta} + \beta_2^\eta (\frac{r(1+\mu_\theta)\lambda^{\alpha_\theta}}{A_\theta})^{1-\eta})^\eta P_y^{1-\eta}$$

Replacing the y in profit equation π yields the maximum profit.

Using the cost minimization criteria (as shown for Cobb-Douglas case), the price P_y is computed as,

$$P_y = (\sum \beta_j^\eta (\frac{\lambda^{\alpha_j} P_j(1+\mu_j)}{A_j})^{1-\eta} + \beta_1^\eta (\frac{\lambda^{\alpha_L} W(1+\mu_L)}{A_L})^{1-\eta} + \beta_2^\eta (\frac{\lambda^{\alpha_\theta} r(1+\mu_\theta)}{A_\theta})^{1-\eta})^{1/(1-\lambda)}$$

A.2: Proof of the Proposition 2

Assuming Cobb-Douglas utility function,

$$U = c^{\gamma_1} M^{\gamma_2} H^{\gamma_3} l^{\gamma_4} - \zeta(P_y(y - c) + Wz - P_y c - P_M M - K - P_H H - Wl)$$

Differentiating with respect to c , M , H , l , and $zeta$,

$$\begin{aligned} c &= \frac{\gamma_1 P_H H}{\gamma_3 2 P_y} \\ M &= \frac{\gamma_2 P_H H}{\gamma_3 2 P_M} \\ l &= \frac{\gamma_4 P_H H}{\gamma_3 W} \end{aligned}$$

Replacing the value of c , M , and l in the budget constraint to obtain the health function,

$$H = \gamma_3 [P_y y + W(l - z) + \tau/P_h(1 - \gamma_1)]$$

For CES economy, the utility maximization equation is,

$$\begin{aligned} U &= (\gamma_1 c^{\sigma/(\sigma-1)} + \gamma_2 M^{\sigma/(\sigma-1)} + \gamma_3 h^{\sigma/(\sigma-1)} + \gamma_4 l^{\sigma/(\sigma-1)})^{\sigma-1/\sigma} - \\ &\delta(P_y(y - c) + Wz - P_y c - P_M M - K - P_H H - Wl) \end{aligned}$$

On differentiating with respect to c , M , H , l , and δ , and expressing in terms of H ,

$$\begin{aligned} C &= \left(\frac{\gamma_1 P_H}{\gamma_3 P_y} \right)^\sigma H \\ M &= \left(\frac{\gamma_2 P_H}{\gamma_3 P_M} \right)^\sigma H \\ l &= \left(\frac{\gamma_4 P_H}{\gamma_3 W} \right)^\sigma H \end{aligned}$$

Replacing in the budget constraint we get the health state function,

$$H = \frac{P_y y - K + Wz + \tau}{P_H^\sigma ((\gamma_1/\gamma_3)^\sigma P_y^{1-\sigma} + (\gamma_2/\gamma_3)^\sigma P_M^{1-\sigma} + (\gamma_4/\gamma_3)^\sigma W^{1-\sigma})}$$

Tables and Figures

Table 1a: Birth Outcomes and natal care in agri-based households, 2015

	LBW	LBS	IMR [#]	ANC	IB
Farm Size					
Marginal	17.48	14.17	45.29	70.88	72.57
Small	16.71	14.88	38.77	72.61	73.63
Semi Medium	17.92	14.37	40.91	64.00	74.11
Medium	17.62	13.8	35.99	65.07	74.91
Large	17.13	13.09	36.57	64.89	77.19
<i>Prob>F</i>	0.237	0.000	0.005	0.000	0.000
Irrigated land					
Yes	16.74	13.82	36.44	68.07	77.28
No	17.85	13.62	38.95	64.03	72.5
<i>Prob>t</i>	0.167	0.371	0.000	0.000	0.000
Bank Account					
Yes	17.33	13.33	40.29	64.66	77.73
No	19.55	18.59	46.87	43.06	56.2
<i>Prob>t</i>	0.000	0.000	0.000	0.000	0.000
Water Pump					
Yes	16.95	12.67	34.52	72.06	84.63
No	17.67	14.85	42.38	60.22	73.28
<i>Prob>t</i>	0.001	0.000	0.000	0.000	0.000
Health Insurance					
Yes	16.10	14.06	34.38	72.98	78.41
No	17.83	14.62	42.34	60.12	74.33
<i>Prob>t</i>	0.001	0.003	0.000	0.000	0.000
Cooking Fuel					
Clean	15.95	11.62	27.89	77.91	89.76
Unclean	18.41	15.73	47.85	54.74	68.86
<i>Prob>t</i>	0.000	0.05	0.000	0.000	0.000

Note: 1. Abbreviations: LBW (Low Birth Weight); LBS (Low Birth Size); IMR (Infant mortality Rate); ANC (Ante natal check-up); IB (Institutional Birth). 2. Definitions: .# IMR is defined as number of deaths in the period 0-364 days of birth per 1000 live births. LBW is birth weight under 2500 grams; LBS is self-reported by the mother; ANC: Complete ANC check-up is defined 3 or more visits to health centre during pregnancy; IB is birth in healthcare centres .# IMR is defined as number of deaths in the period 0-364 days of birth per 1000 live births.

Table 1b: Access to resilience factors by land size, 2015-16

	Marginal	Small	Semi Medium	Medium	Large	<i>Prob>F</i>
Irrigated land	59.29	58.86	56.53	60.42	66.47	0.000
Bank Account	93.07	91.07	88.57	89.37	91.16	0.094
Water Pump	7.05	9.97	11.22	16.19	25.36	0.000
Health Insurance	12.46	13.13	19.41	19.11	18.04	0.000
Clean Cooking Fuel	76.79	79.02	83.58	82.61	79.09	0.006

Note: The numbers are expressed in percentage. Marginal, small, semi-medium, medium and, large are defined according to the land size in hectares. The criteria is as follows: marginal (<0.1 hectare), small (1-2 hectare), semi-medium (2-4 hectare), medium (4-10 hectare), and large (>10 hectare)

Table 2: District level summary statistics for rice, wheat, and maize

	1961-70	1971-80	1981-90	1991-00	2001-11
Rice					
Total Production ('000 tons)	117.07	146.26	201.04	262.27	292.39
	160.32	193.67	265.14	351.1	401.25
Total Area ('000 hectares)	118.11	125.64	132.13	137.63	139.67
	149.03	155.45	159.14	167.89	169.8
Fraction irrigated	0.327	0.428	0.456	0.458	0.494
	1.39	0.39	1.1	1.66	2.44
Price (Rs. Per quintal)	34.3	47.96	87	136.21	257.9
	60.76	85.18	150.59	307.31	541.61
Wheat					
Total Production ('000 tons)	55.93	89.72	150.63	210.84	241.52
	103.69	155.14	269.91	369.32	426.96
Total Area ('000 hectares)	49.23	64.27	76.16	83.54	88.63
	50.73	60.04	85.16	78.22	90.19
Fraction irrigated	0.379	0.571	0.699	0.733	0.973
	1.29	0.74	0.35	0.96	11.65
Price (Rs. Per quintal)	61.08	90.82	155.45	351.37	570.5
	47.48	68.02	110.33	262.09	466.54
Maize					
Total Production ('000 tons)	17.09	17.64	22.04	30.11	48.35
	31.04	31.93	40.56	55.29	93.42
Total Area ('000 hectares)	16.62	17.40	17.13	18.35	23.15
	27.58	28.18	28.91	32.03	39.50
Fraction irrigated	0.205	0.227	0.245	0.248	0.264
	0.46	0.36	0.43	0.35	0.47
Price (Rs. Per quintal)	35.77	57.22	88.16	231.08	388.17
	34.82	60.09	89.85	212.49	345.91

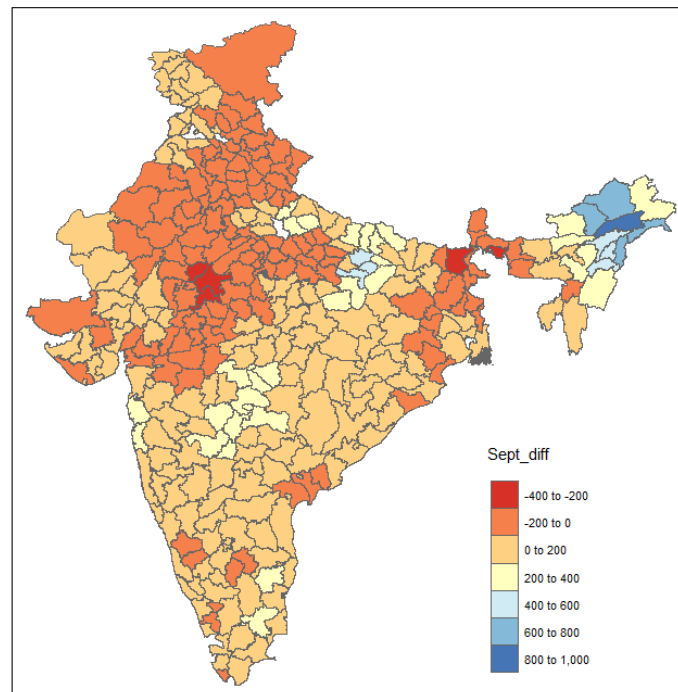
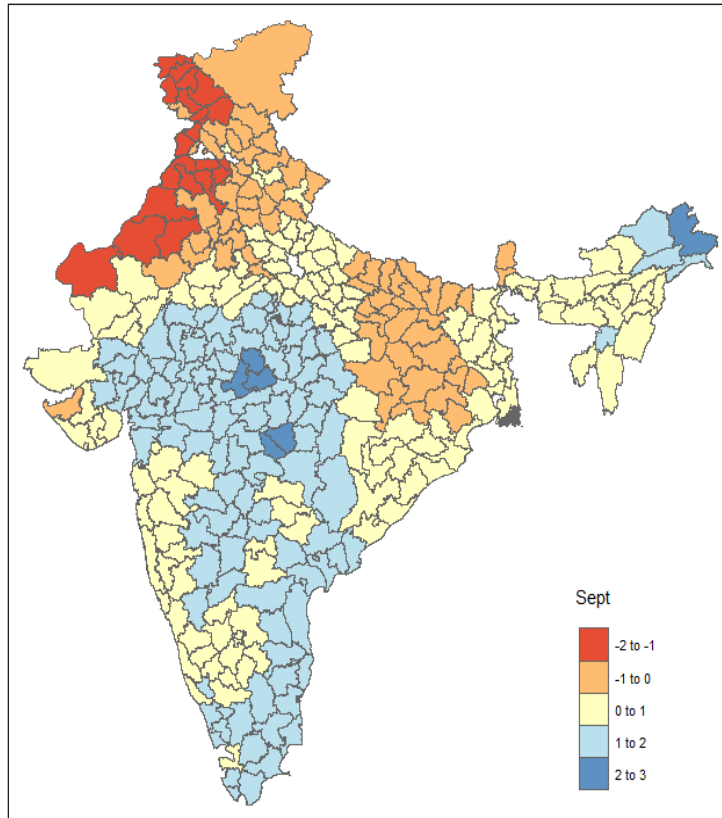


Figure 1: Change in spatial pattern of Precipitation and Rainfall between 1961 to 2011 for the month of September. September is selected as it coincides with cropping season of Rice, Wheat , and Maize.

Table 2: Maximum Likelihood Estimates of Stochastic Frontier Cobb-Douglas Production Function

	Log(rice Quantity)	Log(wheat Quantity)	Log(maize Quantity)
Frontier			
log area	1.0451*** (0.005)	1.0761*** (0.005)	1.0114*** (0.004)
log fertilizer	0.1673*** (0.002)	0.1971*** (0.002)	0.1522 (0.003)
σ_u	1.8731*** (0.172)	1.4403** (0.3522)	2.993*** (0.244)
σ_v	0.1828*** (0.003)	0.1741 (0.003)	0.284*** (0.004)
λ	10.241*** (0.172)	8.278*** (0.351)	10.534*** (0.245)
Estimated Inefficiencies			
Mean	0.202	0.183	0.242
SD	0.156	0.135	0.139
Min	0.017	0.03	0.003
Max	0.984	0.946	0.974

Data Source: ICRISAT Macros

Production frontier is defined as function of land and fertilizer. Labor is considered as constant. Distribution of inefficiency u is distributed as Truncated normal with covariates as monthly temperature and precipitation. Months are selected based on cropping season, namely, Rabi and Kharif. Kharif Months: May to September; Rabi: September to March. Rice is planted in Kharif season, wheat in Rabi, and Maize in both seasons. Area is defined in hectares. Fertilizer is measured in Tonnes.

Table 3a: Effects of Temperature on rice productivity

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
Main Effect			
May			
low	0.00228 (0.00988)	-0.0151 (0.0175)	0.000839 (0.0249)
high	0.00274 (0.00958)	0.00866 (0.0166)	0.0320 (0.0253)
June			
low	-0.0145* (0.00875)	0.0193 (0.0164)	-0.00476 (0.0204)
high	0.00109 (0.0108)	0.00610 (0.0190)	0.0200 (0.0280)
July			
low	0.0127 (0.00866)	0.0255* (0.0152)	0.0336 (0.0214)
high	-0.0283*** (0.0101)	-0.0720*** (0.0196)	-0.107*** (0.0309)
August			
low	-0.00831 (0.00766)	-0.0129 (0.0139)	-0.0237 (0.0181)
high	-0.0240** (0.00967)	-0.0714*** (0.0180)	-0.0602** (0.0256)
September			
low	0.0130 (0.00802)	0.0284** (0.0145)	0.0323* (0.0185)
high	-0.0456*** (0.00889)	-0.0834*** (0.0163)	-0.125*** (0.0239)
Irrigated		0.189*** (0.0409)	0.165*** (0.0559)
HYV seeds			0.155*** (0.0512)
Interaction with Irrigation			
May			
low*Irrigated		0.0353 (0.0224)	0.0832*** (0.0305)
high*Irrigated		-0.0101 (0.0206)	0.0188 (0.0279)
June			
low*Irrigated		-0.0733*** (0.0219)	-0.100*** (0.0290)
high*Irrigated		-0.00962 (0.0230)	-0.0352 (0.0318)
July			
low*Irrigated		-0.0163 (0.0205)	-0.0457 (0.0283)
high*Irrigated		0.0752*** (0.0237)	0.0185 (0.0325)
August			
low*Irrigated		0.00689	0.0114

		(0.0189)	(0.0249)
high*Irrigated		0.0773***	0.115***
		(0.0231)	(0.0329)
September			
low*Irrigated		-0.0260	-0.0257
		(0.0190)	(0.0264)
high*Irrigated		0.0625***	0.0575*
		(0.0219)	(0.0305)
Interaction with HYV seeds			
May			
low*HYV			-0.0625*
			(0.0354)
high*HYV			-0.0509
			(0.0342)
June			
low*HYV			0.0630**
			(0.0307)
high*HYV			0.0264
			(0.0390)
July			
low*HYV			-0.000330
			(0.0331)
high*HYV			0.0956**
			(0.0406)
August			0.0153
low*HYV			
			(0.0284)
high*HYV			-0.0559
			(0.0363)
September			-0.0285
low*HYV			
			(0.0295)
high*HYV			0.0547
			(0.0353)
Constant	0.283***	0.164***	0.0763**
	(0.0106)	(0.0257)	(0.0375)
Observations	10,232	8,867	6,635
R-squared	0.847	0.849	0.851

Note: Temperature variable is defined as: low(0-25th percentile), high(75th-100th percentile) for each month. Irrigated variable is fraction of total land irrigated and HYV seeds is fraction of total land with HYV seeds being used. The estimates are based on district level production data from 1970-2011.

Table 3b: Effects of Temperature on wheat productivity

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
Main Effect			
October			
low	-0.00306 (0.00741)	0.00959 (0.0199)	0.0123 (0.0241)
high	-0.00879 (0.00730)	-0.0565** (0.0223)	-0.0596** (0.0292)
November			
low	-0.0162** (0.00760)	-0.0391* (0.0234)	-0.0104 (0.0314)
high	-0.0235*** (0.00755)	-0.0932*** (0.0249)	-0.0684** (0.0322)
December			
low	0.0208*** (0.00700)	0.0637*** (0.0213)	0.0530** (0.0266)
high	-0.00393 (0.00745)	-0.0258 (0.0216)	-0.00612 (0.0295)
January			
low	0.00502 (0.00746)	0.0119 (0.0209)	-0.00415 (0.0247)
high	-0.00246 (0.00822)	-0.0256 (0.0218)	-0.0263 (0.0295)
February			
low	-0.00395 (0.00906)	-0.0160 (0.0218)	-0.0349 (0.0269)
high	-0.0148* (0.00827)	0.0217 (0.0233)	0.0246 (0.0318)
March			
low	0.0214** (0.00909)	0.0478** (0.0221)	0.0476* (0.0275)
high	0.000230 (0.00951)	-0.0377 (0.0243)	-0.0655** (0.0308)
April			
low	0.00610 (0.00852)	0.0477** (0.0208)	0.0633** (0.0265)
high	0.000718 (0.00913)	0.0306 (0.0218)	0.0226 (0.0277)
Irrigated		0.413*** (0.0531)	0.380*** (0.0668)
HYV seeds			0.168*** (0.0483)
Interaction with Irrigation			
October			
low*Irrigated		-0.0140 (0.0236)	-0.00980 (0.0318)
high*Irrigated		0.0546** (0.0267)	0.0387 (0.0353)
November			
low*Irrigated		0.0403 (0.0268)	0.0307 (0.0366)
high*Irrigated		0.0861*** (0.0283)	0.0229 (0.0403)
December			
low*Irrigated		-0.0535** (0.0253)	-0.0317 (0.0334)
high*Irrigated		0.0242	0.00557

	(0.0254)	(0.0357)
January		
low*Irrigated	-0.0145	-0.00481
	(0.0245)	(0.0322)
high*Irrigated	0.0331	0.0433
	(0.0258)	(0.0360)
February		
low*Irrigated	0.00604	-0.00544
	(0.0256)	(0.0320)
high*Irrigated	-0.0363	-0.0239
	(0.0262)	(0.0376)
March		
low*Irrigated	-0.0359	2.03e-05
	(0.0260)	(0.0351)
high*Irrigated	0.0502*	0.0748**
	(0.0280)	(0.0371)
April		
low*Irrigated	-0.0438*	-0.00585
	(0.0243)	(0.0349)
high*Irrigated	-0.0326	-0.0221
	(0.0250)	(0.0351)
Interaction with HYV seeds		
October		
low*HYV		-0.0123
		(0.0270)
high*HYV		0.0173
		(0.0332)
November		
low*HYV		-0.0254
		(0.0317)
high*HYV		0.0372
		(0.0336)
December		
low*HYV		-0.0160
		(0.0276)
high*HYV		-0.0222
		(0.0354)
January		
low*HYV		0.0255
		(0.0314)
high*HYV		-0.00466
		(0.0297)
February		
low*HYV		0.0306
		(0.0289)
high*HYV		-0.0223
		(0.0321)
March		
low*HYV		-0.0538*
		(0.0292)
high*HYV		0.0295
		(0.0310)
April		
low*HYV		-0.0617*
		(0.0334)
high*HYV		-0.0114
		(0.0346)
Constant	0.392***	0.0854**
	(0.0106)	(0.0424)
		-0.0537
		(0.0613)

Observations	9,452	8,092	5,544
R-squared	0.867	0.885	0.889

Note: Temperature variable is defined as: low(0-25th percentile), high(75th-100th percentile) for each month. Irrigated variable is fraction of total land irrigated and HYV seeds is fraction of total land with HYV seeds being used. The estimates are based on district level production data from 1970-2011.

Table 1c: Effects of precipitation on rice productivity

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
Main Effect			
April			
low	0.0416*** (0.0140)	0.0864*** (0.0298)	0.0817 (0.0558)
high	-0.0164* (0.00974)	-0.0271 (0.0169)	-0.0236 (0.0337)
May			
low	0.0176 (0.0109)	0.0412** (0.0192)	0.0355 (0.0319)
high	-0.0324*** (0.0123)	-0.0881*** (0.0219)	-0.127*** (0.0450)
June			
low	-0.0309*** (0.00942)	-0.0794*** (0.0176)	-0.0358 (0.0316)
high	0.0143 (0.00896)	0.0319** (0.0158)	0.0694*** (0.0255)
July			
low	-0.00661 (0.00958)	-0.0352* (0.0191)	0.0238 (0.0350)
high	-0.00818 (0.00959)	-0.0190 (0.0165)	-0.0487 (0.0319)
August			
low	-0.0368*** (0.0110)	-0.0950*** (0.0215)	-0.119** (0.0534)
high	0.0235*** (0.00838)	0.0366** (0.0149)	0.0675*** (0.0240)
September			
low	-0.0487*** (0.0118)	-0.102*** (0.0219)	-0.146*** (0.0457)
high	0.00839 (0.00727)	0.0345** (0.0141)	0.0256 (0.0259)
Irrigated		0.180*** (0.0328)	0.140*** (0.0541)
HYV seeds			0.0994*** (0.0348)
Interaction with Irrigation			
April			
Low*Irrigated		-0.0702* (0.0399)	-0.0759 (0.0624)
High*Irrigated		0.00587 (0.0240)	-0.0143 (0.0390)
May			
Low*Irrigated		-0.0162	-0.0338

		(0.0273)	(0.0481)
High*Irrigated		0.100***	0.106***
		(0.0273)	(0.0408)
June			
Low*Irrigated		0.0967***	0.103***
		(0.0231)	(0.0357)
High*Irrigated		-0.0465**	-0.0646**
		(0.0221)	(0.0314)
July			
Low*Irrigated		0.0630**	0.105**
		(0.0261)	(0.0425)
High*Irrigated		0.0372	0.0595*
		(0.0227)	(0.0324)
August			
Low*Irrigated		0.102***	0.141***
		(0.0272)	(0.0448)
High*Irrigated		-0.0368*	-0.0581*
		(0.0209)	(0.0312)
September			
Low*Irrigated		0.109***	0.227***
		(0.0296)	(0.0463)
High*Irrigated		-0.0424**	-0.0270
		(0.0195)	(0.0293)
Interaction with HYV seeds			
April			
low*HYV			0.0189
			(0.0574)
high*HYV			0.00536
			(0.0422)
May			
low*HYV			0.00618
			(0.0401)
high*HYV			0.0475
			(0.0503)
June			
low*HYV			-0.0775**
			(0.0392)
high*HYV			-0.0541*
			(0.0316)
July			
low*HYV			-0.114**
			(0.0464)
high*HYV			0.0236
			(0.0377)
August			
low*HYV			0.0114
			(0.0630)
high*HYV			-0.0123
			(0.0328)
September			
low*HYV			-0.00308
			(0.0519)
high*HYV			-0.00420
			(0.0324)
Constant	0.270***	0.153***	-0.0427

	(0.00522)	(0.0173)	(0.0316)
Observations	10,232	8,867	5,135
R-squared	0.848	0.850	0.830

Note: Precipitation is standardized and defined as: low(-5 to -1), high(1 to 5) for each month. Irrigated variable is fraction of total land irrigated and HYV seeds is fraction of total land with HYV seeds being used. The estimates are based on district level production data from 1970-2011.

Table 3d: Effects of precipitation on wheat productivity

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3
Main Effect			
October			
low	-0.00569 (0.0135)	-0.0841* (0.0456)	-0.0592 (0.0512)
high	-0.00706 (0.00820)	0.0466* (0.0252)	0.0667** (0.0316)
November			
low	0.0102 (0.0226)	0.102* (0.0621)	0.0644 (0.0702)
high	-0.0251** (0.0102)	-0.0248 (0.0277)	-0.000757 (0.0347)
December			
low	-0.117*** (0.0375)	-0.0845 (0.0778)	-0.185** (0.0889)
high	0.0223** (0.00930)	0.106*** (0.0249)	0.0813** (0.0316)
January			
low	0.0147 (0.0117)	-0.0897* (0.0509)	-0.0441 (0.0580)
high	0.0111 (0.00762)	0.0231 (0.0249)	0.000297 (0.0303)
February			
low	-0.00354 (0.0131)	0.00210 (0.0370)	0.0475 (0.0558)
high	-0.00523 (0.00873)	-0.0225 (0.0226)	-0.0144 (0.0299)
March			
low	-0.0242 (0.0180)	-0.134*** (0.0482)	-0.161** (0.0631)
high	0.00921 (0.00824)	-0.00286 (0.0252)	-0.0357 (0.0324)
April			
low	0.0426** (0.0167)	0.0747* (0.0427)	0.0561 (0.0526)
high	0.00275 (0.00854)	-0.0358 (0.0240)	-0.0418 (0.0269)
Irrigated		0.439*** (0.0306)	0.426*** (0.0368)

HYV seeds		0.124*** (0.0248)
Interaction with Irrigation		
October		
low*Irrigated	0.104* (0.0554)	0.0697 (0.0664)
high*Irrigated	-0.0605** (0.0306)	-0.0443 (0.0390)
November		
low*Irrigated	-0.149 (0.0968)	-0.134 (0.109)
high*Irrigated	0.00244 (0.0332)	0.00182 (0.0437)
December		
low*Irrigated	-0.0611 (0.127)	-0.166 (0.223)
high*Irrigated	-0.111*** (0.0290)	-0.153*** (0.0468)
January		
low*Irrigated	0.127** (0.0554)	-0.00237 (0.0800)
high*Irrigated	-0.0268 (0.0295)	-0.0129 (0.0374)
February		
low*Irrigated	0.00297 (0.0418)	-0.0306 (0.0637)
high*Irrigated	0.0225 (0.0256)	-0.00181 (0.0354)
March		
low*Irrigated	0.124** (0.0607)	-0.125 (0.122)
high*Irrigated	0.00883 (0.0301)	0.0473 (0.0469)
April		
low*Irrigated	-0.0519 (0.0670)	-0.0414 (0.0877)
high*Irrigated	0.0566* (0.0290)	0.0250 (0.0400)
Interaction with HYV seeds		
October		
low*HYV		0.000700 (0.0589)
high*HYV		-0.0480* (0.0289)
November		
low*HYV		0.0628 (0.0912)
high*HYV		-0.0458 (0.0371)
December		
low*HYV		0.372*** (0.131)
high*HYV		0.0842* (0.0477)
January		
low*HYV		0.0879*

			(0.0492)
high*HYV			0.0143
			(0.0321)
February			
low*HYV			-0.0444
			(0.0536)
high*HYV			0.0169
			(0.0340)
March			
low*HYV			0.303***
			(0.112)
high*HYV			0.0141
			(0.0437)
April			
low*HYV			-0.0154
			(0.0546)
high*HYV			0.0417
			(0.0383)
Constant	0.384***	0.0635***	-0.0661**
	(0.00388)	(0.0232)	(0.0312)
Observations	9,452	8,092	5,544
R-squared	0.867	0.884	0.889

Note: Precipitation is standardized and defined as: low(-5 to -1), high(1 to 5) for each month. Irrigated variable is fraction of total land irrigated and HYV seeds is fraction of total land with HYV seeds being used. The estimates are based on district level production data from 1970-2011.

Table 4: Marginal Impact of Extreme Weather Shocks on Child Mortality

VARIABLES	Child Mortality amongst agriculture based HHs			Overall Rural Area
	Model 1	Model 2	Model 3	Model 4
Temperature				
Extremely Low	0.0370*** (0.00463)	0.0186*** (0.00557)	0.0119** (0.00568)	0.00357 (0.00356)
Extremely High	0.0336*** (0.00426)	0.0165*** (0.00509)	0.0104** (0.00519)	0.00592* (0.00337)
Precipitation				
Extremely Low	0.0280*** (0.00473)	0.0146*** (0.00525)	0.00984* (0.00529)	0.00570* (0.00340)
Extremely High	0.0424*** (0.00417)	0.0217*** (0.00530)	0.0148*** (0.00547)	0.00608* (0.00346)
State Fixed Effects	No	No	Yes	Yes
Household Fixed Effects	No	Yes	Yes	Yes
Individual Fixed Effects	No	No	Yes	Yes
Observations	11,544	11,077	11,077	26,382
R-squared	0.044	0.054	0.060	0.059

Note: First three models estimate the marginal impact of extreme weather shocks on likelihood of child mortality amongst the Agriculture dependent household with different specifications for fixed effects. Model 4 shows the marginal impact for the overall Rural area, which comprises Non-Agriculture dependent Household.

Extreme events are defined as follows: Extreme Low- up to 30th percentile and Extreme High: More than 70th percentile.

Table 4a : Marginal Impact of Extreme Weather Shocks on low birth weight

VARIABLES	Low Birth Weight Agriculturally Based Household		
	Model 1	Model 2	Model 3
Temperature			
Extremely Low	0.138*** (0.0103)	0.0661*** (0.0119)	0.0475*** (0.0122)
Extremely High	0.118*** (0.00951)	0.0436*** (0.0112)	0.0256** (0.0116)
Precipitation			
Extremely Low	0.0827*** (0.0103)	0.0271** (0.0113)	0.0132 (0.0114)
Extremely High	0.146*** (0.00917)	0.0659*** (0.0117)	0.0429*** (0.0122)
Household Fixed Effects	No	Yes	Yes
Individual Fixed Effects	No	No	Yes
State-year Trends	Yes	Yes	Yes
Observations	7,349	7,134	7,134
R-squared	0.144	0.172	0.179

Note: The estimates are corrected for selection bias in birth weight reporting. The data is available for those who received birth card post-delivery. We adopted two-stage Heckman selection model, where the bias in reporting is linear function of state fixed effects. Choice of covariate in the first stage is based on the facilities provided by state, which varies, as health is a matter of State jurisdiction.

Table 4b: Marginal Impact of Extreme Weather Shocks on low birth weight

VARIABLES	Low Birth Size Agriculturally Based Household		
	Model 1	Model 2	Model 3
Temperature			
Extremely Low	0.108*** (0.00796)	0.0491*** (0.00280)	0.0224*** (0.00595)
Extremely High	0.100*** (0.00760)	0.0472*** (0.00252)	0.0282*** (0.00544)
Precipitation			
Extremely Low	0.0888*** (0.00824)	0.0386*** (0.00260)	0.0206*** (0.00518)
Extremely High	0.116*** (0.00720)	0.0518*** (0.00276)	0.0263*** (0.00565)
Household Fixed Effects	No	Yes	Yes
Individual Fixed Effects	No	No	Yes
State-year Trends	Yes	Yes	Yes
Observations	10,290	14,190	23,873
R-squared	0.124	0.136	0.150

Note: Birth size is based on recall basis.

Table 5: Adaptation tools and marginal impact on child mortality

VARIABLES		Likelihood of Child Mortality in Agriculture HHs				
Extremely Low Temp*Bank Account		-0.0371***				
		(0.0108)				
Extremely High Temp*Bank Account		-0.0242**				
		(0.0102)				
Extremely Low Rainfall*Bank Account		-0.0163				
		(0.0104)				
Extremely High Rainfall*Bank Account		-0.0398***				
		(0.0103)				
Extremely Low Temp*Fraction Irrigated	-0.0388***					
	(0.0137)					
Extremely High Temp*Fraction Irrigated	-0.0398***					
	(0.0128)					
Extremely Low Rainfall*Fraction Irrigated	-0.0215					
	(0.0132)					
Extremely High Rainfall*Fraction Irrigated	-0.0435***					
	(0.0128)					
Extremely Low Temp*BPL		-0.0189*				
		(0.0106)				
Extremely High Temp*BPL		-0.0324***				
		(0.0101)				
Extremely Low Rainfall*BPL		-0.0326***				
		(0.0102)				
Extremely High Rainfall*BPL		-0.0339***				
		(0.0102)				
Extremely Low Temp*Health Insurance		-0.0211				
		(0.0142)				
Extremely High Temp* Health Insurance		-0.0216				
		(0.0133)				
Extremely Low Rainfall* Health Insurance		-0.0272**				
		(0.0136)				
Extremely High Rainfall* Health Insurance		-0.0110				
		(0.0134)				
Extremely Low Temp*Television		-0.0374***				
		(0.0106)				
Extremely High Temp* Television		-0.0257**				
		(0.0100)				
Extremely Low Rainfall* Television		-0.0220**				
		(0.0102)				
Extremely High Rainfall* Television		-0.0312***				
		(0.0101)				
State Trends	Yes	Yes	Yes	Yes	Yes	
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Husband Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Observations	7,313	11,422	11,422	11,422	11,422	
R-squared	0.052	0.053	0.054	0.051	0.052	

Note: Fraction of irrigated land is continuous variable, computed as irrigated land/total land; Choice of adaptation tools is based on capability to reduce crop loss, smooth household consumption, and transmit information. BPL cards ensures access to free raw food provided by government. It also involves cash transfers. Savings accounts enable HH to save money from their income, which may come handy in situation of crop loss. Health insurance protects the HH from out-of-pocket expenditure and covers the cost of child delivery, ante-natal, and post-natal care. Television transmits information regarding the cropping methods and knowledge to adapt in weather shocks, provided as Extension services by Government of India.

Appendix B-Variation in Temperature and Rainfall

Table B.1: Decadal Variation- fraction of extreme temperature instances

	Low Temperature					High Temperature				
	1961-70	1971-80	1981-90	1991-00	2001-11	1961-70	1971-80	1981-90	1991-00	2001-11
January	14.67	17.5	12.24	19.24	15.82	8.46	11.64	20.92	14.3	17.18
February	27.34	22.84	16.72	14.62	8.43	22.07	9.85	12.27	10.35	26.21
March	18.29	21.16	24.03	15.97	6.4	15.38	13.68	14.45	18.22	22.36
April	18.7	11.74	16.22	21.81	7.78	11.48	23.59	8.93	16.19	20.01
May	11.75	22.56	24.41	14.34	6.64	11.83	19.99	16.69	15.54	10.5
June	15.2	21.38	10.21	13.45	20.18	15.45	11.84	14.55	22.52	18.32
July	10.77	24.01	15.98	9.21	6.32	16.03	8.33	14.44	12.99	20.78
August	15.92	22.52	11.89	17.5	5.97	8.94	10.68	12.42	19.43	24.78
September	21.36	24.33	14.21	14.44	7.46	16.86	13.04	18.29	8.26	23.5
October	23.07	11.05	21.56	15.23	6.93	11.19	21.63	10.96	15.15	19.18
November	27.4	23.4	19.5	11.67	4.33	11.89	25.08	5.33	14.62	18.6
December	24.62	23.62	8.76	17.06	3.4	10.06	10.6	12.41	7.8	26.89

Table B2: Decadal Variation in percentage of extreme precipitation instances

	Low Precipitation					High Precipitation				
	1961-70	1971-80	1981-90	1991-00	2001-11	1961-70	1971-80	1981-90	1991-00	2001-11
January	6.33	2.31	3.77	1.07	5.29	13.2	8.64	17.75	18.43	6.66
February	4.79	3.21	3.45	1.92	5.36	9.29	13.88	14.24	12.74	15.43
March	3.14	2.6	2.29	0.71	1.61	12.42	8.22	14.83	12.01	10.8
April	5.21	4.41	5.98	5.34	3.68	4.42	12.45	13.44	11.85	13.25
May	8.52	10.17	6.4	7.72	5.07	6.69	13.8	21.49	11.24	15.82
June	15.86	12.06	12.67	14.45	11.58	12.37	25.55	12.24	11.64	17.75
July	12.49	13.8	15.79	15.22	18.85	15.09	18.96	18.22	11.36	13
August	16.45	13.01	14.37	17.36	16	19.71	20.89	17.18	11.77	10.6
September	16.33	15.05	15.16	12.84	13.29	15.09	17.4	18.03	9	17.04
October	14.2	6.4	11.24	4.84	6.89	10.24	17.53	13.48	17.93	11.54
November	3.73	3.45	3.63	1.85	1.15	7.63	18.07	12.27	15.33	6.6
December	2.13	1.1	0.46	1.39	0.86	13.67	10.64	15.98	16.43	3.82

Table B3: Percentage of high-low precipitation-temperature instances

	<i>Hh</i>	<i>Hl</i>	<i>Ll</i>	<i>Lh</i>	p-value
January	15.75	15.5	12.94	21.27	0.002
February	6.38	20.01	6.14	27.97	0
March	5.41	50.47	3.14	41.18	0
April	4.72	39.41	2.84	39.65	0
May	1.91	50	2.17	47.99	0
June	2.71	46.68	1.06	41.23	0
July	2.71	29.88	2.58	42.05	0
August	3.27	31.25	3.12	39.99	0
September	2.93	35.93	3.13	43.91	0
October	4.54	33.17	5.82	33.62	0
November	23.56	15.41	22.25	12.43	0
December	12.66	16.73	9.79	16.78	0.044

Hh: High precipitation high temperature, *Hl*: High precipitation low temperature,

Ll: Low precipitation low temperature, *Lh*: Low precipitation high temperature
p-value of the chi-square statistics