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Barbora Sedova, Matthias Kalkuhl and Robert Mendelsohn

CESifo GmbH • Poschingerstr. 5 • 81679 Munich, Germany
Tel.: +49 (0) 89 92 24 - 1410 • Fax: +49 (0) 89 92 24 - 1409 • E-Mail: office@cesifo.de • www.cesifo.org/venice

Distributional impacts of weather and climate in rural India

Barbora Sedova[*†‡] Matthias Kalkuhl[*†] Robert Mendelsohn[§]

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Abstract

Climate-related costs and benefits are unevenly distributed across the population. To design policies effectively mitigating welfare losses under future climate change, it is crucial to better understand the distributional implications and identify the underlying sources of heterogeneity of climate-related effects. We study distributional implications of seasonal weather and climate on within-country inequality in rural India. We draw on the India Human Development Survey, Era-Interim reanalysis data and ISIMIP climate projections. We conduct a panel data analysis utilizing a first difference approach. We find that the poor are more sensitive to weather variations than the non-poor. They respond more strongly to (seasonal) temperature changes: negatively in a hot season, positively in a cold season. Moreover, while the poor respond strongly to precipitation variations, the non-poor do not. Rainfall in (dry) rabi season is beneficial for the poor, but in (dry) spring it is not. We further find that bank account ownership, land ownership, access to technology and historical climate explain the heterogeneity in responses to weather variations. We predict that under a high greenhouse gas emissions scenario (RCP8.5), inequality in rural India will increase. Hence, policies that improve access to financial institutions and adaptation technologies could reduce the welfare losses under climate change.

Keywords: climate change, weather, inequality, household analysis, India, econometrics.

JEL Classification: D30, I31, Q54. **MSC:** 91B76.

[*]Mercator Research Institute on Global Commons and Climate Change, EUREF-Campus 19, Torgauer Straße 12-15, 10829 Berlin, Germany

[†]University of Potsdam, Faculty of Economic and Social Sciences, August-Bebel-Straße 89, D-14482 Potsdam, Germany

[‡]Correspondence to Sedova@mcc-berlin.net.

[§]Yale School of Forestry and Environmental Studies, Yale University, 195 Prospect Street, New Haven, CT 06511, USA

1 Introduction

Inequality has far-reaching detrimental impacts on economic prosperity [Easterly, 2007] and its reduction has become one of the defining challenges of the 21st century [UNDP, 2018b]. Economists have long understood that climate change, manifested through changing average climatic conditions and extreme weather events, threatens to further exacerbate inequality [Hsiang et al., 2019]. For instance, climate change-related weather shocks already aggravate the North-South economic divide [Burke et al., 2015, Diffenbaugh and Burke, 2019, Kalkuhl and Wenz, 2018, Mendelsohn et al., 2006] and are further projected to affect the poorest countries in the future the hardest [King and Harrington, 2018, Schleussner et al., 2016]. While the inequality implications of climate change across countries have been studied extensively, the within-country implications have not received much attention [Hallegatte and Rozenberg, 2017, Islam and Winkel, 2017, Karim and Noy, 2016]. Because the poor represent only a small fraction of the national incomes, the climate-related effects on the poor may have a negligible impact on the income at the national level. Therefore, the studies providing the more aggregate perspectives may be missing an important part of the story [Hallegatte and Rozenberg, 2017]. Yet, a better understanding of the climate change-inequality nexus is crucial, to design welfare-enhancing policies focused on reduction of the vulnerabilities to adverse climate-related events. With this research, we contribute by studying the implications of climate change on within-country inequality in rural India.

In India, almost 70% of the population lives in rural areas. Despite a decrease in rural employment in agricultural sector from almost 78% in 1993-1994 to 62% in 2015-16 [ILO, 2016], the rural population is still strongly reliant on the agriculture [Krishna Kumar et al., 2004]. Since formal insurance to buffer against adverse weather events is rare and agricultural production is still heavily dependent on weather, Indian agriculture is particularly vulnerable to yield damage under adverse weather events [Auffhammer and Carleton, 2018, Carleton, 2017, Fishman, 2016]. Already, climate change has affected the monsoon patterns in India in two important ways; the rainfall in the monsoon season has decreased [Auffhammer et al., 2012, Dash et al., 2007, Ramanathan et al., 2005] and the distribution of the rainfall has become more extreme [Goswami et al., 2006]. Moreover, surface temperature increases have accelerated over time [Padma Kumari et al., 2007]. Since the poor have generally less access to credit or adaptation technologies and/ or inhabit locations that have less favorable climatic conditions [Hsiang et al., 2019], we hypothesize that they are particularly vulnerable to the adverse weather events. Therefore, we expect climate change to have adverse distributional implications in the future. In this study, we focus on these distributional issues and address the following set of questions: *How do adverse weather events affect different welfare groups in rural India? What are the sources of households' vulnerabilities to adverse weather events? What are the distributional implications of climate change in India under future scenarios?*

We use the India Human Development Survey (IHDS) collected in 2004-2005 and in 2011-2012, Era-Interim reanalysis data and climate projections provided by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP). First, we analyze the distributional implications of changes in seasonal temperature and precipitation on households' consumption by conducting a first difference panel data analysis. Second, we interact the weather variables with a set of household-specific characteristics to explore the sources of hosueholds' vulnerabilities to weather variations. Third, using the ISIMIP projections that correspond to the Representative Concentration Pathway 8.5 (RCP 8.5) scenario, we estimate the magnitude of future consumption losses for different wealth groups.

Our results suggest that the poor are more sensitive to weather variations compared to the non-poor. They respond more strongly to (seasonal) temperature changes: negatively in a hot season, positively in a cold season. The cumulative effect of temperature for poor is, however, not significant (i.e. a homogeneous increase in temperature among both seasons would have no effect). Moreover, while the poor respond strongly to precipitation variations, the non-poor do not respond at all. Rainfall in (dry) rabi season is beneficial for the poor, but in (dry) spring it is not. Too much (summer) monsoon is bad for the agricultural production. The weather impacts are, however, not solely channeled via agriculture. Economic factors (bank account ownership, land ownership or access to adaptation technology) and historical climate are crucial for explaining the heterogeneity in weather responses. Households that are able to smooth their consumption (i.e. access to financial institutions, wealth) or can afford the avoidance technology (e.g. irrigation) face lower marginal damages from adverse weather events. Households that live in less favorable climates (e.g. hotter climates), on the other hand, face higher marginal damages. We predict that under a high greenhouse gas emissions scenario (RCP8.5), inequality in rural India will increase. Therefore, policies that improve access to financial institutions and adaptation technologies would reduce the welfare losses under adverse weather events.

The next section presents the theoretical framework and methodological approach. In section 3, we provide an overview of the data and constructed variables. Findings are presented in sections 4 and 5 and projections in section 6. The last section provides concluding remarks.

2 Theoretical and methodological approaches

2.1 Theoretical framework

We apply the framework presented by Hsiang et al. [2019] for studying the distributional implications of environmental goods. Here, an environmental externality (i.e. damage) is a social cost that can be expressed as a function of two factors: the level of *exposure* to environmental conditions and the *socioeconomic attributes* that may affect the implications of exposure for welfare. Formally, this function is captured by the following equation:

$$D = f(e, x) \tag{1}$$

Here, D is environmental damage, e is level of exposure and x captures socio-economic attributes. Exposure refers to the state of the environment at a given time in a given space, such as for instance, air pollution, deforestation, or temperature. The socioeconomic attributes may interact with exposure via the damage function. They are the potential sources of vulnerability, whereby vulnerability is here defined as the rate at which exposure to environmental conditions generates harm given some initial conditions. Individual vulnerability depends, for instance, on baseline health, gender, avoidance behavior or defensive investments (e.g., buying an air conditioner).

This framework assumes that, conditional on the same levels of exposure and socioeconomic attributes, the damage function is constant across individuals. Change in the environmental exposure might have important distributional implications for two reasons. First, if the change in environmental exposure differs across individuals, the change in environmental damages is likely to differ as well, regardless of the initial level of exposure or the structure of the damage function. Second, even if the change in exposure is relatively uniform across individuals, the distributional implications may result from differing vulnerability across individuals [Hsiang et al., 2019].

As this study focuses on the distributional implications of weather and climate, we further focus on the environmental damages resulting from climate change. Based on the literature analysis, Hsiang et al. [2019] argue that the exposure of poor and rich to current and future climate change is comparable. However, the poorer exhibit larger marginal damages from climate change, i.e. comparable changes in e.g. temperature or precipitation impose greater damage on the poorer segments of population. Hsiang et al. [2019] argue that the two main origins of these vulnerabilities are: i) economic (e.g. less access to credit or technology) and ii) nonlinear damage function (i.e. poorer people generally inhabit locations whose baseline climates are less favorable, i.e. correspond with the steeper portions of damage functions).

In this study, we build upon the insights from Hsiang et al. [2019] to understand whether poor and non-poor react differently to climate-related events, and if so then why. Firstly, we conduct a formal test, to see whether the level of exposure to changing temperature and precipitation is different for poor and non-poor in rural India. The outcomes (Appendix A, Table 6) suggest that poor and non-poor were exposed to different changes in weather. Between the two IHDS rounds (for more details on data, see section 3.1) the poor faced on average smaller decrease in spring temperature, larger decrease in summer temperature and smaller increase in the winter temperature compared to non-poor. Moreover, the poor faced larger decrease in monsoon and winter precipitation compared to non-poor. Further, we test whether poor and non-poor are predicted to be exposed to significantly different changes in temperature and precipitation in the future, under RCP8.5 (for more details on projections, see section 3.3). The outcomes (Appendix B, Table 7) suggest that the rural poor in India will face larger increase in spring, but a smaller increase in summer temperature. Moreover, the poor are forecasted to experience larger decrease in summer monsoon, smaller increase in rabi precipitation and a smaller decrease spring precipitation compared to non-poor. We also conducted a formal test, whether rural poor inhabit locations with different climatic conditions compared to rural non-poor. The test in Appendix C suggests that as for temperature, poorer households seem to live in slightly warmer climates.

Overall, these findings suggest that in rural India the heterogeneity in the responses to changing weather may stem from: i) different levels of exposure and ii) different levels of initial conditions. Additionally, to analyze whether the the poor and non-poor have different responses to marginal changes in weather and whether these responses stem from differences in their socio-economic characteristics, we conduct a series of regression analyses (see next section). We hypothesize that the poorer segments of population face larger climate-related marginal damages (for evidence, see outcomes in section 4) as a result of their higher vulnerability, originating in their economic situation. Understanding the causes of individuals' vulnerability remains a challenge for economists, as it requires an exogenous variation in factors determining this vulnerability. We discuss how we approach this issue in sections 2.2 and 3.

2.2 First difference approach

The first difference approach addresses the problem of omitted variables with panel data, by accounting for household-specific (h), time-invariant fixed-effects (λ_h). It enables us to identify a causal relationship between average temperature (T) and precipitation (P) at the district-level (d), and a variable approximating households' welfare (W). By interacting temperature and precipitation with household-specific characteristics from IHDS-I (X), we explore the distributional implications of, or households' vulnerabilities to weather variations.

Consequently, our equation for the first time period ($t = 1$) is defined as follows:

$$W_{hd1} = \alpha + \beta_1 T_{d1} + \beta_2 T_{d1} X_{hd1} + \beta_3 X_{hd1} + \beta_4 P_{d1} + \beta_5 P_{d1} X_{hd1} + \lambda_h + \epsilon_{hd1} \tag{2}$$

The equation for the second time period ($t = 2$) is defined in the same manner, enabling us to take the first difference over the two periods in the following way:

$$\begin{aligned} W_{hd2} - W_{hd1} = \alpha - \alpha &+ \beta_1 (T_{d2} - T_{d1}) + \beta_2 ((T_{d2} - T_{d1}) X_{hd1}) + \beta_3 (X_{hd1} - X_{hd1}) \\ &+ \beta_4 (P_{d2} - P_{d1}) + \beta_5 ((P_{d2} - P_{d1}) X_{hd1}) + (\lambda_h - \lambda_h) + (\epsilon_{hd2} - \epsilon_{hd1}) \end{aligned} \tag{3}$$

This leads to dropping out of the time-invariant effects (intercept, household-specific fixed-effects).

We can rewrite the equation to get:

$$\Delta W_{hd} = \beta_1 \Delta T_d + \beta_2 \Delta T_d X_{hd1} + \beta_4 \Delta P_d + \beta_5 \Delta P_d X_{hd1} + \Delta \epsilon_{hd} \tag{4}$$

Additionally, we employ a constant β_0, controlling for any unobserved trend common to the whole rural India and estimate the following equation:

$$\Delta W_{hd} = \beta_0 + \beta_1 \Delta T_d + \beta_2 \Delta T_d X_{hd1} + \beta_4 \Delta P_d + \beta_5 \Delta P_d X_{hd1} + \Delta \epsilon_{hd} \tag{5}$$

The standard errors are clustered at the district level, given that there is some spatial correlation in our treatment.

3 Data

To build our sample we combine household panel data from the India Human Development Survey (IHDS) produced by the University of Maryland and the National Council of Applied Economic Research, New Delhi with Era-Interim reanalysis data produced by the European Centre for Medium-Range Weather Forecasts and climate projections provided by the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) from Potsdam Institute for Climate Impact Research and the International Institute for Applied Systems Analysis.

3.1 Household data

IHDS has collected nationally representative data from 41,554 households in 1,503 villages and 971 urban neighborhoods across India in two rounds; 2004-2005 (IHDS-I) and 2011-2012 (IHDS-II) [Desai et al., 2005, 2015]. Our final sample contains approximately 26,000 rural households in 354 districts that were interviewed in both rounds. Our sample contains approximately 15,000 farming and approximately 11,000 non-farming households. We categorize rural Indian households as farming households, if they are involved into crop production on land that they either own or rent, using the information from IHDS-I.

Using the information on households' consumption, we construct the dependent variable that aims to approximate households' welfare, namely the logarithms of households' total yearly consumption expenditures per adult equivalent household member in Indian rupees. In both rounds, IHDS asks households a set of questions to estimate their total consumption expenditures. Questions about consumption of frequently purchased items (mostly food) apply a monthly framework (i.e. *how much of these items have been consumed in the past 30 days?*) and questions on the remaining items (e.g. medical items, transportation etc.) apply a yearly framework (i.e. *how much did you spend in the last 365 days on...?*). Based on this information a measure of annual consumption per household member for both IHDS rounds is created. We adjust the values for the differences in the price levels that in India differ by state, rural/urban areas and over time.[1] To produce a measure comparable across households and account for households' economies of scale, we follow Keerthiratne and Tol [2018] and utilize the modified equivalence scale by Organisation for Economic Co-operation and Development (OECD). This scale assigns a value of one to the household head, of 0.5 to each additional adult household member and of 0.3 to each child. This scale accounts for the size and the age of the household members. However, its drawback is that it does not take into account other characteristics that might affect households' needs, such as the number of disabled or sick household members. For the robustness analysis, we utilize a logarithm of households' number of valuable assets per adult equivalent households member (*log(Assets)*). Even more than consumption expenditures, household asset scales reflect the long-term economic level of the household.

In order to analyze the distributional implications via the first difference approach (see section 2.2), we employ a binary variable *Poor* from IHDS-I that captures, whether a household is below the poverty line.[2] We interact this variable with the change in weather between the IHDS rounds. This enables us examining the heterogeneous implications of weather on households' consumption by wealth group. We assume that the values from IHDS-I are exogenous to the changes in consumption and changes in weather between the two IHDS rounds. Even though we are aware that the exogeneity assumption might not perfectly hold, this approach minimizes the reversed causality

[1] We adjust consumption information for the differences in the price levels that differ by state and rural/urban areas by constructing a multiplicator using information on region-specific poverty lines provided by IHDS. We convert the values from IHDS-I to 2012 price levels to make the values in both rounds comparable.

[2] The poverty line is a nation-wide set poverty line that is adjusted for rural/urban and state-specific purchasing power.

and the over-controlling problems and allows for examination of the heterogeneous effects.

To examine households' sources of vulnerability to climate-related damages, we utilize a set of variables from IHDS-I capturing households' economic status (e.g. access to credit or technology) and historical climate, as suggested by Hsiang et al. [2019] (see section 2.1). Also here, we assume that the values from IHDS-I are exogenous to the changes in consumption and changes in weather between the two IHDS rounds. To capture households' access to credit, we employ a binary variable *Bank account* that takes on a value of one, and a zero otherwise. Moreover, we employ a binary variable *Land* that takes on a values of one, if a household owns land. We perceive Land ownership as a form of security/ insurance. To capture households' access to adaptive technologies, we employ a binary variable *Air conditioner* that takes on a value of one if a household owns an air conditioner, we also employ a binary variable *Irrigation* that takes on a value of one if a household has access to irrigation of any type.

The summary statistics presented in Table 1 indicate that a yearly consumption of an adult equivalent household member in rural India amounted to approximately 36000 Indian rupee during the IHDS periods. Moreover, in IHDS-I approximately 23% of rural Indian households live below poverty line, an average rural household owns 4 valuable assets per adult equivalent household member, 63% of rural households own land, 25% have a bank account, 7% have an air conditioner and 33% of rural households have access to irrigation.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Units**
log(Consumption)	10.2766	0.5997	5.2824	14.2905	Log of Consumption
Consumption	35745.4672	33988.6066	196.8435	1607961.25	Indian rupee
log(Assets)	1.226	0.6485	-1.7579	3.1355	Log of Assets
Assets	4.1237	2.5154	0.1724	23	Nr. of assets
Poor	0.2259	0.4182	0		Binary
Land	0.6238	0.4844	0	1	Binary
Bank account	0.2497	0.4328	0	1	Binary
Air conditioner	0.074	0.2617	0	1	Binary
Irrigation	0.3278	0.4694	0	1	Binary
$N_{observations}$			53048		
$N_{households}$			26524		

Table 1: Summary statistics: household-specific variables (IHDS data).

3.2 Weather data

Era-Interim is a high-quality reanalysis dataset, which relies on information from weather stations, satellites, and sondes. It provides data at a variety of grid resolutions, with temporal resolution of up to 6 hours, from January 1979 onwards. Reanalysis data solves for the endogeneity problem resulting from the weather stations placement, variation in the quality of data collection, and variation in the quantity of collected data and produces a consistent best estimate of atmospheric parameters over time and space [Auffhammer et al., 2013, Colmer, 2018, Donaldson and Storeygard, 2016]. This is of a particular importantce in India, where the spatial and temporal coverage of weather stations has deteriorated over time [Colmer, 2018]. We draw on the monthly temperature averages and precipitation totals and aggregate them at the district level. Districts are the finest geographical level that we are able to identify the IHDS households at.

Moreover, Massetti et al. [2016] suggest that to understand climate-related impacts it is important to distinguish between seasons as the coefficients between seasons might be significantly different. Moreover, Massetti et al. [2016] argue that degree days and temperature levels are almost perfect substitutes. Hence, as it should not make a difference which measure is taken, in our analysis we use levels of seasonal temperature and precipitation. There are two major cropping seasons in India. The kharif season lasts from June to September and coincides with the summer monsoon. The rabi cropping season starts in November-December and can stretch to spring (January - March) [Auffhammer and Carleton, 2018, Carleton, 2017, Guiteras, 2009]. Rainfall at the end of the kharif season provides moisture to the soil and in this way determines irrigation for the rabi crop. Hence, kharif monsoon strongly determines both, kharif and rabi yields. For the analysis, we generate variables capturing the change in the district-specific spring, kharif and rabi averages of monthly mean temperature and total monthly precipitation between the two IHDS rounds using weather data from the year preceding the interview. As mentioned in section 3.1, IHDS collected data on consumption using information from the last 30 days and from the last 365 days. Hence, households' consumption is strongly affected by weather from the year preceding the interview. For demonstration, if a household was surveyed in 2004 within IHDS-I, we create six variables capturing average spring, kharif and rabi temperature and precipitation utilizing information from 2003. In a similar manner, we create variables corresponding to IHDS-II. Then we calculate the changes in spring, kharif and rabi temperature and precipitation between the two IHDS rounds. These changes serve as the main source of identification, as described in section 2.2. Because of their high correlation we employ simultaneously temperature and precipitation variables into the regression models to avoid omitted variable bias [Auffhammer et al., 2013].

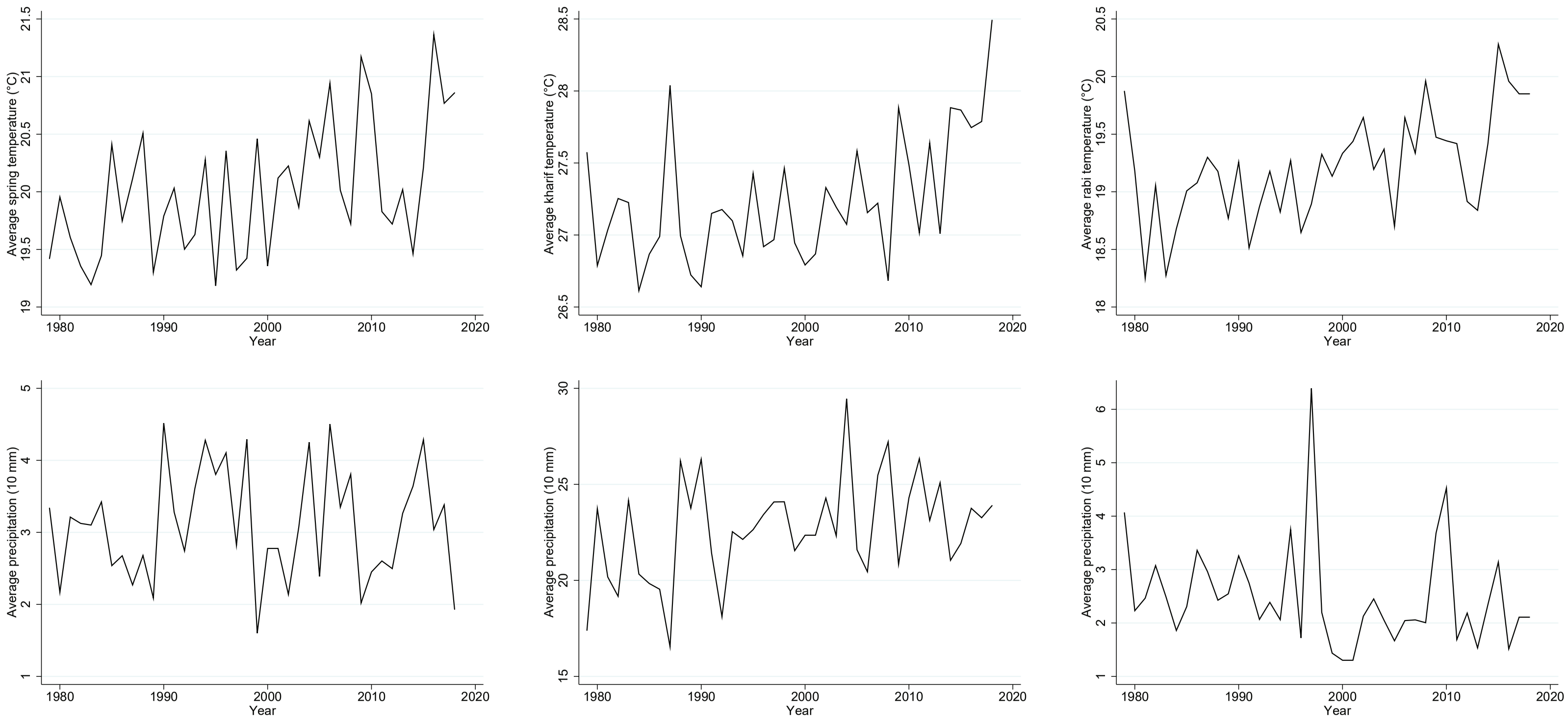
Additionally, we create historical (1979-1998) district-specific averages of monthly spring, kharif and rabi temperature and total precipitation. These variables capture district-specific climate (as opposed to the variables capturing weather, discussed in the previous paragraph). By interacting the weather variables with the historical district-specific averages, we distinguish the effects of temperature and precipitation variations in warmer/ cooler and in drier/ wetter climates, respectively (see section 2.2). These interactions enable us to test whether damages respond conditional on prevailing long-term climate. Weather is expected to have a different effect in every climate (see section 2.1).

Figure 1 depicts the average levels of temperature and precipitation since 1979 till 2018. The upward trend in temperature is obvious when looking at the average spring, kharif and rabi temperatures. As for precipitation, spring and rabi seasons demonstrate a downward trend. When looking at the kharif precipitation, it has an increasing trend.

Table 2 presents summary statistics of the variables generated for the analysis. It shows that between the two IHDS rounds, on average Indian households were exposed to lower spring and kharif and higher rabi temperatures. Moreover, spring and kharif precipitation decreased and rabi precipitation increased between the two IHDS rounds.

3.3 Climate projections data

We derive temperature and precipitation projections from ISIMIP [Warszawski et al., 2013]. ISIMIP provides climate data until 2099 that are in line with five major climate models [Warszawski et al., 2013]. We utilize data at 0.5 degree resolution that are originally from the Princeton Earth System Model of the Geophysical Fluid Dynamics Laboratory (GDFL-ESM2M, [Dunne et al., 2012]) and include a bias-correction technique [Hempel et al., 2013] ensuring long-term statistical agreement of the projections with observational data from the WATCH database [Weedon et al., 2011].



(a) Spring

(b) Kharif

(c) Rabi

Figure 1: Average average temperature (°C) and precipitation (100 mm) over time (1979-2018), (Era-Interim weather data).

Variable	Mean	Std. Dev.	Min.	Max.	Units
Hist. spring temp.	20.6166	5.4054	-3.3525	27.3889	°C
ΔSpring temp.	-0.497	0.7895	-2.7095	2.2815	°C
Hist. temp. kharif	27.4185	2.9445	12.8052	32.1479	°C
ΔTemperature kharif	-0.0272	0.4872	-1.3912	1.3658	°C
Hist. temp. rabi	19.6166	4.5131	-1.1713	25.9024	°C
ΔTemperature rabi	0.2046	0.6311	-1.9343	1.5983	°C
Hist. precip. spring	2.6314	3.0355	0.0254	21.2922	10 mm
ΔPrecip. spring	-1.7345	1.595	-7.7708	3.196	10 mm
Hist. precip. kharif	19.8012	8.7672	3.0819	53.9322	10 mm
ΔPrecipitation kharif	-0.7983	7.1167	-33.7587	17.104	10 mm
Hist. precip. rabi	2.5485	2.6837	0.317	16.1696	10 mm
ΔPrecipitation rabi	0.1045	2.511	-4.9156	8.5522	10 mm
$N_{observations}$			53048		
$N_{households}$			26524		

Table 2: Summary statistics: climate-related variables (Era-Interim weather data).

We draw on the projections corresponding to Representative Concentration Pathway 8.5 (RCP8.5) scenario. RCP8.5 is one of the four greenhouse gas concentration scenarios adopted by the Intergovernmental Panel on Climate Change for the fifth Assessment Report. It is a "business as usual" case, based on forecasts corresponding to low income, high population and high energy demand that results from only modest improvements in energy intensity. RCP8.5 thus represents the pathway with the highest greenhouse gas emissions [Riahi et al., 2011]. We generate district-specific temperature and precipitation averages for the time span 2095-2099. Using 5-year averages ensures that the results are more robust and do not depend on one specific year.

Table 3 presents summary statistics capturing the predicted temperature and precipitation under RCP8.5 and the change compared to weather corresponding to IHDS-I. According to RCP8.5, an average spring temperature is predicted to increase by 4.86°C, average kharif temperature is predicted to increase by 5.6°C and rabi temperature by almost 6°C by the end of this century. Moreover, on average spring precipitation is expected to decrease by 25 millimeters, kharif precipitation is expected to decrease by 28 millimeters and rabi precipitation is expected to increase by almost 3 millimetes.

Variable	Mean	Std. Dev.	Min.	Max.	Units
Temperature spring (2095-2099)	26.3325	4.5648	4.0309	32.6633	°C
Δ Temperature spring	4.86	1.1659	1.1886	9.2788	°C
Temperature kharif (2095-2099)	33.1147	3.3305	18.7242	39.3135	°C
Δ Temperature kharif	5.642	1.4406	0.7007	11.0887	°C
Temperature rabi (2095-2099)	25.9906	3.6975	7.0457	32.1358	°C
Δ Temperature rabi	5.889	1.404	2.0497	9.9485	°C
Precipitation spring (2095-2099)	1.1907	1.7217	0	9.9455	10 mm
Δ Precipitation spring	-2.4294	3.0449	-27.19	4.5793	10 mm
Precipitation kharif (2095-2099)	21.8628	19.324	0	167.6535	10 mm
Δ Precipitation kharif	-2.7911	15.5524	-54.9148	107.8885	10 mm
Precipitation rabi (2095-2099)	2.0221	2.8626	0	17.8214	10 mm
Δ Precipitation rabi	0.379	2.1285	-8.9638	12.2825	10 mm
$N_{observations}$			53048		
$N_{households}$			26524		

The sample size for the temperature variables is with 51900 observations lower, as there are less district-specific temperature predictions. The changes in temperature and precipitation capture differences between weather in IHDS-I and the average for the time span 2095-2099.

Table 3: Summary statistics: climate projections (ISIMIP data).

4 Outcomes

Section 4.1 presents the regression results from the main analysis utilizing the first difference approach. For every set of results, we run the regression on the full sample of rural households, on farming households and on non-farming households. This enables us to test, whether farming households are relatively more vulnerable to climate variations, as they are more strongly dependent on agricultural production and have smaller flexibility (tied to land) to change occupation.

4.1 Distributional effects

Overall, the main results presented in Table 4 suggest that the effects of weather differ by season. Warmer spring temperatures are good for non-poor and have no significant effect on poor households. Warmer temperatures in the monsoon (kharif) season significantly reduce consumption of all types of poor households and do not affect non-poor. The winter (rabi) temperatures increase consumption of all types of poor households and decrease consumption of the non-poor households. The larger magnitudes of the response coefficients of the poor farming households suggest that they react more strongly to weather. However, the poor non-farming households respond to weather variations, likewise. Since in rural India, many individuals are engaged into agricultural labor work, agriculture plays an important role also for non-farming households. To better understand, whether the effect of weather variations is channeled via agricultural labor work, we run the seasonal model separately for non-farming households that in IHDS-I had income from agricultural labor work and for non-farming households that in IHDS-I had zero income from agricultural labor work (see Appendix D, Table 9). The coefficients of spring and rabi temperatures are significant only for poor non-farming households with income from agricultural labor work. This suggests that spring and rabi temperature variations may affect households beyond their agricultural activities, i.e. through labor market effects, local economy effects or non-agricultural impacts (e.g. on health). The effect of kharif temperature variations is negative and significant for both types of non-farming households, suggesting that it is not channeled solely via agriculture. Too high summer temperatures are bad for all poor rural households in India.

The main outcomes further show that the non-poor do not react significantly to precipitation variations in any season. Moreover, spring precipitation is negatively associated with consumption of all types of poor households. Monsoon is negatively associated with consumption of poor farming households only. Winter precipitation is, on the other hand, positively associated with consumption of poor in all three models. These outcomes may reflect that the poor are more vulnerable to the monsoon floods (because they have lowland along the rivers) and that poor farmers are most likely dryland farmers so they need the rain in the winter. To better understand, whether agriculture channels the significant effect of spreing and rabi precipitation for non-farmers, we draw again on the results in Appendix D, Table 9. Spring as well as rabi precipitation matter for both types of non-farming households. This suggests that during the drier spring and winter seasons, rain is good also for other purposes than agricultural production. Even though spring is a relatively dry season, precipitation are harmful and the impact reaches beyond agriculture.[3]

To test the robustness of the main outcomes, we run the main models and use households' assets as a dependent variable (see Appendix E, Table 10). We find further evidence of a significant and positive effect of spring temperature for the non-poor, a positive effect of rabi temperature for the

[3]To understand what role irrigation plays we also run the seasonal models and control additionally for households' access to irrigation. The results, however, do not change compared to the results in Table 4 and hence are not displayed.

non-farmers and a negative effect of rabi temperature for non-poor as well as of the positive effect of rabi precipitation for the poor households.

The bottom part of Table 4 further presents the cumulative temperature and precipitation coefficients of the agricultural seasons in India for poor and non-poor. As for the poor households, the negative value of the cumulative effect of temperature is insignificant. The cumulative effect of precipitation is negative and significant. For the non-poor, the positive cumulative effect of temperature and the positive cumulative effects of precipitation are both insignificant. The extent of the distributional implications will depend on the relative magnitude of the predicted climate-related seasonal changes. For overall distributional implications of the future climate change, see section 6.

log(Consumption)	(1) All rural	(2) Farmers	(3) Non-farmers
Temp. spring×Non-poor	0.0713***	0.0491**	0.103***
	(0.0186)	(0.0205)	(0.0235)
Temp. spring×Poor	-0.0300	-0.0170	-0.0515
	(0.0369)	(0.0459)	(0.0376)
Temp. kharif×Non-poor	0.0395	0.0225	0.0443
	(0.0303)	(0.0305)	(0.0385)
Temp. kharif×Poor	-0.181***	-0.217***	-0.145***
	(0.0517)	(0.0615)	(0.0543)
Temp. rabi×Non-poor	-0.0614***	-0.0556**	-0.0680***
	(0.0189)	(0.0222)	(0.0215)
Temp. rabi×Poor	0.167***	0.189***	0.150***
	(0.0427)	(0.0528)	(0.0418)
Precip. spring×Non-poor	0.00261	0.00316	0.00171
	(0.00953)	(0.0107)	(0.0101)
Precip. spring×Poor	-0.174***	-0.175***	-0.170***
	(0.0122)	(0.0154)	(0.0124)
Precip. kharif×Non-poor	-0.00110	-0.000583	-0.00176
	(0.00258)	(0.00287)	(0.00272)
Precip. kharif×Poor	-0.00557	-0.00818**	-0.00149
	(0.00371)	(0.00411)	(0.00397)
Precip. rabi×Non-poor	0.000638	-0.00387	0.00421
	(0.00650)	(0.00691)	(0.00733)
Precip. rabi×Poor	0.0538***	0.0562***	0.0493***
	(0.0121)	(0.0172)	(0.0117)
N	53048	30798	22250
R^2	0.170	0.154	0.195
Trends	Yes	Yes	Yes
Temp. (cum) x Non-poor	.0494	.016	.0795
Temp. (cum) x Non-poor [SD]	.0371	.0405	.0416
Temp. (cum) x Poor	-.0441	-.0453	-.0469
Temp. (cum) x Poor [SD]	.0673	.0779	.0708
Precip. (cum) x Non-poor	.0021	-.0013	.0042
Precip. (cum) x Non-poor [SD]	.0093	.0103	.0106
Precip. (cum) x Poor	-.1255	-.1274	-.122
Precip. (cum) x Poor [SD]	.014	.0173	.0142

Standard errors clustered at the district-level in parentheses.

* p<0.10, ** p<0.05, *** p<0.01.

Table 4: Distributional effects of seasonal weather variations on households' welfare in rural India, first difference approach.

5 Source of vulnerabilities

In this section, we analyze the sources of households' vulnerabilities to weather variations. The coefficients from the regressions are presented in Figure 2 (for the complete regression results, see Table 11, Appendix F).

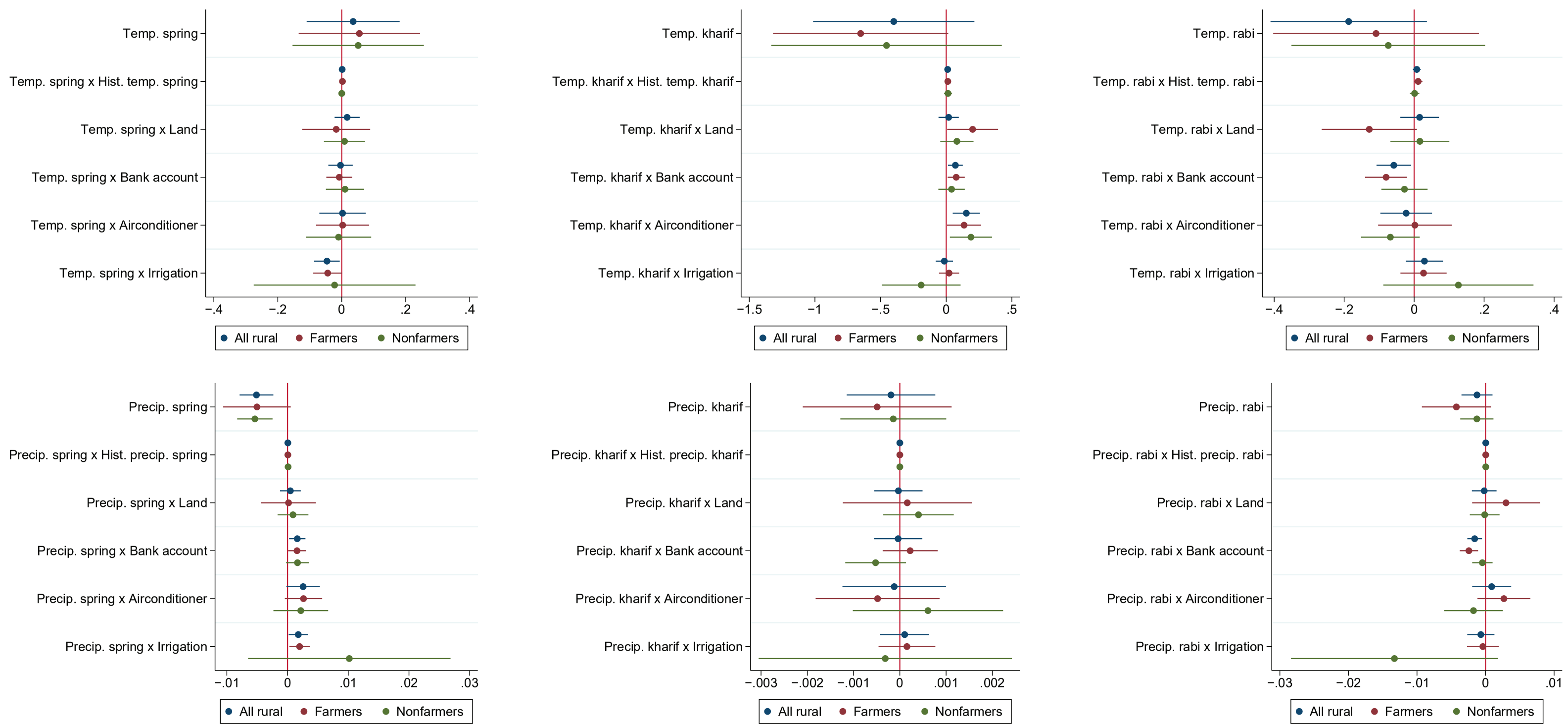
We find a significant interaction term with historical climatic conditions for the rabi season. The positive coefficient of rabi temperature in model 2 suggests that farming households that are warmer in winter have higher consumption. The magnitude of the interaction term for rabi precipitation is so small that we abstract from its interpretation. For the figures presenting the results from model 1 on marginal effect of temperature conditional on historical climate see Appendix G, and on marginal effect of precipitation see Appendix H.

The significantly positive interaction term between kharif temperature and land ownership in model 2 suggests that if temperature in summer increases, farming households that own land have higher consumption compared to farming households that rent land. Moreover, the significantly negative interaction term between rabi temperature and land ownership in model 2 implies that if winter temperature decreases, farming households that own land have higher consumption compared to farming households that rent land. Hence, land ownership provides farmers with more economic security and lower vulnerability to weather variations.

We find evidence that bank account ownership mitigates the adverse effects of weather and it has a significant effect for farming households. The significantly positive interactions (models 1 and 2) with kharif temperature suggest that households with bank account have higher consumption if summer temperature increases compared to households without a bank account. The significantly negative effect of winter temperatures suggest that househodls that have a bank account have higher consumption if the winter temperature decreases compared to households without a bank account. Moreover, the negative effect of spring precipitation can also be mitigated by bank account ownership for all types of households. Households that face lower precipitation during the dry rabi season have higher consumption if they have a bank account. Access to banks and a bank account ownership enable households to smooth their consumption by saving up or borrowing money and make them less vulnerable to the estimated adverse weather events.

The positive and significant (in all three models) effect of the interaction term between kharif (summer) temperature and air conditioner ownership suggests that all types of households that own an air conditioner have higher consumption if summer temperature increases compared to households without an air condition. Whether this outcome implies welfare enhancement is, however, not clear. Consumption can increase in summer from air conditioning but this might not be a welfare improvement. It may simply be more money spent on air conditioning. The higher consumption may in fact be a decrease in welfare.

Lastly, we find significantly positive interaction terms of spring precipitation and irrigation in models 1 and 2. Hence, farming households that have access to irrigation can mitigate the negative effect of spring precipitation and have higher consumption compared to households without access to irrigation.



(a) Spring

(b) Kharif

(c) Rabi

Figure 2: Sources of households' vulnerabilities to temperature (left) and precipitation (right) variations (for complete regressions results, see Appendix F)

6 Predictions

We utilize the estimated coefficients from the main model (Table 4, model 1) to quantify the past change in consumption that households have experienced between the two IHDS rounds due to weather variations. We also predict the future change in consumption households are forecasted to experience as a response to changes in average temperature and precipitation under RCP8.5 by the end of the 21st century. For the predictions, we only utilize the estimated significant seasonal coefficients. The outcomes are presented in Table 5.

We calculate the linear prediction (fitted values) of change in consumption for poor (0.49) and non-poor (0.11) households from the main model. As a next step, we model a set of past and future scenarios to quantify the change in consumption in response to past and future climate-related changes, by type of household. For demonstration, to predict the past consumption change in response to kharif temperature variations for poor households, we set the kharif temperature change between the two IHDS round to zero and calculate the linear prediction from the model (0.48). The difference between this value and the linear prediction from the main model using the original data gives the change in consumption caused by kharif temperature variations between the two IHDS rounds (0.49-0.48=0.01) for the poor households. To predict the consumption change in response to future kharif temperature change for poor, we set the kharif temperature change to the changes predicted under RCP8.5 and calculate the linear prediction from the main model (-0.53). The difference between this value and the linear prediction from the model using the original data gives the average change in consumption for the poor due to future increase in kharif temperature (-0.53-0.49=-1.02) under RCP8.5.

The non-poor households react significantly only to the variations in spring and rabi temperature. Therefore, for them we only predict the past and future changes in consumption in response to temperature changes in these two seasons. The predictions show that non-poor households have lost 3% of their consumption in response to past (between IHDS rounds) weather variations and are expected to gain 3% in consumption by 2099 under RCP8.5. The poor households react significantly to the kharif and rabi temperatures and spring and rabi precipitation variations in both seasons. The outcomes suggest that the poor had overall by 34% higher consumption due to weather variations between the two IHDS rounds. Moreover, by 2099, the rural poor in India are expected to loose on average 6% of their consumption under RCP8.5 compared to scenario with no changes in temperature and precipitation. Overall, these results show that the temperature and precipitation changes predicted under RCP5.5 will aggravate inequality in rural India. The poor are expected to become poorer and the non-poor are expected to gain.

7 Conclusion

A better understanding of climate-related effects on wealth inequality is critical for achieving equitable economic development under the threat of climate change. While most of the studies in this area provide evidence at a more aggregate level (regional or national economies), the within country implications of climate-related events on wealth distribution and poverty have not received much attention. In this study, we contribute to this research gap with evidence of weather and climate-related effects on within-country inequality in rural India.

The main limitation of our study is that the data structure only enables us to analyze short-run weather variations. To study responses to changing climate, ideally we would need data stretching over a longer period of time (i.e. 30 years at least). Therefore, our predictions of climate change impacts presented in section 3.3 are based on short-run responses to weather and may fail to consider households' adaptation in the long-run. Despite these shortcomings, our study provides the first comprehensive analysis of attributing weather variations to within-country wealth distribution at the household level.

Our results show that the poor are more sensitive to weather variations compared to the non-poor. They respond more strongly to (seasonal) temperature changes: negatively in a hot season, positively in a cold season. The cumulative effect of temperature for poor is, however, not significant (i.e. a homogeneous increase in temperature among both seasons would have no effect). Moreover, while the poor respond strongly to precipitation variations, the non-poor do not respond significantly. Rainfall in (dry) rabi season is beneficial for the poor, but in (dry) spring it is not. Hence, in order to understand the impacts of weather, it is important to distinguish between the seasons as the coefficients differ.

Scenario	Poor		Non-poor	
	Predicted value	Δ Main model	Predicted value	Δ Main model
Main model	0.49		0.11	
Temperature spring				
Past zero Δ			0.13	-0.02
Future Δ			0.49	+0.38
Temperature kharif				
Past zero Δ	0.48	+0.01		
Future Δ	-0.53	-1.02		
Temperature rabi				
Past zero Δ	0.47	+ 0.02	0.12	-0.01
Future Δ	1.46	+0.97	-0.24	-0.35
Precipitation spring				
Past zero Δ	0.16	+0.33		
Future Δ	0.46	-0.03		
Precipitation kharif				
Past zero Δ				
Future Δ				
Precipitation rabi				
Past zero Δ	0.51	-0.02		
Future Δ	0.51	+0.02		
Total past Δ		0.34(+34%)		-0.03(-3%)
Total future Δ		-0.06(-6%)		+0.03(+3%)

Table 5: Predicted past (between IHDS rounds) and future (between IHDS-I and 2099, according to RCP8.5) changes in households' consumption due to weather and climate.

The outcomes further suggests that the weather impacts in rural India are not solely channeled via agriculture. Moreover, the economic factors (bank account ownership, land ownership or access to adaptation technology) and historical climate are crucial for explaining the heterogeneity in households' responses to weather. Individuals that are able to smooth their consumption (i.e. access to financial institutions, wealth) or can avoid the adverse weather effects (e.g. via access to irrigation) face lower marginal damages from adverse weather events. Individuals that live in less favorable climates (e.g. hotter climates), on the other hand, face higher marginal damages.

In conclusion, the outcomes of this study imply that climate as well as weather affect welfare distribution in rural India. Moreover, temperature and precipitation changes predicted under RCP5.5 will aggravate inequality. Hence, policies that improve access to financial institutions or adaptation technologies could mitigate the welfare losses under climate change.

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A Difference in past changes in weather by poor vs. non-poor

	Mean(Poor1=1)	Mean(Poor1=0)	Diff.	Std. Error	Obs.
ΔTemp. spring	-0.3694	-0.5342	-0.1648***	0.0115	26524
ΔTemp. kharif	-0.0987	-0.0063	0.0923***	0.0071	26524
ΔTemp. rabi	0.1596	0.2178	0.0582***	0.0093	26524
ΔPrecip. spring	-1.7356	-1.7342	0.0014	0.0234	26524
ΔPrecip. kharif	-1.5666	-0.5742	0.9924***	0.1043	26524
ΔPrecip. rabi	-0.3375	0.2334	0.5709***	0.0367	26524

Table 6: T-test of differences in past changes in weather by poor (Poor=1) vs. non-poor.

B Difference in future changes in weather by poor vs. non-poor

	Mean(Poor1=1)	Mean(Poor1=0)	Diff.	Std. Error	Obs.
ΔTemp. spring	5.0056	4.8166	-0.1889***	0.0172	25950
ΔTemp. kharif	5.6077	5.6521	0.0444**	0.0213	25950
ΔTemp. rabi	5.8820	5.8911	0.0091	0.0207	25950
ΔPrecip. spring	-1.7604	-2.6246	-0.8642***	0.0444	26524
ΔPrecip. kharif	-5.6106	-1.9685	3.6421***	0.2273	26524
ΔPrecip. rabi	0.1454	0.4472	0.3018***	0.0312	26524

Table 7: T-test of differences in future changes in temperature and precipitation predicted under RCP8.5 by poor (Poor=1) vs. non-poor.

C Difference in historical mean climate inhabited by poor vs. non-poor

	Mean(Poor1=1)	Mean(Poor1=0)	Diff.	Std. Error	Obs.
Hist. temperature	25.1726	24.2994	-0.8732***	0.0373	53048
Hist. precipitation	00.0293	0.0292	-0.0001	0.0002	53048

Table 8: T-test of differences in historical mean climate inhabited by poor (Poor=1) vs. non-poor.

D Role of weather for non-farming households

log(Consumption)	(1) Agricultural labor inc.	(2) No agricultural labor inc.
Temp. spring×Non-poor	0.117***	0.0911***
	(0.0301)	(0.0277)
Temp. spring×Poor	-0.0910**	0.0456
	(0.0420)	(0.0465)
Temp. kharif×Non-poor	-0.0215	0.0687*
	(0.0555)	(0.0400)
Temp. kharif×Poor	-0.173***	-0.146**
	(0.0607)	(0.0713)
Temp. rabi×Non-poor	-0.0537*	-0.0699***
	(0.0304)	(0.0247)
Temp. rabi×Poor	0.200***	0.0590
	(0.0494)	(0.0527)
Precip. spring×Non-poor	0.0144	-0.00954
	(0.0113)	(0.0118)
Precip. spring×Poor	-0.145***	-0.197***
	(0.0151)	(0.0133)
Precip. kharif×Non-poor	-0.00242	-0.00133
	(0.00346)	(0.00312)
Precip. kharif×Poor	-0.00121	0.000436
	(0.00438)	(0.00507)
Precip. rabi×Non-poor	0.0111	0.00340
	(0.00907)	(0.00829)
Precip. rabi×Poor	0.0531***	0.0410***
	(0.0123)	(0.0129)
Trends	Yes	Yes
N	10054	12196
R^2	0.238	0.169

Standard errors clustered at the district-level in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

Table 9: Distributional effects of annual weather variations on welfare of non-farming households in rural India, first difference approach.

E Distributional effects - robustness analysis

log(Assets)	(1) All rural	(2) Farmers	(3) Non-farmers
Temp. spring×Non-poor	0.0308**	0.0207	0.0409*
	(0.0152)	(0.0150)	(0.0211)
Temp. spring×Poor	-0.0238	0.00478	-0.0604*
	(0.0241)	(0.0237)	(0.0340)
Temp. kharif×Non-poor	0.0817***	0.0814***	0.0773***
	(0.0171)	(0.0177)	(0.0257)
Temp. kharif×Poor	0.0622*	0.0404	0.0794*
	(0.0336)	(0.0366)	(0.0447)
Temp. rabi×Non-poor	-0.0313**	-0.0253*	-0.0426***
	(0.0133)	(0.0145)	(0.0156)
Temp. rabi×Poor	0.0387	0.0118	0.0777**
	(0.0302)	(0.0318)	(0.0364)
Temp. spring×Non-poor	0.0226***	0.0225***	0.0235***
	(0.00509)	(0.00557)	(0.00621)
Temp. spring×Poor	-0.00514	-0.00801	-0.000257
	(0.00789)	(0.00875)	(0.00972)
Precip. kharif×Non-poor	0.000597	-0.000243	0.00197
	(0.00156)	(0.00171)	(0.00180)
Precip. kharif×Poor	-0.00400	-0.00388	-0.00530
	(0.00250)	(0.00258)	(0.00331)
Precip. rabi×Non-poor	-0.00169	-0.00124	-0.00473
	(0.00425)	(0.00448)	(0.00524)
Precip. rabi×Poor	0.0147*	0.0171*	0.00811
	(0.00773)	(0.00925)	(0.00939)
Trends	Yes	Yes	Yes
N	53048	30798	22250
R^2	0.319	0.296	0.351

Standard errors clustered at the district-level in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table 10: Distributional effects of seasonal weather variations on households' consumption in rural India, first difference approach.

F Vulnerabilities

Table 11: Sources of households' vulnerabilities to weather variations

	(1)	(2)	(3)
log(Consumption)	All rural	Farmers	Non-farmers
Temp. spring	0.0357	0.0551	0.0514
	(0.0738)	(0.0964)	(0.104)
Temp. spring×Hist. temp. spring	0.00135	0.00218	0.0000706
	(0.00344)	(0.00361)	(0.00483)
Temp. spring×Land	0.0169	-0.0172	0.00868
	(0.0199)	(0.0539)	(0.0327)
Temp. spring×Bank account	-0.00383	-0.00772	0.0103
	(0.0194)	(0.0206)	(0.0304)
Temp. spring×Air conditioner	0.00248	0.00287	-0.00989
	(0.0369)	(0.0421)	(0.0518)
Temp. spring×Irrigation	-0.0462**	-0.0439*	-0.0224
	(0.0203)	(0.0229)	(0.128)
Temp. kharif	-0.400	-0.652*	-0.454
	(0.312)	(0.339)	(0.446)
Temp. kharif× Hist. temp kharif	0.0110	0.0122	0.0137
Trends	Yes	Yes	Yes
N	53048	30798	22250
R^2	0.094	0.087	0.108

Standard errors clustered at the district-level in parentheses.

* p<0.10, ** p<0.05, *** p<0.01.

Table 11 – *Continued from previous page*

log(Consumption)	(1) All rural	(2) Farmers	(3) Non-farmers
	(0.0108)	(0.0115)	(0.0155)
Temp. kharif× Land	0.0184	0.201**	0.0813
	(0.0392)	(0.0984)	(0.0643)
Temp. kharif×Bank account	0.0698**	0.0760**	0.0406
	(0.0286)	(0.0331)	(0.0511)
Temp. kharif×Air conditioner	0.153***	0.136**	0.188**
	(0.0527)	(0.0660)	(0.0815)
Temp. kharif×Irrigation	-0.0144	0.0217	-0.191
	(0.0336)	(0.0389)	(0.152)
Temp. rabi	-0.187	-0.109	-0.0739
	(0.114)	(0.149)	(0.141)
Temp. rabi×Hist. temp. rabi	0.00759	0.0115*	0.00134
	(0.00565)	(0.00623)	(0.00686)
Temp. rabi×Land	0.0157	-0.128*	0.0164
	(0.0280)	(0.0691)	(0.0428)
Temp. rabi×Bank account	-0.0581**	-0.0801***	-0.0276
Trends	Yes	Yes	Yes
N	53048	30798	22250
R^2	0.094	0.087	0.108

Standard errors clustered at the district-level in parentheses.

* p<0.10, ** p<0.05, *** p<0.01.

Table 11 – *Continued from previous page*

log(Consumption)	(1) All rural	(2) Farmers	(3) Non-farmers
	(0.0251)	(0.0305)	(0.0335)
Temp. rabi×Air conditioner	-0.0227	0.00222	-0.0679
	(0.0375)	(0.0534)	(0.0426)
Temp. rabi×Irrigation	0.0295	0.0268	0.127
	(0.0270)	(0.0335)	(0.109)
Precip. spring	-0.0512***	-0.0503*	-0.0538***
	(0.0141)	(0.0283)	(0.0148)
Precip. spring× Hist. precip. spring	0.000519	0.000560	0.000940
	(0.00147)	(0.00151)	(0.00231)
Precip. spring×Land	0.00468	0.00169	0.00899
	(0.00868)	(0.0229)	(0.0129)
Precip. spring×Bank account	0.0161**	0.0156**	0.0164*
	(0.00683)	(0.00744)	(0.00957)
Precip. spring×Air conditioner	0.0257*	0.0263*	0.0219
	(0.0140)	(0.0156)	(0.0229)
Precip. spring×Irrigation	0.0177**	0.0199**	0.102
Trends	Yes	Yes	Yes
N	53048	30798	22250
R^2	0.094	0.087	0.108

Standard errors clustered at the district-level in parentheses.

* p<0.10, ** p<0.05, *** p<0.01.

Table 11 – *Continued from previous page*

	(1)	(2)	(3)
log(Consumption)	All rural	Farmers	Non-farmers
	(0.00805)	(0.00858)	(0.0847)
Precip. kharif	-0.00191	-0.00489	-0.00141
	(0.00486)	(0.00817)	(0.00581)
Precip. kharif×Hist. precip. kharif	1.75e-06	2.29e-06	5.34e-06
	(0.0000148)	(0.0000162)	(0.0000172)
Precip. kharif×Land	-0.000304	0.00161	0.00404
	(0.00265)	(0.00708)	(0.00387)
Precip. kharif×Bank account	-0.000363	0.00223	-0.00524
	(0.00265)	(0.00302)	(0.00333)
Precip. kharif×Air conditioner	-0.00122	-0.00481	0.00608
	(0.00569)	(0.00680)	(0.00825)
Precip. kharif×Irrigation	0.00105	0.00153	-0.00315
	(0.00269)	(0.00312)	(0.0139)
Precip. rabi	-0.0125	-0.0425*	0.000317**
	(0.0115)	(0.0256)	(0.000140)
Precip. rabi×Hist. precip. rabi	0.000315**	0.000289*	0.000317**
Trends	Yes	Yes	Yes
N	53048	30798	22250
R^2	0.094	0.087	0.108

Standard errors clustered at the district-level in parentheses.

* p<0.10, ** p<0.05, *** p<0.01.

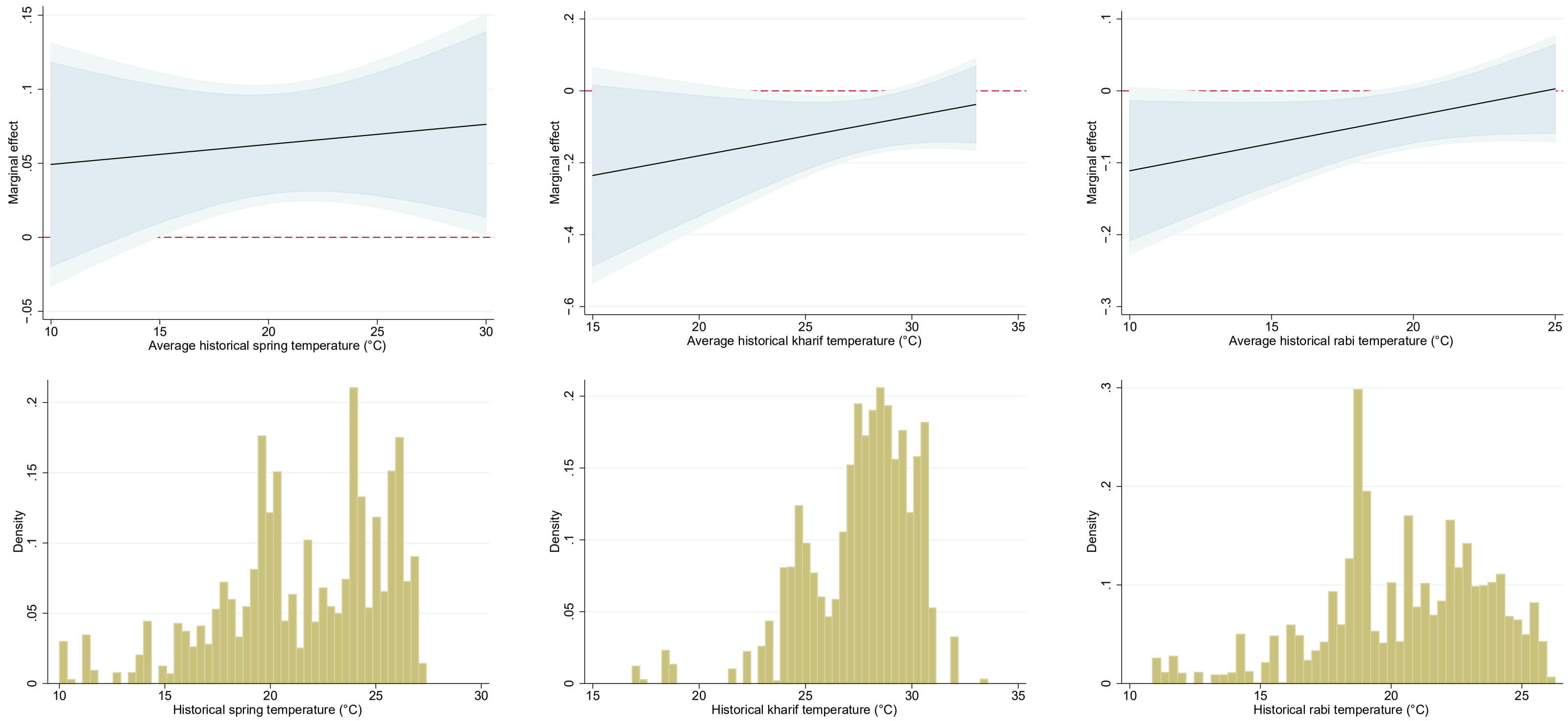
Table 11 – *Continued from previous page*

log(Consumption)	(1) All rural	(2) Farmers	(3) Non-farmers
	(0.000131)	(0.000162)	(0.000140)
Precip. rabi×Land	-0.00191	0.0299	-0.00123
	(0.00914)	(0.0251)	(0.0110)
Precip. rabi×Bank account	-0.0159***	-0.0243***	-0.00459
	(0.00544)	(0.00682)	(0.00756)
Precip. rabi×Air conditioner	0.00899	0.0268	-0.0176
	(0.0145)	(0.0196)	(0.0217)
Precip. rabi×Irrigation	-0.00683	-0.00389	-0.133*
	(0.0101)	(0.0117)	(0.0766)
Trends	Yes	Yes	Yes
N	53048	30798	22250
R^2	0.094	0.087	0.108

Standard errors clustered at the district-level in parentheses.

* p<0.10, ** p<0.05, *** p<0.01.

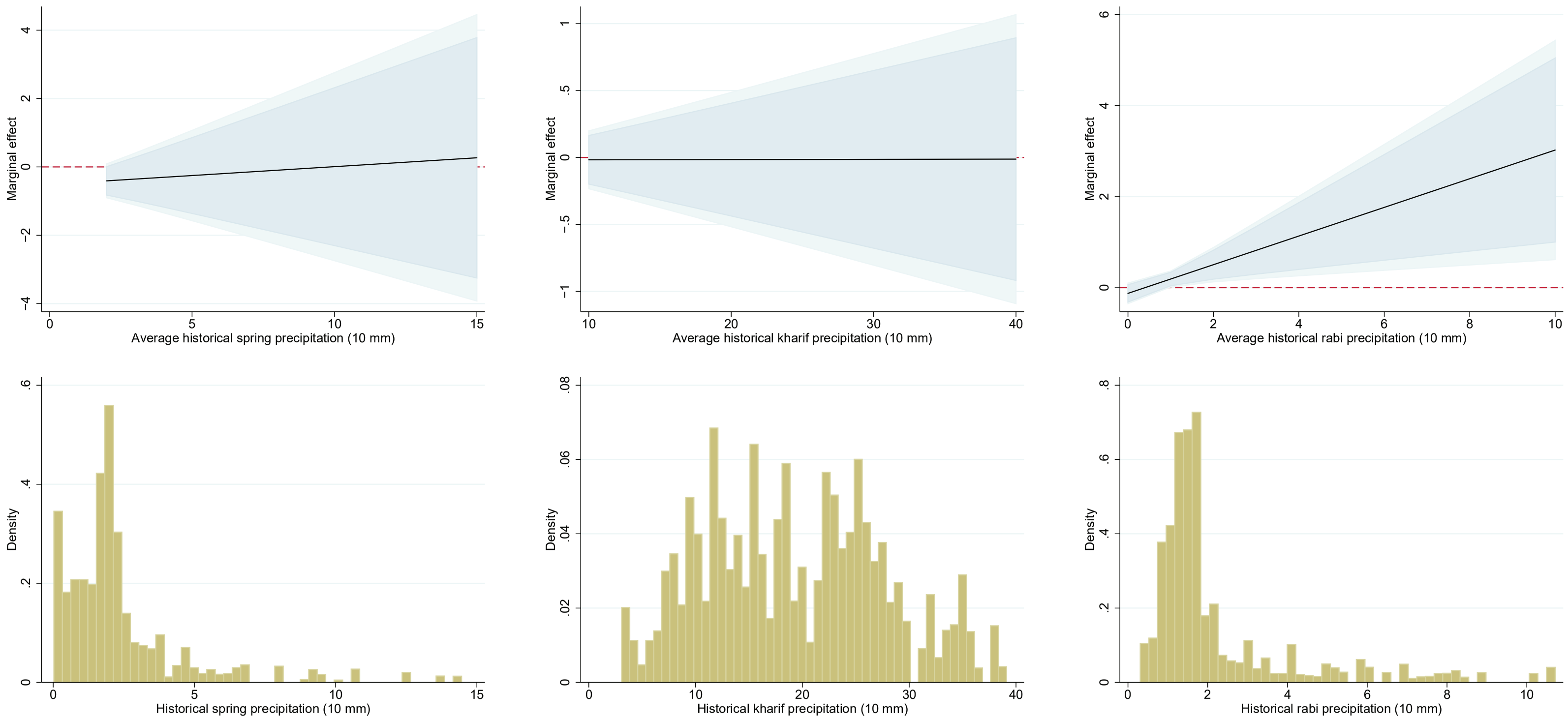
G Marginal effect of seasonal temperature conditional on historical climate



(a) Spring (b) Kharif (c) Rabi

Figure 3: Marginal effect of seasonal temperature conditional on historical climate, coefficients from model (1) in Table 11, Appendix F

H Marginal effect of seasonal precipitation conditional on historical climate



(a) Spring

(b) Kharif

(c) Rabi

Figure 4: Marginal effect of seasonal precipitation conditional on historical climate, coefficients from model (1) in Table 11, Appendix F