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RESEARCH ARTICLE

Impacts of climate shocks on household consumption and inequality in India

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Abstract

This paper examines the impact of climate shocks, measured as temperature and precipitation variability, on real monthly per capita consumption expenditure of Indian households over the 1988–2012 period, utilising data from the National Sample Survey Organisation's Consumer Expenditure Surveys. The regression results show an increase in consumption by 1.2 per cent on average, in response to a one standard deviation rise in temperature, with heterogeneous impacts across economic sectors. While agricultural and industrial households experience consumption declines of 1.7 per cent and 8.3 per cent on average, service sector households exhibit consumption increases by 2.4–9.6 per cent on average across rural and urban regions, in response to a one standard deviation rise in temperature. The analysis suggests an increase in inequality of consumption across sectors due to climatic shocks, with implications for climate policy and sustainable development in India.

Key words: agriculture; climate change; India; industry; inequality

JEL classification: Q54; Q50; Q15; O14

1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) has documented an increase in global average surface temperature of 0.6°C since 1861 and an average global sea level rise of 0.1–0.2 m over the 20*th* century (Cubasch *et al*., 2013). In addition, the World Meteorological Organisation (WMO, 2019) has observed a warming of 0.99 ± 0.13°C above pre-industrial levels, making 2015–2018 the warmest period in global climate records (WMO, 2019). This rise in average temperature is *extremely likely* to have been caused by an unprecedented increase in anthropogenic GHG emissions, such as carbon dioxide, methane, nitrous oxide (IPCC, 2014).

Climate change is one of the most pertinent challenges of this century, which could potentially undermine economic growth and exacerbate poverty, hunger and conflict. The Food and Agricultural Organization (FAO) has observed a trend of rising world hunger since 2014, with an estimated 821 million undernourished people in 2017, up from 804 million in 2016 (FAO *et al.*, 2018) with the key reasons cited being economic recession, war and climate change. Poor households are particularly vulnerable due to the compounding of climatic and socioeconomic stressors. In coastal Bangladesh, for instance, intrusion of saltwater, lower crop productivity and prevalence of disease has raised the propensity of households to enter chronic poverty (Olsson *et al.*, 2014). In light of this, the United Nations released its sustainable development agenda in 2015, crucially focusing on mitigation of climate change as part of countries' growth efforts.

This paper addresses a number of research questions relating to climate change and economic development in India. First, what is the impact of climate shocks (defined as higher temperature and precipitation variability) on average household consumption expenditure? Second, how do climatic impacts differ across the agricultural, industrial and service sectors, and by rural-urban strata? Third, what are the distributional consequences of climate shocks across economic sectors and consumption quantiles? Lastly, is there a role for government policies to offset the potentially negative effects of climate shocks on household consumption expenditure?

This article focuses on the Indian economy, as it is the seventh largest in the world by GDP (World Bank, 2018) and the third largest contributor to global GHG emissions, following China and the United States (IEA, 2018). India's real monthly per capita income stands at Rs. 7,975 in fiscal year 2019–20 (MOSPI, 2020), equivalent to US$640 for 2018 (World Bank, 2018). Despite robust economic growth, 22 per cent of Indians live in poverty, i.e., under US$1.90 a day (World Bank, 2019) and close to 800 million people in the Indian subcontinent reside in regions that will be severely vulnerable to climate change by 2050 in the absence of strong policy action to reduce emissions (i.e., the business-as-usual scenario) (Mani *et al.*, 2018).

This is the first study, to the best of our knowledge, that captures the effects of climate shocks at the household-level and across consumption quantiles in India, using nationally representative survey data from the National Sample Survey Organisation (NSSO) over the period 1988–2012. Spanning a long time horizon, the analysis takes into account long-term adaptation by households, while examining short-run responses to climate-induced weather shocks. It further examines heterogeneous climatic impacts across households differentiated by economic sector, rural-urban region and consumption quantile, thus enabling comparisons between not only rich and poor households, but also between poor agricultural households and rich service sector households, for instance. By addressing questions of inequality, economic growth and climate change, this paper contributes empirical evidence to the literature on inclusive growth and sustainable development, with the aim of informing economic and climate policy.

The empirical results reveal an increase in average real per capita consumption expenditure by 1.2 per cent in response to a one-standard-deviation rise in temperature, whereas equivalent precipitation shocks have no statistically significant effects on consumption. Agricultural and rural industrial households on average experience consumption declines of 1.7 and 8.3 per cent, respectively, while consumption of service sector households rises by 2.4–9.6 per cent on average across rural and urban areas, in response to a one-standard-deviation increase in temperature. The distributional analysis, based on quantile regression methods, reinforces these conclusions for the urban industrial and service sectors, but reveals a divergence in agricultural impacts with lower-income households exhibiting consumption increases in rural areas and upper-income households consumption declines in both rural and urban regions.

The paper is structured as follows. Section 2 reviews the existing literature, section 3 describes the econometric framework, including mechanisms, data sources and the empirical methodology, while section 4 presents the empirical results. Section 5 highlights the importance of addressing inequality, section 6 discusses the role of social protection in this context and section 7 concludes.

2 Literature review

Existing research has analysed the economic impact of climate change through empirical econometric models that relate exogenous temperature changes to income losses in linear or quadratic forms (Dell *et al.*, 2014). Dell *et al.* (2012) examine the impact of a rise in temperature and fall in precipitation on the level and growth of economic output, spanning 125 countries over the 1950–2003 period. Their findings reveal a negative relationship, with a 1°C rise in temperature lowering the economic growth rate by 1.3 percentage points in poor countries, with growth effects persisting in the medium run. Similarly, Kalkuhl and Wenz (2018) find long-term reductions of gross regional product by 4.6 per cent in response to a 1°C temperature increase in tropical regions.

Deryugina and Hsiang (2014) similarly estimate the effect of daily temperature on daily and annual income in United States counties over the 1969–2011 period, by aggregating the number of days in a particular temperature category, in a non-linear fashion. They find that daily average productivity declined by 1.7 per cent in response to a 1°C increase in temperature above 15°C. Hsiang and Meng (2015) study the determinants of annual fluctuations in temperature and precipitation in relation to the El Ni no-Southern Oscillation (ENSO), a phenomenon germane to tropical regions, including India in particular. They find that a 1°C increase in the ENSO index raises country-level temperature in the tropics by 0.27°C and lowers precipitation by 4.6 cm on average, with consequent adverse impacts on agricultural output and incomes of around 2 per cent.

Sector-specific evidence in industry and agriculture examines different channels through which climate shocks affect economic activity. Somanathan *et al.* (2015) provide evidence of adverse effects of high temperatures on worker productivity and firm output in Indian manufacturing firms, premised on the mechanism of physiological heat stress. Employing a piece-wise linear function to capture non-linearity, they find that a 1°C rise in temperature above 25°C contracts annual firm output by 3 per cent.

Climate impacts on agriculture in the United States and in developing countries such as India are well documented in the recent literature. Burke and Emerick (2016) find reductions in crop yields due to higher temperatures in the United States, with each additional day at a higher temperature by 1°C, above 29°C, (the optimum temperature for corn production) reducing yields by 0.5 per cent, translating into a 15 per cent yield reduction by the end of the growing season. Their results provide limited evidence of mitigation of short-run damages from climate change through longer-term adaptation by farmers.

A Government of India (2018) study finds adverse effects of temperature and rainfall shocks (defined as values in the top and bottom quintiles of the respective climate distributions) on crop yields in the two agricultural seasons – Kharif (July-September) and Rabi (October-March) – with yields declining significantly more in unirrigated regions than in irrigated ones. Taraz (2017) conducts similar analysis to study adaptation by farmers in response to rainfall shocks by exploiting changes in the monsoon rainfall regimes in India. The key mechanisms highlighted are adaptation through irrigation investment and crop choice. Evidence suggests that farmers plant more drought-tolerant crops following a decade with relatively low levels of precipitation and, similarly, invest more in irrigation following dry years than wet years.

Analogously, Taraz (2018*a*) evaluates the impact of high temperature on crop yields in Indian districts, exploring whether districts that exhibit historically higher temperatures incur smaller damages relative to districts with lower average temperatures. This long-term exposure to heat signals an adaptation mechanism. Second, the presence of groundwater aquifers as a mitigation mechanism for excessive heat stress on crops is tested. The results provide evidence for adaptation through long-term exposure to temperatures up to 30°C, beyond which yield reductions do not differ significantly across traditionally hotter and colder districts.

Another important mechanism of climatic impacts on agricultural households could be migration to more productive regions across states or 'out-migration' to the secondary or tertiary sector for higher wage employment. Dallmann and Millock (2017) examine the impact of increased climatic variability – such as greater frequency, duration and magnitude of drought as well as excess precipitation – on state-level migration flows in India, introducing a lag of five years between the climate anomaly and consequent migration. They find evidence for important channels such as income and agriculture in inducing rural-rural state migration.

A number of recent papers evaluate the human health effects of climate change, by assessing relationships between higher temperatures and mortality rates. Taking into account long-term adaptation, Barreca *et al.* (2015) find that states in the U.S. with historically low temperatures (lowest decile of the temperature distribution) experience a 31 per cent increase in the monthly mortality rates due to an additional day's exposure to temperatures above 90°F. On the other hand, states in the top decile of the temperature distribution witness a mere 0.68 per cent increase in mortality rates in response to equivalent temperature increases. In contrast, Deschênes and Greenstone (2011) find that the mortality risk of higher temperature is highest at both the bottom and top deciles of temperature, relative to the middle of the distribution. Further, their results show that annual energy consumption rises by 0.4 per cent due to a single additional day above 90°F, highlighting the role of energy as a potential adaptation measure by individuals in response to higher temperatures.

Beyond the average effects of weather shocks on consumption, analyzing heterogeneous effects across the consumption distribution is relevant for the discourse on poverty and inequality. Jacoby *et al.* (2011) employ a rural household model to analyse the effects of changes in land prices, wage rates and food prices on household per capita consumption in India, further considering effects across the consumption distribution. The highest distributional effects appear to be due to changes in wage rates, with the distribution highly skewed to the left and large adverse effects on consumption of low-income households. A parallel review of the empirical evidence by Skoufias *et al.* (2011) suggests that climate change may raise poverty rates and have adverse distributional consequences. Quoting studies on Brazil, Sub-Saharan Africa (SSA) and South Asia, they highlight a potential increase in the poverty rate by 3.2 percentage points and an average increase in the number of poor people by 10 million (in SSA and South Asia) relative to a no climate change scenario. Further, there may be differences in the ability of the rich and poor to save and build assets to mitigate the adverse impacts of climate shocks (Olsson *et al.*, 2014). Consequently, socioeconomic stressors compounded by climatic effects may expose low-income households to greater vulnerability and exacerbate existing economic inequality. This preliminary evidence offers a direction for future research on the relationships between poverty, inequality and climate change.

Lastly, while the above studies provide estimates of climate change impacts on economic activity, the policy implications drawn at this juncture are limited. Greenstone and Hanna (2014) investigate the impacts of environmental regulations in India on air and water pollution levels in Indian cities, highlighting the importance of citizen awareness and increased public demand for improvements in air quality, as a mechanism for concerted policy action. A study by Taraz (2018*b*) analyses the effects of a large-scale social protection program, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), in potentially ameliorating the adverse climatic impacts faced by farmers in India. Contrary to expectation, it finds that the implementation of MGNREGA exacerbates the deleterious impact of climate shocks on crop yields, as non-agricultural employment in MGNREGA rises in response to adverse weather shocks. Insofar as this raises a household's total income, the net effect on welfare is still positive. However, the reduction in crop yields raises concerns for national food security. Hence, social insurance programs and state protection through public policy are important in providing protection from climate change damages and analysing their efficacy in mitigating long-term adverse climatic impacts is pertinent in this context.

3 Econometric framework

This framework models the relationship between climate shocks and household consumption, through different mechanisms depending on the sector of the household's principal occupation. Formally,

$$C = f(T, P, \text{NIC}, \text{Region}). \tag{1}$$

A household's consumption expenditure, C, is related to climate variables (temperature T and precipitation P), the sector of employment (National Industrial Classification (NIC) Code) and the region of residence, which differs by rural or urban in the analysis.[1] The regression specification does not include controls such as income or wages as explanatory variables as they are potential outcome variables and, therefore, would form 'bad controls', as discussed by Angrist and Pischke (2009).

3.1 Mechanisms

A number of mechanisms can be outlined through which climate change may affect households, depending on the principal source of income and regional factors. Within the agriculture, forestry and fishing sector, there are four key mechanisms which may influence farm income and consumption. First, higher temperatures and/or low rainfall may reduce crop yields and in turn farm productivity. Insofar as risk mitigation strategies such as availability of irrigation pumps and groundwater aquifers are available to farmers, these effects would be alleviated (Taraz, 2017). As crop yields decline, food prices are expected to rise, which would benefit households that are net producers, while harming those that are net consumers (Jacoby *et al.*, 2011). Hence, average effects on farm revenue and in turn household consumption are ambiguous. Second, loss of animal production due to heat stress may lead to loss of assets, particularly livestock (Walthall *et al.*, 2012). In case of floods, other physical assets of the household may directly be lost or damaged. Third, farmers may respond to a changing climate and reduced crop yields by migrating

[1] Ideally, the region should correspond to the agro-climatic zone in which the household is located. However, this information is not precisely available in the National Sample Survey dataset.

to a different sector, such as manufacturing or services for employment. Lastly, farmers may migrate out of the region to another district within the state or across states in response to unfavourable climatic conditions (Dallmann and Millock, 2017).

Industry would be affected by weather shocks primarily through their adverse impact on labour productivity in the form of physiological heat stress. This is particularly so for mining, manufacturing and construction activities as the strenuous working conditions of workers are compounded with climate-induced heat stress (Somanathan *et al.*, 2015). However, there may be an increase in demand for construction and rebuilding of infrastructure in the aftermath of extreme climate events (Hallegatte *et al.*, 2011). Hence, the net effect appears ambiguous. Higher temperatures may further result in higher energy demand, thus boosting revenues for the electricity sector (Deschênes and Greenstone, 2011). Therefore, the overall effect on industry is ambiguous and further analysis by sub-sector would be required to understand which mechanisms dominate. Lastly, the services sector is expected to be negatively impacted by climate change through reduced worker productivity. However, the dominance of service firms in urban regions, along with the urban heat island effect, which results in higher temperatures in urban regions relative to neighbouring rural areas, may raise energy demand, leading to higher consumer expenditure, thereby also offsetting the reduced productivity (Santamouris *et al.*, 2015). Hence, the net effect of climate shocks on this sector is also unclear. Identifying the precise mechanisms driving impacts by sector involves developing sector-specific models and lies beyond the scope of this paper. Nonetheless, keeping the potential mechanisms in mind provides intuition for the observed differential climatic impacts across various sectors of the economy.

3.2 Data sources

Household-level economic data[2] are drawn from the NSSO, Ministry of Statistics and Programme Implementation (MOSPI), Government of India's Consumer Expenditure Surveys,[3] for the years 1987–88, 1999–2000, 2004–05, 2009–10 and 2011–12. The years 1983 and 1993–94 are excluded from the analysis as these rounds do not provide district codes corresponding to the households and hence cannot be mapped to the climate data. The National Sample Survey (NSS) is conducted on a quinquennial basis with a sample size of approximately 100,000 households per survey (or round). The survey is further conducted uniformly throughout the year, in the form of four sub-rounds (July–September; October–December; January–March; and April–June), following a stratified multi-stage sampling design, to ensure statistical representativeness of the population.

These surveys provide data on household-level monthly per capita consumption expenditure (MPCE) as well as expenditure incurred on a range of food and non-food items including energy (fuel and light), durable goods such as clothing, footwear, education, healthcare, recreation, transport, communication, furniture, appliances, rent, taxes and other personal items.[4] Real MPCE is computed by deflating the nominal MPCE values by the Consumer Price Indices for agricultural labourers for the rural sector and

[2]The merged climate and economic dataset is available from the author upon request.

[3]The National Sample Survey unit-level data are available on the website of MOSPI, at http://mospi.gov.in/98-consumption-surveys-and-levels-living.

[4]The MPCE reflects a household's standard of living and is used as a proxy for household income.

industrial workers for the urban sector respectively, using the base year of 1987–88, drawn from the NSS published reports (NSSO, 2010, 2012).

The 55th round (1999–2000) suffers from comparability issues with the remaining rounds due to a distinction in its design (Datta, 2006). The survey adopted a 365-day recall period for five non-food items, namely, clothing, footwear, durable goods, educational and medical expenses, instead of the 30-day recall for these items, as in the previous rounds. Consequently, MPCE values were significantly underestimated in 1999–2000 relative to the other rounds. However, the comparability issues with the 55th round are ignored as the regression analysis is not expected to be affected by the underestimation, which is uniform throughout the distribution.

An important issue is the lack of a historical income survey in India, which is hence proxied by household-level consumption expenditure. A number of advantages exist for the use of income vis-à-vis consumption, and vice versa. Since income comprises both consumption and savings, the effects of climate shocks on assets and potential consumption smoothing behaviour by individuals can be more precisely examined. Furthermore, evidence of asset-smoothing behaviour by the poor and consumption-smoothing behaviour by the rich in climatic adversity has also been recorded, which would be easier to identify with data on both consumption and savings or assets (Olsson *et al.*, 2014). In addition, consumption inequality is found to be lower than income inequality through consumption-smoothing behaviour and hence the use of consumption rather than income may mask many underlying dynamics between various income groups (Attanasio and Pistaferri, 2016).

On the other hand, consumption may be a better measure of permanent income, as it would be less influenced by transitory shocks, in line with the permanent income hypothesis. Further, consumption may not equal income, through inter-temporal borrowing and lending among households, and hence may better reflect regular household expenditures. Moreover, wealth effects may be better captured through consumption than income, e.g., the purchase of luxury goods. In addition, consumption smoothing may occur through receipt of government transfers, which would not be captured by income. Finally, it is typically easier to accurately measure consumption for low-income households, rather than income, which may be drawn from multiple sources and economic activities, particularly in developing countries (Attanasio and Pistaferri, 2016). Nonetheless, both measures – income and consumption – drawn from household survey data, suffer from under-reporting, particularly at the top of the distribution. Although there is likely to be measurement error in reported consumption, this is not a concern in the regression analysis as the error is expected to be uncorrelated with the explanatory variables, temperature and precipitation. The lack of correlation ensures that the exogeneity assumption is not violated and the regression coefficients are estimated consistently (Pischke, 2007).

Climate data for mean temperature and precipitation over the 1983–2012 period[5] are drawn from the Climatic Research Unit at the University of East Anglia (UEA) which provide data at the level of $0.5^\circ \times 0.5^\circ$ grids on a monthly frequency[6] (Harris *et al.*, 2014). The data were aggregated to the district level based on a simple average using R-GIS.[7]

[5]This period is used to compute the long-run district temperature and precipitation averages.

[6]This paper uses CRU TS version 3.26, a gridded time-series dataset, covering the period 1901–2017.

[7]The 'cruts2poly' package was used for extraction. A step-wise guide is available at https://cran.r-project.org/web/packages/cruts/readme/README.html.

3.3 Methodology

The econometric equation to be estimated is:

$$lnC_{htr} = \alpha_d + \tau_t + \beta T_{dtr} + \delta P_{dtr} + \phi X_{htr} + \epsilon_{htr}, \tag{2}$$

where lnC_{htr} is ln consumption of household h in year t and NSS sub-round r; α_d is a vector of district dummy variables; τ_t are survey year dummies; X_{htr} is a vector of household-specific controls; and ϵ_{htr} is a normally-distributed error term. T_{dtr} and P_{dtr} are temperature and precipitation at the district level, expressed as four different measures: (1) absolute values of T and P in district d, year t and sub-round r; (2) deviations of observed values from their district-sub round-specific long-term means (e.g. $T_{dtr} - \bar{T}_{dr}$); standardized z-scores averaged over the sub-round (e.g., $(T_{dtr} - \bar{T}_{dr})/sd(T_{dtr})$); and standardized z-scores corresponding to the first month of the NSS sub-round (SR), i.e., July (SR-1), October (SR-2), January (SR-3) and April (SR-4). The key identifying assumption is that within-district variation in temperature and precipitation (relative to historical means in a given year t and sub-round r) is exogenous to household consumption expenditure, conditional on local geographic and time varying factors, controlled for by the district and year dummy variables, respectively.

Standard errors are clustered at the district level to account for correlation and heteroskedasticity among households within a district. A limitation of the analysis is that the standard errors are not corrected for spatial and temporal correlation of the climate data, typically done using the Conley (2008) approach, due to the large sample size of the data which proved computationally costly. While this biases the standard errors, the regression coefficients remain unaffected and hence should be asymptotically consistent.

The survey year dummy variables are important not only to capture the trend in mean consumption over the three decades of analysis but also the changing consumption distribution over time, which relies on the assumption of independent, but not identically distributed errors (Wooldridge, 2002). Hence, estimation is conducted distinctly for each time period, in which observations are *i.i.d.* across strata (which ensures asymptotic normality and standard hypothesis testing), with results averaged over time. In addition, the stratification dummies account for cross-sectional correlation among households within a stratum and capture unobserved heterogeneity at the district level such as socioeconomic characteristics as well as the natural geography of the region, which may be correlated. Since there are 580 districts for which the climate and NSS data merge perfectly, including district dummies should not lead to an incidental parameters problem.

Since households are sampled randomly across survey years, the estimation strategy employs pooled cross-sections, rather than household-level panel regressions. Hence, the unobserved heterogeneity is not eliminated as in the case of a fixed effects 'within' estimator; instead, we obtain differential intercept terms across strata. It is important to conduct household-level analysis in order to understand the sector-specific mechanisms driving differential climatic impacts. This regression model is thus estimated using OLS, with a panel fixed-effects regression model subsequently employed to corroborate the results of the pooled cross-section regressions. This is done by averaging household consumption values to the district level and matching them to the district-specific climate parameters. Lastly, the quantile regression method is used for the distributional analysis.

The quantile regression estimator is obtained by minimising the following absolute loss function, at the τ^{th} quantile:

$$\min_{\alpha \in \mathbb{R}, \beta \in \mathbb{R}^k} \sum_{i=1}^{n} c_\tau (y_i - \alpha - x_i \beta),$$

where

$$c_\tau(k) = (\tau - 1 \cdot [k < 0])k,$$

the intercept and slope coefficients, α and β, differ by consumption quantile τ.

Dell *et al.* (2014) discuss how local climatic variables like temperature, soil quality and elevation might be correlated with economic ones such as institutional quality and the level of development. Due to many potential confounders, the cross-sectional approach typically suffers from omitted variable bias, which is circumvented by the panel fixed effects method (Mani *et al.*, 2018). The key identifying assumption in the current analysis is that while district-level economic and climate variables might be correlated with average temperature or rainfall, they would be uncorrelated with exogenous annual fluctuations, or deviations in these climatic parameters from their district-specific long-run mean values. Hence, studying mean deviations and standardized z-scores of climate variables rather than absolute increases in their average values over time is important for identification.

4 Empirical results

4.1 Descriptive statistics

This section presents summary statistics (table 1) for the climate and economic variables used for analysis for the 1983–2012 and 1988–2012 periods, respectively. The mean temperature in India over the 1983–2012 period was 25°C, with a standard deviation of 5.6°C, ranging from −10°C in the northern-most, snowy state of Jammu and Kashmir (in 2011–12) to around 34°C in the more temperate and monsoonal state of Maharashtra. Mean precipitation was 111 mm over the corresponding period, with a large standard deviation of 126 mm. Many states and union territories in diverse climatic regions witnessed no precipitation on average during January to March. These include the hot, arid regions of Rajasthan and Gujarat, the temperate state of Madhya Pradesh and the equatorial regions of Maharashtra, Andhra Pradesh, Karnataka, Goa, Daman & Diu and Dadra & Nagar Haveli.[8] On the other hand, the state of Meghalaya, in particular the East Khasi Hills district, recorded the highest mean rainfall in the country at 781 mm over 1983–2012.[9]

Household-level real MPCE shows a steady increase from Rs. 195 in 1987–88 to Rs. 312 in 2011–12, on average. It is interesting to note that the standard deviation of consumption exceeds the mean in each year of the survey. This does not imply negative expenditures at the bottom of the distribution but simply clustering of poor households toward zero, thus highlighting the vast disparity in consumption between high- and low-income households, with the large upper tail consumption patterns raising the standard

[8] These climate descriptions are based on the KöppenGeiger climate classification, available at https://cran.r-project.org/web/packages/cruts/readme/README.html.

[9] The town of Cherrapunji, until recently known as the wettest place on Earth, lies within the East Khasi Hills district of Meghalaya.

Table 1. Summary statistics

Variables	Mean	Std. Dev.	Min	Max	Interquartile range	Skewness	Kurtosis	Jarque-Bera statistic*
Mean temperature (°C)	24.90	5.649	−10.41	33.88	7.167	−1.333	6.323	410,000
Mean precipitation (mm)	111.1	125.9	0	781.3	175.481	1.452	4.902	270,000
Std. temp.	0.151	0.623	−1.750	1.724	0.963	0.0829	2.334	11,000
Std. pre.	−0.0254	0.563	−1.680	2.268	0.799	0.474	3.048	21,000
Std. temp. (1mo)	0.160	0.883	−2.162	2.189	1.306	−0.0222	2.285	12,000
Std. pre. (1mo)	−0.0848	0.874	−2.202	2.268	1.214	0.664	2.743	41,000
Real MPCE (Rs.)	Mean	Std. Dev.	p10	p25	Median	p90	p99	J-B statistic
1987–88	194.7	209.4	82.08	107.6	149.0	342.5	823.0	25,000
1999–2000	201.5	255.4	88.6	114.2	156.3	352.8	811.7	8,825
2004–2005	233.8	309.3	92.95	121.0	169.4	415.6	1177.6	25,000
2009–10	269.0	461.7	102.2	134.5	188.2	479.1	1323.9	18,000
2011–12	312.2	459.1	116.7	154.5	221.0	554.6	1637.8	21,000
Sector (NIC Code)	% (1988)	% (2012)						
Agriculture	59.48	43.38						
Industry	16.89	24.93						
Services	23.62	31.69						

Std. temp. (1mo) and Std. pre. (1mo) refer to the first month of the NSS sub-round.
*The histogram of real MPCE and kernel density plots of real MPCE, temperature, precipitation and the regression residuals are presented in the online appendix.

Table 2. Correlation matrix for 1988–2012 (excluding 1999–2000)

	ln(real MPCE)	Temperature	Precipitation
ln(real MPCE)	1		
Temperature	−0.0225***	1	
Precipitation	0.00143	0.272***	1

***$p < 0.001$.

deviation. Consumption averages at different quantiles of the distribution further reflect the underlying inequality. Over 1988–2012, mean consumption of the poorest 25 per cent of individuals rose slowly, stabilising at around half of mean consumption in the country.

Similarly, the median household has always consumed less than the mean household, indicating inequality in the distribution of households, with the mean being driven by consumption levels at the top (as also discussed in Chancel and Piketty, 2019). Finally, the rise in consumption levels of the top 1 per cent of households is particularly noteworthy. This subgroup witnessed a doubling of consumption over the period, compared to an increase of 62 per cent for the top 10 per cent of individuals, and only 44 per cent for the bottom 25 per cent of individuals.

The pair-wise correlation matrix (table 2) reveals a statistically significant and negative correlation between *ln* real MPCE and temperature, and a positive but insignificant correlation between *ln* real MPCE and precipitation. The negative correlation can be explained by unobserved factors which affect both consumption and local climate such as topography, elevation and institutional quality, which has typically been lower for less developed countries and more tropical climates (Dell *et al.*, 2014). However, this correlation does not reflect the causal effect of higher temperature and precipitation on consumption, which is now investigated through regression analysis.

4.2 Average impacts

The pooled cross-section regression results (table 3) reveal an increase in *ln* real MPCE of Indian households in response to temperature shocks, by 0.1–1.2 per cent across specifications. A 1 mm increase in precipitation, on the other hand, has no detectable effect on consumption expenditure. All regressions include dummy variables for the survey year, with standard errors being clustered at the district level. The first column reports the effect of higher absolute temperature and precipitation levels on consumption expenditure, excluding district dummy variables. This regression effectively measures the correlation among the three variables, with higher temperatures and lower precipitation being associated with lower consumption expenditures. However, the inclusion of district dummy variables is important to account for unobserved heterogeneity and other omitted variables. Hence, the subsequent estimations include district dummies. The coefficient signs for both temperature and precipitation now reverse, with both higher absolute temperatures and greater variability in temperature raising consumption expenditure. On the other hand, higher precipitation and increased precipitation variability appear to lower consumption expenditure. As discussed earlier, variables that capture climate shocks, i.e., measured as deviations and standardised Z-scores better reflect unexpected fluctuations in local climate and may influence household consumption more than average increases in temperature and precipitation, which may instead be anticipated by individuals based on past trends.

Table 3. Pooled cross-section regression results (1988–2012, excluding 1993–94)

ln(real MPCE)	(1)	(2)	(3)	(4)	(5)	(6)
Temp.	−0.0053*** (.0013)	0.0009** (0.0003)				
Pre.	0.0002*** (0.0001)	−0.00002 (.0000)				
Dev. temp.			0.0116*** (0.0036)			
Dev. pre.			−0.0000 (0.0000)			
Std. temp.				0.0118*** (0.003)	0.012*** (0.0032)	
Std. pre.					0.0004 (0.0036)	
Std. temp. (1mo)						0.0063** (0.0023)
Std. pre. (1mo)						−0.0031 (0.0021)
Constant	5.314*** (0.0322)	5.794*** (0.0106)	5.814*** (0.0067)	5.815*** (0.0067)	5.815*** (0.0067)	5.815*** (0.0068)
N	545,831	545,831	545,831	545,831	545,681	542,765
R^2	0.897	0.915	0.915	0.915	0.915	0.921
District dummies	No	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses; ** $p < 0.01$, *** $p < 0.001$.
Inclusion of year dummy variables.

While the point estimates obtained in the regressions are comparable in absolute value to those found in other studies, typically in the range of 1–3 per cent (reviewed by Dell *et al.*, 2014), most other studies perform regression analyses using income data, rather than consumption, and typically observe income declines in response to climate shocks. Income would encompass more channels than consumption alone, particularly the role of savings in either consumption- or asset-smoothing behaviour. However, the increase in consumption in response to climate shocks is interpreted as a 'cost of adaptation' incurred by households due to unexpected variability in temperature relative to historically observed trends in a particular three-month season within the year. This increase in consumption or the cost of adaptation may be operating through a variety of channels such as rise in energy consumption for cooling effects (as observed by Deschênes and Greenstone, 2011) rise in food consumption due to heat stress or potential increases in health expenditures.

It is important to note that the increase in consumption is unlikely to reflect a rise in living standards, due to productivity increases. However, this mechanism could be better examined using direct income data with alternative sources, such as the India Human Development Surveys (IHDS) which are available until 2011–12.[10]

[10]Additional data sources include the NSS Employment and Unemployment Surveys and the NSS Debt and Investment Surveys.

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Table 4. Panel fixed-effects regression results (1988–2012, excluding 1993–94)

ln(real MPCE)	(1)	(2)	(3)	(4)
Temp.	0.0023 (.0081)			
Pre.	−0.0005*** (0.0001)			
Dev. temp.		0.0452*** (0.0134)		
Dev. pre.		−0.0004** (0.0001)		
Std. temp.			0.0501*** (0.0114)	
Std. pre.			−0.0208 (0.0132)	
Std. temp. (1mo)				0.0296*** (0.0086)
Std. pre. (1mo)				−0.0221** (0.0082)
Constant	5.069*** (0.2037)	5.072*** (0.0094)	5.071*** (0.0095)	5.073*** (0.0090)
N	2,588	2,588	2,588	2,588
R^2 - Overall	0.968	0.969	0.969	0.969

Clustered standard errors in parentheses; $^{**}p < 0.01$, $^{***}p < 0.001$.
Includes district and year fixed effects.

The results from the pooled cross-sectional analysis are now corroborated using panel data fixed effects regressions by averaging the household data to the district level, using the household survey weights provided by the NSS. The fixed effects methodology is chosen over random effects as the district-specific unobserved heterogeneity is expected to be correlated with the explanatory variables, i.e., local climatic variability. This would not satisfy the key assumption of the random effects model, in that the unobserved heterogeneity should be uncorrelated with the regressors. Results are presented in table 4. The first key observation is that all coefficient signs are identical to those from the pooled cross-section regressions, with the temperature variables being statistically significant at the 99 per cent confidence level and precipitation variables now also becoming significant at the 90 per cent confidence level. Second, the coefficients on the temperature variables are larger in magnitude, implying higher effects of climate shocks on mean per capita consumption at the district level. Specifically, a one standard deviation increase in temperature relative to its district-specific historical average leads to a 5 per cent rise in consumption expenditure, whereas an equivalent increase in precipitation reduces consumption by 2.1 per cent. On the other hand, the effects of shocks at the beginning of the sub-round are dampened relative to effects due to the mean shock experienced over the duration of the sub-round, owing to potential adaptation by households.

4.3 *Heterogeneous impacts*

The pooled cross-section results differentiated by the sector of the household's primary occupation, interacted with the region of residence, are presented in table 5.

Table 5. Heterogeneous effects of climate shocks by a household's primary occupation and region of residence (1988–2012)

ln(Real MPCE)	(1) Temp.	(2) Std. temp.
Rural agriculture	−0.0041*** (0.0004)	−0.0169*** (0.0052)
Urban agriculture	−0.0006 (0.0005)	−0.0178* (0.0102)
Rural industry	−0.007*** (0.0004)	−0.0833*** (0.0069)
Urban industry	0.0039*** (0.0005)	0.0087 (0.0075)
Rural services	0.0021*** (0.0004)	0.0239*** (0.0049)
Urban services	0.0108*** (0.0004)	0.0964*** (0.0061)
Constant	5.769*** (0.0115)	5.81*** (0.0067)
N	512,020	511,877
R^2	0.925	0.919

Clustered standard errors in parentheses.
* $p < 0.1$, *** $p < 0.01$.
Inclusion of precipitation controls, year and district dummies.

Heterogeneous effects across economic sectors and geographical areas reveal interesting disparities in climatic impacts across sub-groups of the Indian population. The dummy variables for NIC codes (sectors) and region are interacted with the climate variables to produce differentiated impacts. Agricultural and rural industrial households appear to be adversely affected by both higher temperature and its increased variability, with a one standard deviation increase in temperature causing per capita consumption declines between 1.7 and 8.3 per cent, in the two sectors respectively. On the other hand, per capita consumption levels of households employed in the services sector rise by 2.4 and 9.6 per cent in response to a one standard deviation rise in temperature, in rural and urban areas, respectively. Urban industrial households also experience consumption increases, although the effect is not statistically significant. Moreover, rural households across economic sectors witness declines in consumption expenditure in agriculture and industry, and smaller increases in consumption levels in the service sector, relative to households residing in urban areas, thus highlighting rural-urban inequalities.

These results are broadly in line with expectation, although one would perhaps expect consumption declines in the service sector instead of increases, on account of physiological heat stress on workers. However, as discussed in the econometric framework, a rise in energy consumption and potentially other adaptation measures such as increased use of private transport to protect oneself against the deleterious health effects of hot weather may lead to an overall increase in consumption expenditure in this sector. Another interesting and perhaps surprising result is the greater absolute decline in consumption levels of households employed in the rural industrial sector, compared to agriculture. This points to potentially differing mechanisms across sectors. While in agriculture the key channel of reduced consumption would be lower crop yields, in the industrial sector, individuals are expected to suffer greater heat stress and therefore reduced labour productivity, in addition to reduced firm output (Somanathan *et al.*, 2015). Consequently, their daily wages or monthly income may be lower, in turn leading to reduced consumption capacity.

The results for the services sector appear somewhat counterintuitive as the channels driving them are determined by both supply and demand factors. While labour supply might be lower due to heat stress and hence reduced productivity, the demand for certain kinds of goods might also be lower in hotter weather. For example, in the city of Roorkee within the state of Uttarakhand, rickshaw pullers have in recent years switched from manual rickshaws to battery operated ones even though the latter offer lower profits, simply due to reduced public demand for the former. They further observe a drop in their number of rides in hotter weather, particularly in the summer season, as individuals prefer to remain within their homes at peak hours of the day and on hotter days in the season.[11] On the other hand, higher demand for climate control technology, such as air conditioners, electric fans and coolers, would raise revenues for service-sector households, which typically operate grocery and retail stores, repair and maintenance shops, shopping complexes and commercial centres. In turn, this may be responsible for their observed increases in consumption expenditures due to climate shocks. The differential rise in consumption levels of 9.6 in urban areas vis-à-vis 2.4 per cent in rural areas is particularly noteworthy and reflects increases in consumption inequality as a result of climate shocks.

The sectoral effects obtained above are now re-examined at various quantiles of the consumption distribution (table 6). Prima facie, impacts of climate shocks on consumption expenditure significantly diverge across the agriculture, industry and service sectors, as well as along the consumption distribution. While the lowest quartile of rural agricultural households experience consumption increases in the order of 0.4–1.4 per cent in response to a one standard deviation increase in temperature, the median household witnesses a 0.8 per cent decline in consumption, whereas those in the top quartile exhibit consumption declines of around 3.9–9.6 per cent.

Importantly, the increase in consumption of poor rural agricultural households may be due to higher food prices as a result of reduced crop yields, thus leading to overall higher farm income. Evidence for this is provided in Taraz (2018*a*) and Government of India (2018). Alternatively, higher wage incomes from increased supply of casual labour by farmers, such as in MGNREGA, in response to weather shocks which reduce crop yields, may also lead to higher consumption levels. This mechanism is discussed in Taraz (2018*b*). Although the rise in food prices temporarily benefits net agricultural producers, the decline in crop yields threatens national food security. At the upper tail, richer agricultural households are typically landowners, who might experience a drop in land values due to heat stress (evidence of which is provided in Jacoby *et al.*, 2011) and, in turn, reduced household consumption.

Urban agricultural households, on the other hand, exhibit consumption declines across the distribution, ranging from 2.2 to 3.3 per cent. While only 8 per cent of agricultural households in the sample reside in urban areas, the distribution of their economic activities across the NIC 3-digit codes, such as growing of crops, animal production and fishing, appears to be uniform across rural and urban areas, implying that the nature of

[11] A brief discussion with some rickshaw pullers in Roorkee in April 2019 revealed this insight.

Table 6. Quantile effects by sector of occupation and region of residence (1988–2012)

ln(Real MPCE)	p10	p25	Median	p75	p90	p99
Rural agriculture * Std. temp.	0.0135*** (0.0027)	0.0043* (0.0024)	−0.0077*** (0.0026)	−0.0392*** (0.0034)	−0.0755*** (0.0048)	−0.0961*** (0.0148)
Urban agriculture * Std. temp.	−0.0332*** (0.0084)	−0.0215*** (0.0074)	−0.013 (0.008)	0.0038 (0.0106)	−0.0275* (0.0152)	−0.0621 (0.0466)
Rural industry * Std. temp.	−0.0209*** (0.0045)	−0.0377*** (0.0022)	−0.0793*** (0.0043)	−0.1445*** (0.0056)	−0.1994*** (0.008)	−0.2103*** (0.0246)
Urban industry * Std. temp.	−0.0046 (0.0045)	−0.0011 (0.004)	0.005 (0.0043)	0.0149*** (0.0057)	0.0102 (0.008)	0.0239 (0.025)
Rural services * Std. temp.	0.0563*** (0.0037)	0.045*** (0.0032)	0.0318*** (0.0035)	0.0098 ** (0.0046)	−0.0143** (0.0066)	−0.019 (0.0203)
Urban services * Std. temp.	0.0617*** (0.0031)	0.083*** (0.0028)	0.1072*** (0.003)	0.103 *** (0.0039)	0.0911*** (0.0056)	0.071*** (0.0173)
Constant	5.0868*** (0.0125)	5.3707*** (0.0109)	5.7463*** (0.012)	6.1803 *** (0.0157)	6.6103*** (0.0224)	7.7185*** (0.0688)
N	511,877	511,877	511,877	511,877	511,877	511,877
Pseudo-R^2	0.8	0.791	0.672	0.562	0.478	0.366

Clustered standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Inclusion of precipitation controls, year and district dummy variables.

urban agriculture does not differ significantly. Nevertheless, perhaps access to smaller areas for cultivation as well as limited opportunities for adaptation to higher temperatures, as opposed to those in rural areas, may be responsible for the greater consumption declines in the bottom quartile of urban households.

Analogously, rural industrial households uniformly experience adverse effects of climate shocks through reduced consumption in the order of 2.1–3.8 per cent for the bottom quartile, rising to 8 per cent for the median household and around 14.5–21.0 per cent for the top quartile of households, with substantial consumption losses for the top 1 per cent of households. In addition to heat stress which is expected to lower labour productivity, the contraction of total firm output (Somanathan *et al.*, 2015), due to both lower labour productivity and heat-induced efficiency losses of capital equipment, would lead to large production and revenue losses across firms. Therefore, it is plausible that workers, firm managers and owners (the latter would form the top 1 per cent of the distribution) suffer financial losses due to lower output and revenue. It is puzzling to find urban industrial households relatively unaffected by climate shocks, and more disaggregated analysis on firm-level data may be required to understand which socioeconomic strata of society comprise the broad category of urban industrial households, and the corresponding mechanisms.

In contrast to agriculture and industry, the majority of the rural and urban service sector households experience consumption increases in the range of 1.0–5.6 per cent and 6.2–10.7 per cent across the respective distributions. Further, at each consumption quantile, the expenditure increases exhibited by urban residents exceed those by rural residents, in proportionate terms. In addition, since the consumption distribution of the services sector lies to the right of that for the agricultural and industrial sectors (i.e., households employed in the former sector have higher incomes or consumption

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levels),[12] it reflects a divergence in sectoral and regional consumption patterns on account of climate shocks. While many agricultural and rural industrial households experience consumption declines, households providing services witness consumption increases in response to unexpected higher temperatures, indicating an increase in consumption-based inequality due to climate shocks.

4.4 The adaptation mechanism

The divergent climatic impacts observed across the agriculture, industry and service sectors are plausibly on account of different mechanisms. Since agriculture and industry are climate-sensitive occupations, households employed in these sectors may experience declines in income and therefore consumption. On the other hand, households employed in the services sector, which is less sensitive to adverse climatic effects, may incur expenditure on adaptation to higher temperatures, with net positive effects on aggregate MPCE.[13] We now explore the adaptation mechanism by disaggregating the household's MPCE into an adaptation component and the remaining expenditure.

The adaptation component includes per capita expenditure on electric fans, coolers, air conditioners, refrigerators and electricity, following the 30-day recall period in the NSS survey. However, it excludes expenditure on transport, tourism, etc. which may only be applicable to a small percentage of the richest households in the sample. The effects of temperature increases, interacted with the sector of activity and region of residence, on both adaptive expenditures and non-adaptive or remaining expenditures, are presented in table 7. The results show statistically significant increases in adaptive expenditures incurred by both rural and urban service sector households, but reveal declines among rural agricultural and industrial households. The climatic effects on the non-adaptive expenditures are negative for rural agricultural and industrial households, who are typically at the lower end of the consumption distribution, but are positive for urban industrial and service sector households.

These results closely mirror those in table 5 and highlight that the poorest households, typically rural agricultural and industrial (largely wage labourers), do not spend on climatic adaptation measures but rather experience an overall decline in their consumption expenditures. The adaptation phenomenon, therefore, appears limited to richer households, comprising the urban industrial and service sectors.

5 Rising inequality

The empirical analyses above reveal a potential rise in inequality across economic sectors and consumption quantiles, on account of climate-induced shocks, which further exacerbate existing inequalities among Indian households.

The relationship between inequality and climate change can be hypothesized as bidirectional, with the former potentially being both a significant driver of climate change and a consequence of adverse climatic impacts. A review of the evidence by Fleurbaey *et al.* (2014) on emerging consumerist lifestyles sheds light on the role of inequality in consumption-led emissions as a driver of climate change. Specifically, cross-sectional

[12]The mean consumption expenditures for agriculture, industry and services for the year 2011–12 are Rs. 161, 216 and 264 respectively. Their corresponding ranges from the 10th to the 99th percentiles are Rs. 77–573, Rs. 88–904 and Rs. 102–1,155.

[13]I am grateful to an anonymous reviewer for highlighting this crucial mechanism.

Table 7. Adaptation effects by sector of occupation in per capita terms (1987–88, 2004–05 and 2011–12)

	ln(Adaptive exp. per cap.)		ln(MPCE less adaptive exp.)	
	Temp.	Std. Temp.	Temp.	Std. Temp.
Rural agriculture	−0.004*** (0.0008)	−0.0078 (0.0129)	−0.0032*** (0.0005)	−0.009 (0.0076)
Urban agriculture	0.007*** (0.001)	0.0188 (0.0257)	−0.0004 (0.0006)	0.0119 (0.0165)
Rural industrial	−0.0065*** (0.0009)	−0.0165 (0.0199)	−0.0064*** (0.0005)	−0.013 (0.011)
Urban industrial	0.0105*** (0.0009)	−0.0055 (0.0160)	0.0043*** (0.0006)	0.0246 ** (0.0112)
Rural services	0.0023*** (0.0008)	0.0186* (0.0111)	0.003*** (0.0005)	0.0318*** (0.0075)
Urban services	0.0188*** (0.0008)	0.059*** (0.0128)	0.0108*** (0.0005)	0.0653 *** (0.0093)
Constant	1.2636*** (0.0225)	1.481*** (0.0137)	5.745*** (0.013)	5.800*** (0.0059)
N	208,673	208,624	315,441	315,389
R^2	0.841	0.825	0.278	0.226

Clustered standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Inclusion of precipitation controls, year and district dummies.

studies find a strong correlation between consumption expenditures and a household's carbon footprint, with a doubling of consumption leading to an increase in GHG emissions by 57 per cent. In addition, analysis over the 1998–2013 period shows an increase in within-country inequality of CO_2-equivalent emissions on account of economic growth (and associated emissions), although between-country inequality in emissions decreased over the same period.[14] Moreover, while the bottom 50 per cent of the world's individuals account for merely 13 per cent of global emissions, the top 10 per cent of individuals contribute 45 per cent to aggregate emissions, highlighting the stark inequality in GHG emissions (Chancel and Piketty, 2015).

On the other hand, (Olsson *et al.*, 2014) observe unequal impacts of weather shocks such as floods among low- vs. high-income households, with the latter being able to afford insurance against damage to property, whereas poor residents often lose substantial portions of their physical assets, suggesting an increase in inequality post climatic events.

The question for policy relevance emerging from this discourse is: if climatic impacts exacerbate inequality, then can a redistributive system be designed to generate additional fiscal capacity in order to compensate the poor for climate-induced damages, funded by richer individuals? A number of economic and regulatory instruments such as carbon taxes, fuel surcharges and emission standards are at the policymaker's disposal (Somanathan *et al.*, 2014). Analysis of the distributional effects of carbon pricing

[14]This occurred largely due to global convergence of incomes as well as stagnation of emissions in advanced economies.

reveals regressive effects in rich countries but progressive effects in low-income countries, due to small energy expenditure shares among low-income households (Dorband *et al.*, 2019). Although the loss of income due to uniform carbon pricing of US$30 per ton of CO_2 among the lowest income group in India is 2.5 per cent, the net effect of a carbon tax is distribution neutral. While a complete and holistic welfare analysis must be undertaken to evaluate the heterogeneous and potentially adverse effects of mitigation policies on low-income groups, such policy frameworks would address multiple issues of rising inequality as well as mitigation of climate change and may be interesting questions for future research.

6 The role of social protection

This section investigates the effects of government policies such as the Antyodaya Anna Yojana (which provides subsidised food through the Targeted Public Distribution System) in potentially ameliorating the adverse impacts of climate shocks on Indian households. The NSS data allows categorisation of households based on possession of ration cards, in particular, the Antyodaya card, the Below Poverty Line (BPL) card and other ration cards.[15]

The results in table 8 show, firstly, that households possessing any type of ration card witness lower baseline consumption expenditure relative to households without ration cards, in the order of 4–50 per cent, across both specifications. This is intuitive as poorer families are typically the beneficiaries of government schemes and would therefore be expected to possess ration cards. Second, the interaction of the ration card and temperature variable shows that while the average household experiences a consumption increase of 3.12 per cent due to a temperature shock (column 2), households possessing Antyodaya ration cards experience small net declines of consumption expenditure by 0.5 per cent,[16] while those with 'Other' ration cards witness small increases of 0.3 per cent.

Given the lower baseline consumption levels of ration-card holders, it is likely that climate shocks have adverse effects on these households' consumption. However, it is unclear whether the possession of these ration cards ameliorates the negative effects of climate shocks, since the counterfactual effects on households with ration cards cannot be observed with the current data. At the margin, however, the provision of food subsidies and other employment guarantee schemes may have compensatory effects in cushioning the declines in consumption expenditure (for example, 'Other' ration card holders experience net consumption increases due to temperature shocks). The above results suggest that government policies have a pertinent role in potentially ameliorating adverse climatic effects on households. While the identification of precise policies and mechanisms requires more detailed data and extensive analysis, the results highlight the importance of strengthening existing social protection systems, and designing new systems, to mitigate adverse climatic impacts on the poorest members of society. The presence of complementary government support policies may, in addition to mitigating adverse climatic effects for vulnerable households, also reduce existing consumption

[15] Since the NSS questionnaire does not provide further information on the specific schemes availed by the households through these ration cards, it is not possible to disentangle the precise interaction effects of various government schemes with climatic anomalies.

[16] This is obtained as the sum of the coefficient of the temperature variable (row 1) and the interaction term (row 5).

Table 8. The role of social protection (2004–05 and 2011–12)

ln(Real MPCE)	Temp.	Std. temp.
Temperature variable	0.0001 (0.0011)	0.0312*** (0.0107)
Antyodaya ration card	−0.4716*** (0.0533)	−0.4968*** (0.0161)
BPL Ration card	−0.4296*** (0.0365)	−0.4272*** (0.0098)
Other ration cards	−0.0793** (0.0316)	−0.0391*** (0.0083)
Antyodaya card* temperature variable	−0.0019 (0.0022)	−0.0358* (0.0192)
BPL Card* temperature variable	0.0005 (0.0014)	0.0015 (0.0135)
Other card* temperature variable	0.0013 (0.0012)	−0.0282** (0.0118)
Constant	6.0216*** (0.0286)	6.016*** (0.0083)
N	221,746	221,702
R^2	0.297	0.298

Clustered standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Inclusion of precipitation controls, year and district dummies.

inequalities between households possessing ration cards (largely BPL households and the informal sector) and those without – inevitably the richer segments of society.

7 Conclusion

Climate change is a global challenge that demands prompt and well-coordinated international policy action. If the business-as-usual scenario continues, it could undermine economic growth and development, possibly leading to a reversal of the hitherto gains made in poverty reduction and to a loss of biodiversity, as well as having adverse human health impacts. This paper examines the effects of climate shocks, measured as variability in temperature and precipitation, on MPCE of Indian households over the 1988–2012 period. The analysis also delves into heterogeneity by households' sector of occupation, region of residence and consumption quantile.

Evidence for climatic impacts on the average household reveals an increase in consumption expenditure in response to higher temperature variability. This is contrary to the findings from existing research which observes a clear decline in income and productivity of individuals due to heat stress (Deryugina and Hsiang, 2014). The rise in consumption is interpreted as a 'cost of adaptation' to climate change borne by households, largely the services sector, in the presence of temperature anomalies (prior evidence of which is documented in Deschênes and Greenstone, 2011). Furthermore, heterogeneity by the household's primary economic activity, interacted with their region of residence, reveals disparities in impacts across sub-groups of the population. While households employed in the agricultural and industrial sectors on average experience adverse climatic effects on their per capita monthly consumption, households in the services sector witness an increase in consumption, in both rural and urban areas.

Further analysis by sector and consumption quantile reveals a rise in consumption by service sector households at all points of the distribution, albeit a significant decline in consumption of rural industrial and urban agricultural households, while rural agricultural impacts depend on the quantile being examined. Insofar as service sector households exhibit initially higher consumption levels at every quantile relative to agricultural and industrial ones, this signifies a rise in consumption-based inequality across sectors. The large absolute consumption declines experienced by industrial households relative to agricultural ones, i.e., 8.3 per cent vs. 1.7 per cent on average, highlight the importance of analysing climatic impacts in the industrial sector. A direction for future research could be to understand the mechanisms leading to differential impacts within the agricultural sector, particularly at various consumption quantiles, as well as the observed rise in consumption by service sector households.

The empirical analyses discussed above can be qualified due to certain drawbacks. First, the regressions do not correct for the spatial and temporal dependence of the local climatic data, which distorts the normality of the distribution. Applying Conley's (2008) Heteroscedasticity and Autocorrelation Consistent (HAC) estimation technique (which proved computationally inefficient in this paper due to the large sample size) would help correct the standard errors of the regression estimates. In addition, alternative climatic variables such as minimum and maximum temperature rather than the mean temperature, and the Standardized Precipitation Index, could be explored to better assess the economic effects of climate shocks. Lastly, testing income and productivity-related mechanisms using alternative household datasets, such as the IHDS or other NSS surveys, would be important directions for future research.

Notwithstanding the limitations of the empirical analysis, the questions addressed in this paper have important implications for economic and climate policy. The divergent impacts across economic sectors, particularly the industrial and service ones, point to a potential rise in inequality and have implications for the pace of structural change in India. Households' access to government programs such as the Targeted Public Distribution System, the MGNREGA, other BPL schemes and so on, may potentially mitigate the negative climatic effects on consumption expenditure, and lower inequality. Therefore, effective policy action is critical to prevent adverse effects of climate-induced shocks, and to serve the long-term objectives of mitigating climate change and reducing socioeconomic inequality, while promoting inclusive and sustainable growth in India.

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