The impact of climate shocks on consumption and the consumption distribution in India

Raavi Aggarwal

June 2, 2019

Supervisors: Dr. Lucas Chancel and Prof. Thomas Piketty
Referee: Prof. François Libois

Abstract

This dissertation examines the impact of climate shocks, measured as temperature and precipitation variability, on monthly per capita consumption expenditure of Indian households over the 1988-2012 period, utilising data from NSSO's Consumer Expenditure Surveys. 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 consumption deciles. The bottom 70 per cent individuals experience consumption declines, while the top 30 per cent observe a rise in consumption. This rise is explained in part, by an increase in electricity usage in response to temperature shocks, by the top 20 per cent individuals, thus mirroring the rise in total consumption. The findings highlight the increase in inequality due to climate shocks and a rise in energy demand by richer individuals, with implications for future climate and economic policy.

JEL Classification: Q54 Q50 Q15
Keywords: Climate Change; Agriculture; Inequality; Energy; India

Acknowledgements

I would like to thank my dissertation co-supervisor, Dr. Lucas Chancel, for his guidance and valuable suggestions on the research. I am grateful to Prof. François Libois for his insightful comments on the econometric methods and training sessions on QGIS. I thank Prof. Karen Macours for useful suggestions on the identification strategy. In addition, I thank Prof. Katrin Millock for a discussion of ideas and topics, which motivated the research questions in this thesis. Finally, I thank my thesis co-supervisor, Prof. Thomas Piketty, for his encouragement and support of the project.

I would like to extend my gratitude to several colleagues and friends for their support during the research process. I thank Prof. Bappaditya Mukhopadhyay for his workshop on QGIS and R-GIS, which helped with data extraction. A special thanks to Serene Vaid for her help in extraction of the CRU-TS climate dataset. I thank Nitin Kumar Bharti and Zhexun Mo for stimulating discussions and useful suggestions. Thanks also to Shalmali Ghaisas for support in the final stages of the thesis. A special thanks to Debasmita Padhi for her valuable suggestions on earlier drafts of the thesis. I would also like to thank Babaji's tiffin service which greatly helped in the days leading to submission. Lastly, I extend my gratitude to my family and close friends for their moral support throughout the process of writing this dissertation.

Contents

List of Tables

List of Figures

1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) documents an increase in global average surface temperature by 0.6 °C since 1861 and an average global sea level rise of 0.1 - 0.2 metres over the 20th century (Cubasch *et al.* 2013) [IPCC]. This rise in average temperature is *extremely likely* to have been caused by an unprecedented increase in anthropogenic GHG emissions, such as carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), $CFCs$ etc. (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 documented a trend of rising world hunger since 2014, with an estimated 821 million undernourished people in 2017, up from 804 million in 2016 (FAO 2018). The key reasons cited are economic recession and volatility, war and conflict and importantly, climate change. Poor households are particularly vulnerable due to the compounding of climatic and socioeconomic stressors. For instance, in coastal Bangladesh, a combination of factors such as sea level rise and saltwater intrusion, lower crop productivity and prevalence of disease has raised the vulnerability and propensity of households to enter chronic poverty (Olsson *et al.* 2014 [IPCC]). Hence, understanding the economic impacts of climate change is important to devise sustainable development strategies, so as to increase resilience to a changing climate. In view 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.

A recent statement by the World Meteorological Organisation (2019) provides updated temperature records for the year 2018 and observes a warming of 0.99 ± 0.13 °C above pre-industrial levels, making the recent period 2015-2018 the warmest in global climate records (WMO 2019). Given that the world is committed to at least one degree of warming, with a goal of limiting further increase to a total of 2 °C or 1.5 °C, examining the economic, social and distributional impacts of global warming is pertinent. Further, the design of mitigation policies must be based on fair and equitable measures, taking into account the developmental capacities of different world regions and sub-groups of the population within a developing country. In this light, existing literature focuses on the distributional impacts of mitigation policies such as carbon pricing on various income groups in both low- and middle-income countries (Dorband, Jakob, Kalkuhl and Steckel 2019).

This Master's dissertation poses a number of research questions relating climate change and development. First, what is the relationship between higher temperature variability and household consumption in India and the key mechanisms behind potentially adverse effects of higher temperatures on consumption? While in the agriculture sector we expect reduced crop yields due to suboptimal temperatures, does heat stress lower the productivity and therefore income of industrial workers? Further, do individuals employed in the services sector exhibit net adverse effects due to climate induced heat stress or demand more energy, in the form of investment in climate control technology, thus raising their overall household expenditures? Beyond average effects, this study will delve into distributional impacts of climate change to examine in particular, whether low income households are more vulnerable to climate shocks due to a lack of savings or infrastructural assets relative to upper income ones, and hence, the consequences of climate shocks for resulting inequality.

This study focuses on the Indian economy as it is the sixth largest in the world by GDP (World Bank 2017) and third largest contributor to global GHG emissions, following China and the United States (IEA 2018a). Despite robust economic growth, 22 per cent of Indians live in poverty, i.e. under USD 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).

I employ household-level survey data from the National Sample Survey Organisation (NSSO) in India, over the 1988-2012 period to analyse the impact of climate shocks, in the form of increased variability of temperature and precipitation, on monthly per capita consumption expenditures of the average household and households at various deciles of the consumption distribution. I next analyse heterogeneous effects differentiated by the primary sector of occupation of the household (agriculture, industry or services), interacted with their region of residence (rural or urban) in producing differential impacts. In addition, the role of existing state insurance mechanisms through availability of ration cards within households, in mitigating potential adverse effects of climate shocks is investigated. I subsequently test a number of mechanisms to identify the drivers of climatic impacts. First, I test whether energy expenditures in the form of electricity usage by households drives the increase in total consumption expenditure. Second, the analysis delves into disparity in impacts across households situated in districts with historically higher mean temperatures in comparison to relatively "colder" districts, to capture the dual effects of potential adaptation by households exposed to higher temperatures to long-run climate change and a potential rise in productivity of individuals residing in colder districts in response to positive temperature shocks.

The results show an increase in average 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. The panel fixed-effects regression results obtained by averaging consumption to the district-level, are in tandem with the results obtained from the pooled cross-sectional regressions, although with larger magnitudes, i.e. a rise in consumption by 4.8 per cent due to a one standard deviation increase in temperature. Distributional analysis reveals adverse effects on consumption for the bottom 70 per cent individuals, with the median household experiencing a fall in consumption by 16 per cent, whereas the top 30 per cent individuals experience an increase in consumption. Interestingly, while households in the lowest decile experience a loss in monthly per capita consumption of 49 per cent, the top decile of the population witnesses an increase by 38 per cent, highlighting the rise in inequality due to climate shocks. The rise in average consumption and that of the top decile is explained in part, by a significant rise in electricity consumption, of around 1.5 per cent for the average household and 21 per cent for the top 10 per cent individuals in response to a higher deviation of temperature from its long run mean. This points to the importance of energy as a key channel in driving climatic impacts.

This paper contributes to the literature in the following ways. First, it provides estimates of the economic impacts of climate change at the household level for India, investigating heterogeneity by sector of economic activity and the key mechanism of energy in producing impacts. Second, the analysis spans a long time horizon, thus taking into account long-run adaptation by households to climate change, while exploiting short-run temperature variations to examine immediate effects. Lastly, the paper examines climatic effects across the consumption distribution, thus going beyond average impacts. By addressing questions of inequality, economic growth and climate change, this paper would contribute to the debate on inclusive growth and sustainable development by providing empirical evidence, necessary to inform economic policy.

2 Literature Review

Existing research has focused on estimating the economic impact of climate change through the construction of damage functions that relate temperature changes to loss of income (Pindyck 2013). While current models provide broad orders of magnitude of the average effects of slow and steady temperature rise (as is observed in the empirical data), they abstract from estimating the "fat tails" of the temperature distribution. The probability of catastrophic events (i.e. large increases in temperature, for e.g. 7 – 8 °C) is small but damages could potentially be enormous. Further, due to multiple feedback effects in the climate sensitivity [1] process, the estimated increase in temperature from a doubling of anthropogenic emissions is uncertain (Pindyck 2013). Therefore, this caveat must be borne in mind while interpreting the results of climate economy models.

Dell, Jones and Olken (2012) examine the impacts of climate change, via rise in temperature and fall in precipitation, on the level and growth of economic output, spanning 125 countries over the 1950-2003 period. Their results confirm a negative relationship, with a 1 °C rise in temperature lowering economic growth by 1.3 percentage points in poor countries. These growth effects seem to persist in the medium run, with little evidence of long run adaptation, suggesting a reduction in the growth trajectory and potentially counterproductive effects of economic growth. Deryugina and Hsiang (2014) conduct a complementary study to analyse the effects of increased temperature variability on per capita income in United States counties over the 1969-2011 period. Employing data at a daily frequency and the "temperature-binning" approach, they find that daily average productivity declines by 1.7 per cent in response to a 1 °C increase in daily temperature above 15 °C. These studies, therefore,

[1] Climate sensitivity refers to the increase in temperature from a doubling of anthropogenic CO_2e emissions once the new atmospheric equilibrium is achieved. The initial temperature increase creates a feedback effect, causing further temperature increase, through an unknown probability distribution of the feedback parameter. Hence, there exists uncertainty about the resulting temperature increase (Pindyck 2013).

provide evidence of adverse economic climatic impacts in both rich and poor countries. Hsiang and Meng (2015) further study the determinants of annual weather fluctuations, relating them to the El Niño-Southern Oscillation (ENSO), a phenomenon germane to tropical regions. They find that a 1 °C increase in the ENSO index raises country-level temperatures in the tropics by 0.27 °C and lowers precipitation by 4.6 cm on average. Subsequent analysis of ENSO-induced weather variability on agricultural outcomes reveals adverse impacts of higher temperatures and lower rainfall levels on cereal yields, output and agricultural income in the order of around 2 per cent.

A number of recent papers evaluate the human health effects of climate change, by assessing relationships between higher temperatures and mortality rates. Barreca *et al.* (2015) analyse the impact of higher daily mean temperatures on monthly mortality rates in the United States, at the state level for a century long period (1900-2004). Taking into account long-term adaptation, they find states with mean temperatures in the lowest decile of the temperature distribution to experience a 31 per cent increase in monthly mortality rates due to an additional day's exposure to temperatures above 90 °F, relative to historically hotter states (i.e. the top decile of the distribution), which witness a mere 0.68 per cent increase in monthly mortality rates in response to equivalent increases in temperature. Analogously, Deschênes and Greenstone (2011) assess the relationship between higher daily temperatures and annual mortality rates in the United States, examining the channel of a potential rise in residential energy consumption in response to higher temperatures as a measure of self-protection. In contrast to the results obtained by Barreca *et al.* (2015), Deschênes *et al.* (2011) find that the mortality risk of higher temperatures is highest at both the bottom and top deciles of the temperature distribution, leading to about 0.69 and 0.94 additional deaths annually per 100,000 individuals. 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.

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 nonlinearity, 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 (2018a) 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 (2018a) evaluates the impact of high temperatures 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.

The above studies point to an important mechanism through which climate change impacts agriculture, i.e. heat stress due to higher temperatures, resulting in lower crop yields. Yields decline as crops require an optimal temperature as well as a specific amount of rainfall for maximum yields. In addition, there exist alternative mechanisms which lower agricultural output in the face of climate variability. First, heat stress due to rising temperatures may reduce animal production through decreased performance of livestock, higher mortality rates, lower reproduction and loss in production of animal products (Walthall *et al.* 2012). This loss in productivity and breeding problems may deplete farmers' livestock assets. Second, farmers may leave agriculture and migrate to other sectors of the economy such as industry or services, or other regions of the country while remaining in the agriculture sector in search of higher incomes, particularly if opportunities for adaptation are limited.

In a World Bank study, Mani *et al.* (2018) estimate the effects of changes in district-level average seasonal temperature and mean precipitation levels on household consumption expenditures in the Indian subcontinent. Employing a reduced-form model with a quadratic functional form for both temperature and rainfall, the authors find an adverse impact of higher temperatures on consumption, with an average rate of reduction of consumption expenditures by 0.6 per cent in response to a 1 °C increase in temperature beyond the threshold of 24 – 27 °C, in the summer season. The effects differ substantially by season and are smaller in magnitude for precipitation. Importantly, this study identifies specific geographic regions including districts and states within India and more broadly across the subcontinent, which may be particularly vulnerable to climate change in the medium and long run, i.e. up to 2030 and 2050, respectively, thus highlighting the regions that should be targeted on a priority basis for adaptation to climate change through government policy.

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, Rabassa and Skoufias (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, further considering effects across the consumption distribution. The highest distributional effects appear to be due to changes in wage rates, where the distribution of effects is highly skewed to the left with 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 [IPCC]). Consequently, socio-economic 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 (2018b) analyses the effects of a large-scale social protection program, the National Rural Employment Guarantee Act (NREGA) 2005, in potentially ameliorating the adverse climatic impacts faced by farmers in India. Contrary to expectation, it finds that the implementation of NREGA exacerbates the deleterious impact of climate shocks on crop yields, as non-agricultural employment in NREGA 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 Theoretical Framework

3.1 Impacts on the average household

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

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

A household's consumption expenditure, C is related to climate variables (temperature and precipitation), the sector of employment (NIC Code) and the region of residence, which differs by rural or urban in the analysis[2]. X is a vector of control variables such as the possession of ration cards by households, which are a form of social protection or insurance and may help mitigate the adverse impacts of climate change. Furthermore, climate impacts may differ by the consumption level of the household, with poorer households *prima facie* at a higher risk or vulnerability from climate change. This entails analysis across the distribution of initial consumption expenditure.

A number of mechanisms can be outlined through which climate change will affect households, depending on the principal source of income and other regional factors. Within the agriculture, forestry and fishing [3] sector, there are four key mechanisms which may influence farm income. First, as documented above, higher temperatures and/or low rainfall may reduce crop yields and in turn farm productivity. Insofar as risk mitigation strategies are available to farmers, these effects would be subverted. These include investment in irrigation pumps or the presence of groundwater aquifers to satisfy crops' water requirements, in the event of low precipitation. As crop yields decline, food prices are expected to rise. Hence, effects on farm revenue and in turn, household income (or consumption) are ambiguous. Second, loss of animal production due to heat stress may lead to loss of assets, particularly livestock. 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 to a different sector, such as manufacturing or services for employment. However, this effect is difficult to disentangle in the data as structural shifts in employment over time take place for multiple reasons. Lastly, farmers may migrate out of the region to another district within the state or across states in response to unfavourable climatic conditions.

Industry would be affected by weather shocks primarily through its adverse impact on labour productivity in the form of physiological heat stress. Within the industrial

[2] 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 NSS dataset.

[3] The Central Statistical Office (CSO) in India defines sectors of economic activity as: 1. Agriculture, forestry and fishing, 2. Industry (Mining & Quarrying, Manufacturing, Electricity, Gas, Water Supply & Other Utility services and Construction), and 3. Services (Trade, Hotel, Transport, Storage, Communication & Services related to Broadcasting, Financial, Real Estate & Professional Services and Public Administration, Defence & Other Services (Government of India 2018b).

sector, mining, manufacturing and construction activities are expected to be negatively affected due to the strenuous working conditions of workers, compounded with climate-induced heat stress. However, there may be an increase in demand for construction and rebuilding of infrastructure in the aftermath of extreme climate events. Hence, the net effect appears ambiguous. Higher temperatures may further result in higher energy demand, thus boosting consumption expenditures for the electricity sector. Therefore, the overall effect on industry, comprising these four segments, is ambiguous and analysis by sub-sector (using the NIC Codes) would help illuminate which mechanisms dominate and quantify the effects across various sub-sectors. 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. Hence, the net effect of climate shocks on this sector is also ambiguous. 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 Heterogeneous impacts across the consumption distribution

The next part of the analysis entails studying climatic impacts across the distribution of initial consumption among Indian households. The key research question is whether adverse climatic impacts are more pronounced at the lower tail of the consumption distribution than at the median or upper tail, insofar as consumption and in turn income levels inform a household's ability to save and build assets, which may be utilised as self-protection measures against climate shocks. In this scenario, low-income households may be more susceptible to heat stress due to temperature shocks, on account of their low savings and modest stock of assets.

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. The existing literature provides some evidence in support of this hypothesis. A review of the evidence by Fleurbaey *et al.* (2014) [IPCC] on emerging consumerist lifestyles sheds light on the role of inequality in consumption-led emissions as a driver of climate change. Specifically, cross-sectional 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 of inequality in CO_2-equivalent emissions between 1998 and 2013 shows an increase in within-country inequality of emissions on account of economic growth and its associated emissions, although between-country inequality in emissions reduced over the same period, due to global convergence of incomes as well as stagnation of emissions in advanced economies. Moreover, while the bottom 50 per cent of world 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) [IPCC] 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 the poor residents often lose substantial portions of their physical assets, suggesting an increase in inequality post climatic events. While the relationship between inequality and climate change can be studied as a two-part question, in this paper, the latter question of whether adverse climatic impacts propagate inequality, is explicitly addressed by examining differential climatic impacts across the consumption distribution.

Bourguignon and Morrisson (2002) discuss important trends in world income inequality over the 1820-1992 period, observing a rise since the early 19th century until post world war II, around 1950, with the Theil Index increasing from 0.52 in 1820 to 0.8 in 1950. This period was marked by a concomitant rise in both within-country and between-country inequality until 1910, after which inequality within countries declined until 1960, although the latter continued on an upward trajectory. Over 1960-1992, rise in inequality between country groups has been the dominant source of increase in total world inequality. Chancel and Piketty (2017) further examine inequality dynamics in India over the 1922-2015 period. The share of national income accruing to the top 1 per cent individuals appears to have risen from 6.2 per cent in 1982-83 to 21.3 per cent in 2014-15, while the share accruing to the bottom 50 percent of the population has declined from 23.6 per cent to 14.9 per cent over the same period. Furthermore, the share of income accounted for by the middle 40 per cent individuals declined from 46 per cent to 29.2 per cent between 1982-83 and 2014-15.

Rising income inequality implies not only a lack of inclusive growth, which is an important policy objective, but also has significant implications for poverty reduction, given that the latter is a function of both growth in mean incomes and changes in the income distribution (Bourguignon 2003). Simulation exercises demonstrate that an additional 2.15 billion people could have been lifted out of poverty over 1820-1992, given historical growth rates, had the distribution of income remained unchanged (Bourguignon *et al.* 2002). Comparative analysis of existing taxation systems in India and China over the 1986-2015 period reveals lacunae in the implementation of progressive taxation in the former economy, while the latter has been more successful in raising the tax base and consequently, income tax revenues as a proportion of GDP (Piketty and Qian 2015). By keeping the marginal tax rates fixed despite revision of the exemption thresholds from 9,600 yuans per year in 1980-1998 to 19,200 yuans since 2006, the share of the total population within the purview of income taxes in China rose from 0.1 per cent to 20 per cent over 1986-2008. On the other hand, although the Indian government implemented progressive taxation in 1922, there has been a continuous revision of the exemption thresholds, along with a decline in the tax rates or tax schedule. For instance, in 1986-1988, the marginal tax rate corresponding to the highest tax slab, i.e. for earners of Rs. 1,00,000 and above annually, stood at 55 per cent. By 2008, earners of less than Rs. 1,50,000 faced no income taxes, while the top tax bracket, i.e. annual incomes above Rs. 5,00,000, faced only a 30 per cent marginal tax rate. Consequently, the rise in exemption thresholds has mirrored the rise in nominal incomes. This combination of factors has restricted the share of population subject to income taxes at around 3 per cent in India in 2008, compared to almost 15 per cent in China in the same year.

Given current trends in within-country inequality, especially in a developing country such as India, the forthcoming analysis on potentially adverse distributional impacts of climate shocks would contribute to the narrative and debate on curbing rising inequality and promoting more inclusive growth and development. Moreover, insofar as adverse changes in the income distribution reduce the rate of poverty reduction, the current economic growth trajectory appears to be a double whammy. This is because it is the key driver of anthropogenic-led climate change and if climate change exacerbates inequality due to adverse economic impacts, then the process of economic growth is not only unsustainable in the long run, but may also be counter-productive, by leading to a rise in inequality and slowed pace of poverty reduction.

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 [IPCC]). Analysis of the distributional effects of carbon pricing 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 USD 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, whereas it is highly progressive in the neighbouring countries of Bangladesh, China and Sri Lanka. While a complete and wholesome 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.

4 Data Sources and Methodology

4.1 Data Sources

Household-level economic data for India are drawn from the National Sample Survey Organisation (NSSO)'s Consumer Expenditure Surveys, which have been conducted on a quinquennial basis since 1951. These surveys provide data on household-level monthly per capita consumption expenditure as well as expenditure incurred on a range of food and non-food items, including energy (fuel and light), durable goods and others. The survey rounds utilised for the analysis correspond to the years 1987-88, 1999-2000, 2004-05, 2009-10 and 2011-12. The years 1983 and 1993-94 are excluded as these rounds do not provide district codes corresponding to the households, but instead only provide the State-Region codes, which aggregate several districts together [4]. 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 both a 30-day recall period, known as the Uniform Reference Period (URP), to record the food component of consumption, as had been done in the previous rounds, but 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. The survey further adopted a 7-day recall period for food consumption, thereby providing two estimates for monthly consumption - those based on the 7-day recall and the 30-day recall periods. Consequently, MPCE values based on the URP were underestimated relative to the other rounds, whereas those using the Mixed Reference Period (i.e. 7-day recall for food consumption) resulted in an overestimate of consumption. The difference in average consumption values for 1999-2000 and the remaining rounds is evident from Table 2 and Figure 5. In this dissertation, the consumption estimates are drawn based on the 30-day recall period and comparability concerns with the 55th round are ignored as they are not expected to yield differential results in the regression analysis. Nevertheless, robustness checks of the regression equation are conducted by omitting this round from the period of analysis.

An important issue is the lack of a historical income survey in India, which is instead proxied by household-level consumption expenditures. 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 [IPCC]). 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 in consumption than income, for instance, through the purchase of luxury goods. In addition, consumption smoothing may occur through receipt of government transfers, which would not be captured in income. Finally, it is typically easier to accurately measure consumption for low-income households, rather than income, which may be drawn from multiple

[4] Regressions conducted with state-region specific fixed effects yielded imprecise results due to the averaging of temperature values across many districts.

sources and economic activities. However, income may be easier to measure than consumption for high-income households (Attanasio *et al.* 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 are drawn from the Climatic Research Unit at the University of East Anglia (UEA), which provide data at the level of 0.25 $^{\circ}\times$ 0.25 $^{\circ}$grids, on a range of key parameters such as mean, minimum and maximum temperatures, precipitation, vapour pressure, wet day frequency and so on, over the 1901-2017 period on a monthly basis. Data on mean temperature and precipitation are drawn for the 1983-2012 period and aggregated to the district-level based on a simple average using R-GIS [5].

4.2 Methodology

The econometric model used to evaluate the causal impact of increased climatic variability, measured as deviation of temperature (T) and precipitation (P) in year t and sub-round r (corresponding to the NSS survey), from their district-sub round specific historical mean values on household-level monthly per capita consumption expenditure, is as follows:

$$lnC_{htr} = \alpha_d + \tau_t + \beta(T_{dtr} - \bar{T}_{dr}) + \delta(P_{dtr} - \bar{P}_{dr}) + \phi X_{htr} + \epsilon_{htr} \tag{2}$$

where α_d is a vector of district dummy variables, τ_t are survey year dummy variables and X_{htr} is a vector of household characteristics such as sector of occupation, region of residence (rural or urban), access to government insurance programs, as well as interaction terms between climate variables and occupation. Standard errors are clustered at the district-level to account for correlation and heteroskedasticity among households within a district. Although the primary unit of stratification in the NSS survey (which follows a stratified sampling design) is the village rather than the district, the inclusion of a large number of village dummy variables was not possible as the NSSO do not provide comparable village codes across survey rounds. In addition, India has approximately 640,000 villages and a dummy variable with as many categories was not feasible to implement for regression analysis.

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 identically and independently distributed across strata (which ensures asymptotic normality and standard

[5] The 'cruts2poly' package was used for extraction. Follow this link for a step-wise guide.

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 with each other. 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. As households are sampled randomly across survey years, the estimation strategy employs pooled cross-sections, rather than a panel of households over time. 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. Alternatively, one may aggregate household consumption to the district level and employ a panel regression approach. However, household-level analysis is important for understanding the mechanisms, especially the role of sector of employment, the disparity across rural and urban regions, and their interaction. This regression model is thus estimated using OLS and subsequently using interaction terms of the climate variables with consumption deciles, to estimate the effect of climate shocks on consumption at the 10th, 20th, 50th, 90th percentiles and so on. A panel regression model with fixed effects is subsequently estimated to corroborate the results of the pooled cross-section regressions.

Since the survey is conducted in four sub rounds over the year, such that each household is surveyed in a particular sub-round, there is clear seasonality of both the consumption and climate data, although less so for the former due to consumption-smoothing behaviour. The ideal specification entails the inclusion of dummy variables that capture district-year-sub round specific unobserved heterogeneity. However, this would imply a large number of categories for the dummy variable, which is infeasible to implement and offers little advantage. Alternatively, including both year and sub-round effects would introduce perfect collinearity in the regression. Moreover, inclusion of a district-sub round fixed effect is more relevant as different states and districts fall under varying climatic zones in the country, experiencing diverse weather conditions in the same sub-round. For instance, while most of the country experiences winters from October to December, the southern states of Tamil Nadu, Kerala and Karnataka experience monsoonal conditions on account of the north-east monsoon. Rather than including these various dummy variables, however, I simply include a time trend and subsequently analyse results by sub-round of the NSS survey to understand which seasons account for the largest observed impacts.

Dell, Jones and Olken (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 not be correlated with exogeneous annual fluctuations or deviations in these climatic parameters from their district-specific long run mean values. Hence, studying annual deviations from the means of climate variables rather than a simple increase in their average values over time is important for identification.

5 Empirical Specification

The key equation to be estimated is:

$$lnC_{htr} = \alpha_d + \tau_t + \beta T_{dtr} + \delta P_{dtr} + \phi X_{htr} + \epsilon_{htr} \tag{3}$$

where lnC_{htr} is *log* household consumption, α_d are district dummy variables, τ_t are survey year dummies, X_{htr} is a vector of 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; and standardized z-scores corresponding to the first month of the NSS sub-round. This equation is estimated by Ordinary Least Squares (OLS), which relies on the assumption of exogeneity and non-collinearity for consistent estimation of the regression coefficients. Exogeneity of the climate variables has been discussed in the preceding section and non-collinearity is ensured by the omission of any variables which may be strongly correlated with both the climate variables and household-level consumption.

The OLS estimation above is replicated with panel-level fixed effects using the 'within-estimator', which improves on the pooled OLS technique by eliminating the unobserved heterogeneity or the district-level 'fixed-effects', as follows. The household data are first averaged to the district-level to create a panel dataset with district-year-sub round observations. The panel data equation is:

$$lnC_{dtr} = \alpha_d + \tau_t + \beta T_{dtr} + \delta P_{dtr} + \epsilon_{dtr} \tag{4}$$

Now consider the time-average of the above equation:

$$ln\bar{C}_{dr} = \alpha_d + \tau_t + \beta \bar{T}_{dr} + \delta \bar{P}_{dr} + \bar{\epsilon}_{dr} \tag{5}$$

The 'within-estimator' is obtained by regressing the difference of equations (4) and (5), which leads to elimination of the time-invariant fixed effects α_d, which are potentially correlated with the variables of interest, T and P and may confound the coefficient estimates. This ensures exogeneity of the explanatory variables, i.e. $E(T_{dtr}; P_{dtr}|\epsilon_{dtr}) = 0$.

The final specification evaluates the impact of climate shocks on households in various deciles of the consumption distribution. This is estimated by interacting the climate variables with a dummy variable specifying the consumption decile that the household belongs to, in order to obtain differential impacts of shocks across the distribution.

$$lnC_{htr} = \alpha_d + \tau_t + \beta_l T_{dtr} * D_l + \delta_l P_{dtr} * D_l + \phi X_{htr} + \epsilon_{htr} \quad (6)$$

where the slope coefficients β and δ differ by consumption decile l.

6 Stylised Facts

This section presents and discusses descriptive statistics for the climate and economic variables used for analysis for the period 1983-2012 and 1988-2012, respectively.

Variables	Observations	Mean	Std. Dev.	Min	Max
Mean Temperature	545833	24.90	5.649	-10.41	33.88
Mean Precipitation	545833	111.1	125.9	0	781.3
Std. Temp.	545833	0.151	0.623	-1.750	1.724
Std. Pre.	545683	-0.0254	0.563	-1.680	2.268
Std. Temp. (1mo)	545833	0.160	0.883	-2.162	2.189
Std. Pre. (1mo)	542767	-0.0848	0.874	-2.202	2.268

Std. Temp. (1mo) and Std. Pre. (1mo) refer to the first month of the NSS sub-round.

Table 1: Summary Statistics of Climate Variables (1983-2012)

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 [6]. 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 [7].

In the subsequent regression analysis, climate shocks are defined in a number of ways. First, the raw temperature and precipitation distributions are standardized into z-scores by subtracting their long run monthly mean values for each district and subsequently averaging these standard normal scores over the corresponding sub-round of the NSS data. This standardization procedure allows comparison of equivalent magnitudes of climate shocks across the country, comprising diverse climatic zones across the states. These variables are labelled 'Std. Temp.' and 'Std. Pre.' in the above table. The mean temperature shock over the 1983-2012 period was positive and 0.15 standard deviations above its long-run mean, while the mean precipitation shock

[6] These climate descriptions are based on the KöppenGeiger climate classification. Available here.

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

was negative and 0.025 standard deviations below its long-run mean. Taraz (2017) explains the inter-decadal alternating regimes of the Indian monsoon, computing the long-run average of rainfall over 1871-2008. The 1970-2000 period corresponds to a regime in which rainfall was below its historical average. Coupled with the finding of negative precipitation shocks on average relative to long-run values over 1983-2012 computed from the CRU TS dataset implies overall low precipitation over this inter-decadal period, relative to historical climatic conditions over the Indian region.

The next measure of climate shocks used is standardized z-scores for temperature and precipitation corresponding to the first month of each sub-round (henceforth, SR) of the NSS, i.e. July for SR 1, October for SR 2, January for SR 3 and April for SR 4. This technique has two advantages. First, it correlates the climate shock of the relevant month to the entire sub-round without averaging the magnitude of the shock over the 3-month period, which tends to smooth out the shock. This is reflected in lower absolute mean values of climate shocks in the 'Std. Temp.' and 'Std. Pre.' variables compared to the variables corresponding to the first month of the sub-round, along with larger standard deviations and ranges of these later variables (Table 1). Second, it allows analysis of both contemporaneous (same month) and lagged effects (a lag of one or two months) of climate shocks on households that are sampled in the first month of the sub-round vis-à-vis those sampled in the subsequent months within the same sub-round. Lack of information on the month of the NSS survey precludes monthly analysis.

Household-level data for real monthly per capita consumer expenditure drawn from the NSS surveys show a steady increase in mean consumption from Rs. 195 in 1987-88 to Rs. 312 in 2011-12, using the Consumer Price Indices for Agricultural labourers for the rural sector and Industrial Workers for the urban sector respectively, using the base year of 1987-88, drawn from the NSS published reports (NSSO 2011-12; NSSO 2009-10). [8][9] 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 deviation [10].

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

[8] The unit-level estimates differ to an extent from the aggregate statistics reported by the NSS, potentially due to rounding off errors. For example, the unit-level data suggests an increase in the average real MPCE from Rs.169 to Rs. 242 for the rural sector (growth rate of 43 per cent) and from Rs. 280 to Rs. 468 for the urban sector (growth rate of 67 per cent) over 1988-2012. However, these figures overestimate consumption expenditure as the growth rate of real MPCE at the all-India level, as reported by the NSSO was only 40 per cent for the rural sector and 60 per cent for the urban sector. Nevertheless, these slight differences in population estimates would not affect the regression analyses, which is the primary objective of this study.

[9] The significant underestimate of mean consumption in 1999-2000 relative to the remaining survey years, the reasons for which were discussed in the Data section, is evident in Table 2.

[10] I thank Abhijit Tagade for highlighting this phenomenon and offering a detailed explanation.

	Mean	Std. Dev.	p10	p25	p50	p90	p99
1988	194.7	209.4	82.08	107.6	149.0	342.5	823.0
2000	2.442	3.096	1.074	1.384	1.895	4.276	9.839
2005	233.8	309.3	92.95	121.0	169.4	415.6	1177.6
2010	269.0	461.7	102.2	134.5	188.2	479.1	1323.9
2012	312.2	459.1	116.7	154.5	221.0	554.6	1637.8

p refers to percentile.

Table 2: Summary Statistics of Real MPCE, 1988-2012

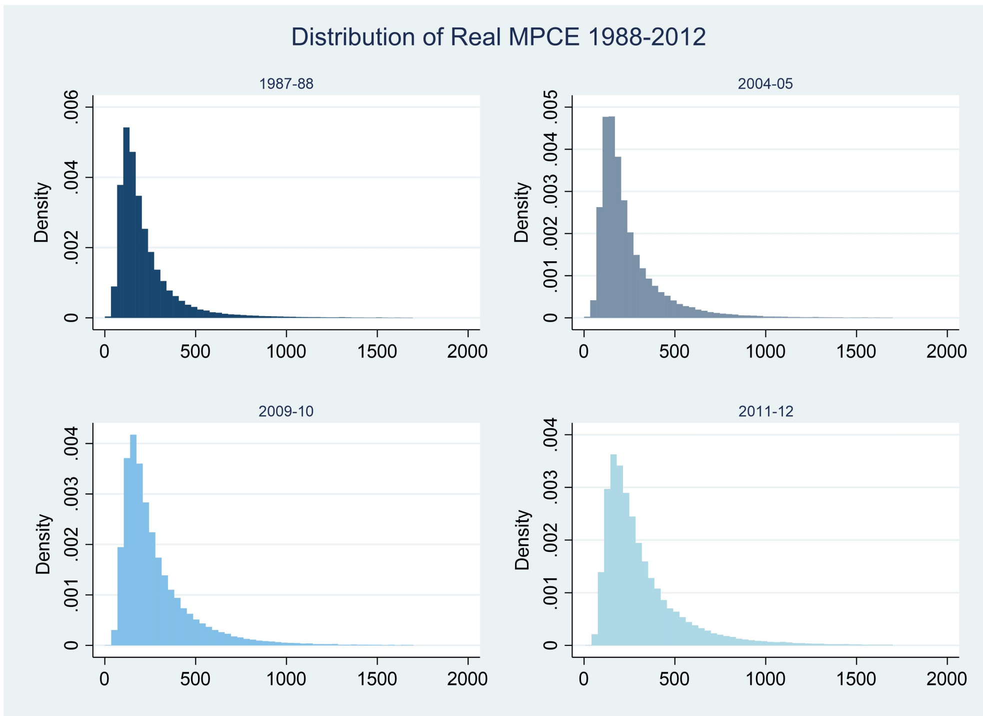

Figure 1: Distribution of Real MPCE, 1988-2012 (excluding 1999-2000)

the median household has always consumed less than the mean household, reflecting underlying inequality in the population of households, with the mean being driven by consumption levels at the top. Finally, the rise in consumption levels of the top 1 per cent of households is particularly noteworthy. This subgroup witnessed a doubling of consumption levels, compared to an increase of 62 per cent for the top 10 per cent individuals and only 44 per cent for the bottom 25 per cent individuals.

Household-level real energy expenditures show an increase from an average of Rs. 64 in 1987-88 to Rs. 99 in 2004-05 (Table 3). Similarly, real expenditures on electricity rose from Rs. 8 to Rs. 29 over 1988-2005. Other components of energy for which data are recorded include coke, firewood, dung cakes, matches and kerosene. Although the energy data for all rounds except the 43rd (1987-88) and 61st (2004-05) appear to be inconsistent with the corresponding household monthly

Year	Real MCE	Energy Exp.	Electricity Exp.	HH Size
1988	884.1	63.90	7.090	5.025
2000	22854.6	82.04	8.781	9486.9
2005	984.3	98.88	28.86	4.744
2010	NA	0.934	0.304	NA
2012	1206.9	1.032	0.332	4.435
Mean (1988-2012)	2952.6	80.27	8.638	894.9

Real MCE = Real MPCE * Household Size ; NA - Not Available

Table 3: Summary Statistics for Mean Real Monthly Consumer Expenditure, Household Energy and Electricity Expenditure and Household Size, 1988-2012

total consumption expenditures, these rounds, excluding the 55th (1999-2000) [11], are nevertheless utilised for the subsequent regression analysis. Lastly, the mean household size appears to have declined from 5 persons in 1987-88 to 4.7 in 2004-05 and stabilised at 4.4 in 2011-12, with a corresponding decrease in its standard deviation.

The availability of food ration cards among households is also included as a dummy variable in the dataset to account for potential consumption-smoothing mechanisms through state-led food security programs. Data from the 2004-05 and 2011-12 rounds show that 76 per cent and 80 per cent of households, respectively, possessed a ration card - either a Below Poverty Line (BPL) card or an Antyodaya Anna Yojana (AAY) card, both of which guarantee these households provision of food grains, notably rice and wheat, at subsidised prices, or any other type of ration card (Table 4).

Ownership of ration card	2004-05	2011-12
0 (No)	22.44	19.58
1 (Yes)	77.56	80.42

Table 4: Possession of Ration Cards by Households (in per cent)

Heterogeneity by the sector of the household's principal occupation and region of residence over the 1990s and 2000s reveals important trends. First, the primary sector of employment continues to be largely agriculture, although the share of households employed in this sector has fallen, from 60 per cent to 43 per cent over 1988-2012. This decline in agriculture has been commensurate with the rise in the share of households employed in services, from 24 per cent in 1988 to 32 per cent in 2012. This is based on the National Industrial Classification 2008, and hence simply reflects the industry of employment rather than the household's primary occupation, which is better informed by the National Classification of Occupations (NCO). Analysing the incidence of climate shocks by sector is important to highlight various channels, as

[11] This round is not utilised as the analysis on electricity expenditures is performed for various quantile categories and the lack of comparability of the 55th round with the others prevents computation of comparable quantile categories across rounds.

discussed in earlier sections. Second, temporal shifts in households' region of residence shows convergence between rural and urban regions over the previous three decades (Table 6). While in 1987-88, 65 per cent of households resided in rural areas, this share dropped to 59 per cent by 2011-12, with a corresponding rise in the share of urban households from 35 per cent to 41 per cent. Lastly, heterogeneity by industry of employment and region of residence confirms the *ex ante* intuition, in that a majority (73 per cent) of agricultural households reside in rural regions, whereas around 33 per cent and 60 per cent of industrial and service-sector households reside in urban regions.

Year	Agriculture	Industry	Services
1988	59.48	16.89	23.62
2000	56.46	17.04	26.50
2005	51.25	20.23	28.5
2010	46.96	22.74	30.30
2012	43.38	24.93	31.69

Table 5: Share of Households by primary occupation based on NIC Codes (in per cent)

Year	Rural	Urban
1988	65.27	34.73
2000	60.38	39.62
2005	64.13	35.87
2010	58.45	41.55
2012	58.66	41.34

Table 6: Share of Households by Region of Residence (in per cent)

Sector	Agriculture (1)	Industry (2)	Services (3)
1 (Rural)	72.84	11.95	15.21
2 (Urban)	7.61	32.55	59.84

Table 7: Share of Households by Primary Occupation and Region of Residence (in per cent)

The kernel density plots for various measures of the climate variables are presented in the Appendix. These include temperature, precipitation, deviations from their long run means, their standardized z-scores by month and aggregated by sub-round; and standardized z-scores for the first month of each sub-round (i.e. July, October, January and April). The kernel density plot for standardized z-scores of temperature and precipitation by sub-round somewhat resembles a normal distribution. However, the Shapiro-Wilks' W test for normality strongly rejects the null hypothesis of a normal distribution. This is perhaps because of the spatial and temporal dependence of climate data. Therefore, it is important to correct the standard errors in the regressions to account for this spatial and temporal dependence (Deyugina and Hsiang 2014). This is typically done using Conley (2008)'s HAC estimation technique. However, due to the large sample size of the dataset, estimation of standard errors using Conley's GMM method cannot be implemented as it is computationally intensive. The lack of correction for standard errors is a limitation of this dissertation.

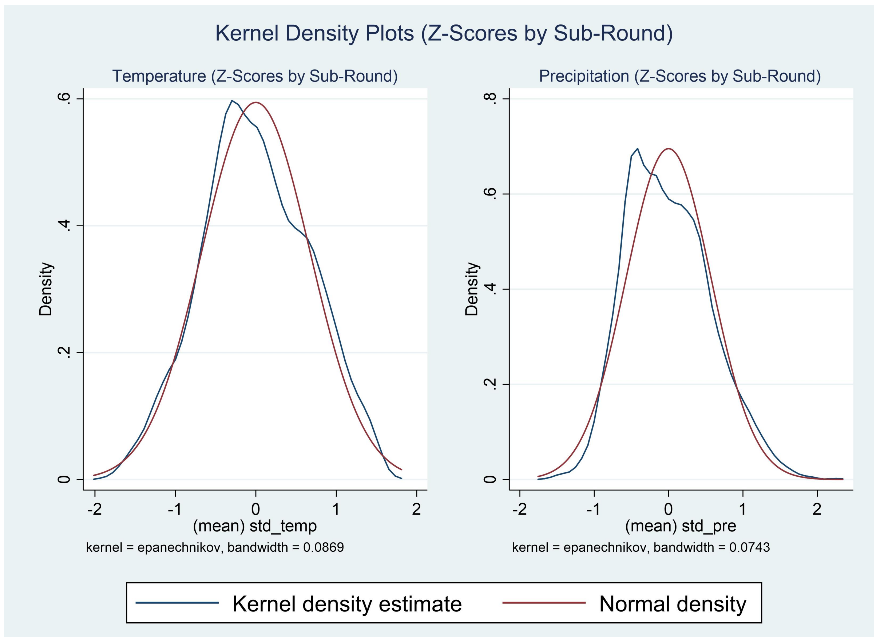

Figure 2: Kernel Density Plots of Temperature and Precipitation (Standardized Z-Scores averaged over the Sub-Round

Kernel density plots for real MPCE are presented in Figure 3. While real MPCE is clearly not normally distributed, log consumption appears close to a normal for each year. However, the Shapiro-Wilks' W test (results presented in Appendix) strongly rejects the null hypothesis of a normal distribution for each year. As Deaton (2018) points out, this is typically the case in household survey data and perhaps the use of nonparametric or semiparametric estimators would ensure more robust hypothesis testing of the regression coefficients. However, the OLS method offers clear interpretations of results and is computationally less intensive than non-parametric estimators, which have significant run times, especially for analysis using large datasets.

	ln(Real MPCE)	Temperature	Precipitation
ln(Real MPCE)	1		
Temperature	-0.0225***	1	
Precipitation	0.00143	0.272***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Correlation Matrix for 1988-2012 (excluding 1999-2000)

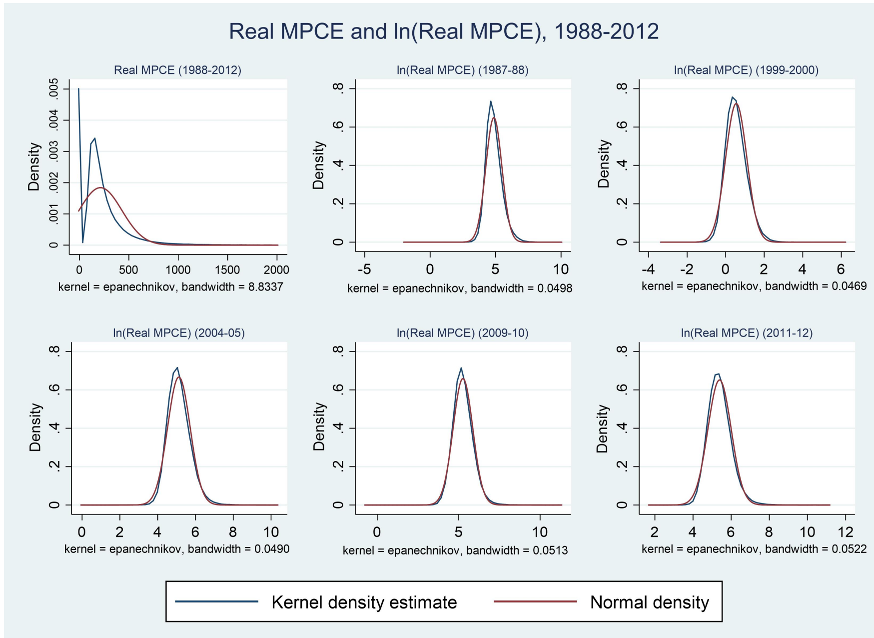

Figure 3: Kernel Density Plots of Real MPCE and ln(Real MPCE), 1988-2012

The pair-wise correlation matrix reveals a statistically significant and negative correlation between *log* real monthly per capita consumer expenditure and temperature, and a positive but insignificant correlation between *log* real MPCE and precipitation (Table 8). The negative correlation can be explained by unobserved factors which affect both consumption and local climate such as topography, elevation, distance of the district from the coast as well as institutional quality, which has typically been lower for less developed countries and more tropical climates (Dell, Jones and Olken 2014). However, this correlation does not reflect the causal effect of higher temperature and precipitation variability on per capita consumption, which is now investigated through regression analysis.

7 Results

The pooled cross-section regression results, presented in Table 11 in the Appendix, reveal an increase in *log* real monthly per capita consumer expenditure (MPCE) of Indian households in response to climate shocks, measured as temperature and precipitation variability, over the 1988-2012 period. 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 district specific unobserved heterogeneity. 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, measured as deviations of observed weather conditions from their historical means for each district, are better measures of unexpected fluctuations, which may influence household consumption more than average increases in temperature and precipitation, which might be better anticipated by individuals based on past trends.

Following the above intuition, a 1 °C rise in mean temperature raises consumption expenditure by 0.1 per cent and the effect is statistically significant at the 99 per cent confidence level. A 1 mm increase in precipitation, on the other hand, has no detectable effect on consumption expenditure, as can be inferred from the statistically insignificant and small regression coefficients on the precipitation variables in all specifications. The negative sign on all coefficients is somewhat counter-intuitive insofar as rainfall shocks can be interpreted as positive income shocks for households. However, as the coefficients are not significant even at the 90 per cent confidence level, inference will be limited to the temperature variables. Results in column 5 of Table 11 show that a one standard deviation increase in temperature relative to its district-specific historical mean raises per capita monthly consumption expenditure by around 1.2 per cent. The results are analogous while using the deviations of temperature rather than the standardized z-scores, whereas those using z-scores of temperature corresponding to the first month of each NSS sub-round show a smaller increase in consumption expenditure, by around 0.6 per cent. The smaller increase can be explained by the fact that only a third of households within a particular sub-round would have faced that specific temperature shock in the month of the NSS survey. The remaining households would have faced this shock either one or two months prior to the survey and hence may have adapted their consumption levels and expenditures accordingly.

While the point estimates obtained in the regressions are comparable in absolute value to those in other studies cited above, i.e. in the range of 1 - 3 per cent, most other studies perform regression analysis using income data, rather than consumption, and typically observe income declines in response to weather shocks. Income would encompass more channels than purely consumption alone such as potential decreases in productivity, yields and so on. However, the increase in consumption in response to weather shocks can be interpreted as a cost of adaptation incurred by households due to unexpected variability in temperature relative to historically observed temperatures 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 food consumption due to heat stress, rise in energy consumption for cooling effects or potential increases in health expenditures. These mechanisms can be better understood by analysing the impacts of climate shocks on sub-components of MPCE. One such mechanism, energy, is examined in the forthcoming analysis. It is important to note that the increase in consumption is highly unlikely to reflect a rise in living standards, through a potential increase in productivity. However, this mechanism could be better examined using direct income data using alternative sources.

Robustness checks for these pooled OLS regressions are conducted by checking the sensitivity of results to analysis over different time periods. Table 14 presents results without the year 1999-2000. This round is not comparable to the remaining NSS rounds, as discussed in the data section, due to differential recall periods. Similarly, Table 15 replicates the above results excluding both the years 1987-88 and 1999-2000. In both specifications, the coefficient signs for all temperature variables and the approximate magnitudes remain unchanged, i.e. within the range of 1-2 per cent. The use of alternative measures for temperature and precipitation further adds robustness to the results.

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 12. The first key observation from the regression table 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 impact of higher mean temperature appears to be insignificant on district-level monthly per capita consumption, due to estimation using the 'within-estimator' which eliminates the fixed effects, thus obviating the effect of unobserved counfounding factors. Third, 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 4.8 per cent rise in consumption expenditure, whereas an equivalent increase in precipitation reduces consumption by 2.7 per cent. On the other hand, the effects of shocks at the beginning of the sub-round are dampened relative to those due to the mean shock experienced over the duration of the sub-round, owing to potential adaptation.

The large magnitudes of these effects suggests that the mechanisms bringing about an increase in mean consumption at the household-level vis-à-vis at the district-level may be different. For example, it is possible that temperature shocks may have spurred migration within rural regions across districts or states. In addition, a large number of household members may have found employment in the secondary or tertiary sector which would have raised incomes and therefore consumption. Alternatively, the potential rise in energy consumption by wealthier households may be driving the average increase in total consumption at the district-level. The channels driving an increase in consumption are diverse and heterogeneous in nature. I begin examining heterogeneity of climatic impacts by first investigating their effects on households at various deciles of the consumption distribution [12].

The distributional effects of climate shocks are now examined, based on results presented in Table 13. The effects of absolute increases in temperature as well as temperature shocks, measured through deviations and standardized z-scores, appear to be negative for households with consumption levels at and below the seventh decile of the distribution (i.e. monthly per capita consumption expenditure of Rs. 190 or less). On the other hand, unexpected temperature variability appears to raise consumption of households at the eighth, ninth and top deciles of the consumption distribution (mean consumption expenditures of Rs. 228, Rs. 296 and Rs. 584 respectively). It is important to note that these mean consumption levels at various deciles further mask significant underlying heterogeneity, as detailed in Table 10. For example, households consuming above the 90th percentile exhibit a large range of consumption expenditures, from Rs. 352 to Rs. 1,02,185. Further, the OLS method would estimate average effects within a decile, which may further be driven by the large upper tail consumption values within that decile category.

Analysing heterogeneous effects of climate shocks provides some intuition for the results obtained in the pooled OLS regressions for the average household. Given the sensitivity of the OLS estimator to extreme values in the dataset (i.e. outlier observations), perhaps the average increase in consumption in response to temperature shocks is being driven by households at the top of the consumption distribution. These results do not however undermine the reasoning developed for the average effects, as the increase in consumption by higher income individuals may still reflect a cost of adaptation to climate change. On the other hand, the mechanisms now need to be examined to understand which sub-components of consumption are rising in response to higher temperatures. While analysing each component of total consumption such as food, health, travel & transport and energy is rather detailed for this study, the potential mechanism of energy, is examined in the succeeding sections. A rise in energy expenditure may raise consumption in two ways - 1) a direct rise through the increased use of climate control technology within homes such as air conditioners and coolers and 2) indirectly by enhancing individuals' productivity and therefore raising their incomes and consumption through cooling effects of climate control, given that the use of climate control is endogeneous to both temperature and productivity.

It is further interesting to note the magnitude of effects of temperature shocks across the consumption distribution. Column 3(a) examines the effects of a one standard deviation increase in temperature on *log* real MPCE. While consumption expenditures decline by 16 per cent for individuals at the median, they progressively decline more at the lower deciles, with the bottom 10 per cent individuals exhibiting declines of 49 per cent. On the other hand, individuals at the eighth decile experi-

[12] The decile categories have been created using data on all households whose real MPCE exceeds the 1 percentile value for the year 1987-88. This corresponds to a monthly per capita consumer expenditure of Rs. 49., ranging to an upper limit of Rs. 1,02,185 in 2011-12. The year 1999-2000 has been excluded as the recorded consumption levels were extremely low in that year compared to the other rounds, which led to imprecise decile categories, such as minimum expenditures of Rs. 1.

ence consumption increases in the order of 2.4 per cent and this positive effect rises steadily toward the upper tail of the distribution, with the top 10 percent individuals experiencing consumption increases of 38 per cent.

These magnitudes are extremely large and can be understood better by studying the temperature distribution. Within the climate dataset employed for the analysis, a one standard deviation of observed temperature relative to its long run mean for a district corresponds on average, to a deviation of 0.8 °C, and ranges from 0.25 - 1.98 °C across districts. This is within the scope of potential future increases in temperature due to climate change. The heterogeneous effects of precipitation shocks can be evaluated in a similar manner. While higher absolute levels of precipitation appear to raise consumption expenditures of the bottom 10 and 20 per cent individuals, positive precipitation shocks appear to lower consumption expenditures of the bottom 30 per cent individuals, with consumption of the bottom 10 percent declining by 27.5 per cent. On the other hand, consumption expenditures of the upper consumption deciles rises by 3.1 per cent at the median, and progressively increases by 8.8 per cent for the top 10 per cent individuals.

These possibly counter-intuitive results can be better explained by examining the precipitation distribution. One standard deviation of observed precipitation relative to its long run mean for a district corresponds to 50 mm of excess rainfall on average and ranges from 0 to 522 mm of excess rainfall. These values are quite large, given that the Indian Meteorological Department defines a 'heavy rainfall day' as one with an excess precipitation of 64.5 mm, with further categorisation as 'very heavy' for the 124.5 - 244.5 mm range and 'extremely heavy' as rainfall exceeding 244.5 mm (Guhathakurta, Sreejith and Menon 2011). This implies that the average household faced extreme amounts of unexpected rainfall, which may be better interpreted as flood events rather than as positive rainfall shocks, which are typically used as a proxy for income shocks in the development literature (Rose 1999). Dallmann and Millock (2017) also provide explanations for why excess precipitation may be interpreted as flood events, employing the same climate dataset for India as in this paper.

8 Heterogeneity

In this section, I examine the effects of climate shocks on per capita consumption, incorporating important covariates which account for heterogeneity by the household's primary occupation (i.e. agriculture, industry or services), region of residence (rural or urban), NSS sub-round which broadly corresponds to different seasons and the presence of state insurance programs such as availability of ration cards within households.

Heterogeneous effects across sectors of economic activity, region of residence and their interaction reveal interesting disparities in climate impacts across sub-groups of the Indian population (Table 16 [13]). Agricultural and industrial households appear to be adversely affected by both higher temperature and its increased variability, with

[13] The dummy variables for NIC codes and region have been interacted with the climate variables.

a one standard deviation increase in temperature causing per capita consumption declines of 3.8 per cent and 6.5 per cent, in the two sectors respectively. On the other hand, per capita consumption levels of households employed in the services sector rise by 3.1 per cent in response to climate shocks. Further, rural households on average witness an increase in consumption by 4.7 per cent, relative to urban households.

These results are broadly in line with *ex ante* expectation, although one would perhaps expect consumption declines in the service sector due to physiological heat stress on workers, rather than increases. However, as discussed in the theoretical 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 industrial sector, relative 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. Consequently, their daily wages or monthly income may be lower, in turn leading to a reduced ability to consume. A puzzling observation is the higher consumption expenditures undertaken by rural households relative to urban ones in response to equivalent temperature shocks. One may have expected the opposite effect, assuming households in urban areas may have a better capacity to utilise protection measures against heat stress such as climate control technology. A possible explanation is the presence of a heat island effect in urban areas which raises temperatures beyond the average levels in the region and perhaps leads to more heat stress compared to neighbouring rural regions even at equivalent temperature levels. These intuitions and differential patterns between rural vis-à-vis urban households need to be investigated deeper and may be interesting questions for future research.

Results from interaction of these two variables further deliver new insights. While agricultural households residing in urban areas witness consumption declines of around 9.7 per cent in response to a one standard deviation increase in temperature, rural agricultural households appear to have higher consumption by 1.4 per cent, on average, in response to equivalent temperature shocks. While only 8 per cent of agricultural households 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 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 significant consumption declines in urban areas. Importantly, the increase in consumption of 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 (2018a) and Government of India (2018). Alternatively, higher wage incomes from increased supply of casual labour by farmers in response to weather shocks which reduce crop yields, may also lead to higher consumption levels. This mechanism is discussed in Taraz (2018b).

Industrial workers in urban regions appear to be more adversely affected by heat shocks than those in rural areas, experiencing consumption declines of 5.4 per cent and 2.9 per cent respectively. The mechanisms driving these impacts might be a combination of differential working hours in rural vs urban factories, varying levels of exposure to outdoor working conditions and hot weather, as well as the potential urban heat island effect, which may produce higher levels of heat stress through the feedback process of higher temperatures. The services sector unambiguously observes consumption increases in response to temperature shocks, with rural households consuming proportionately more than those in urban areas, at 7.4 per cent and 3.3 per cent, respectively. These results further present puzzles, which require further research to discover the mechanisms. The overall results for the services sector appear counter-intuitive as the channels driving them are determined both by supply and demand factors. While labour supply might be lower due to more 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 [14]. Given both these supply and demand-side factors, consumption expenditure may be expected to be lower. However, investments in climate control and other adaptation measures may offset these negative effects, leading to a net positive impact on consumption.

Robustness checks for heterogeneous impacts by sector of occupation interacted with the residential area, are conducted by sequentially omitting the years 1999-2000 and 1987-88 & 1999-2000 from the analysis, results of which are presented in Table 17. All coefficient signs on the interaction variables in both specifications are identical to those in the earlier regression. The magnitudes of the impacts are, however, larger in absolute value in the second set of regressions. For instance, urban agricultural households witness consumption declines of 14 per cent and 16 per cent in the specifications excluding the years 1999-2000 and both 1987-88 & 1999-2000, compared to a decline of 9.7 per cent in the regression with all time periods. Similar results hold for the industrial and service sectors. While the magnitudes are to an extent sensitive to the time period of analysis, the overall results remain robust and the interpretations and conclusions derived earlier continue to hold.

The next piece of analysis studies the role of state insurance mechanisms in the form of ration cards owned by households, which provide a range of benefits depending on the type of card. These include fixed quotas of subsidised food grains, subsidised healthcare, nutritional supplements and so on. In Table 18, I investigate the role of existing state insurance programs in mitigating the potentially adverse effects of tem-

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

perature shocks, particularly at the lower spectrum of the consumption distribution, to which these ration card facilities mostly apply. Column (1) shows the differential per capita consumption levels of households who possess ration cards vis-à-vis those without them, with the former consuming 12 per cent less per month on average. This is intuitive as the ration cards are supplied to individuals below the poverty line and other extremely vulnerable populations. This result, however, contrasts with the coefficient in column (4) which shows a higher monthly household consumption level of ration-card holders vis-à-vis non-holders. Hence, while the per-capita consumption levels of ration card owners may be lower than non-owners, at the aggregate household-level, perhaps with the subsidised food grain received through the Targeted Public Distribution System (TPDS) of the Government of India, these families are able to achieve a consumption level that exceeds those of non-cardholders by 15 per cent on average. Column (2) observes the effect of higher absolute temperatures on *log* real per capita consumption expenditure, but yields insignificant coefficients on both the temperature variable and the interaction term between temperature and the presence of ration cards within the household. The next two columns analyse the differential effects of temperature shocks on per capita and total household consumption levels of families with ration cards, relative to others. A one standard deviation increase in temperature, while raising consumption expenditure on average, significantly lowers both per capita and household-level consumption of families with possession of any kind of ration card (i.e. BPL, Antyodaya or Other), by approximately 3.2 - 3.4 per cent, relative to consumption of non-card holders.

There could be two alternative explanations for this ambiguous result. First, note that the analysis is based on consumer expenditures, rather than quantities of consumption such as yields etc. Therefore, despite observing expenditures in real terms, the reduction in expenditure coupled with highly subsidised foodgrain offered through these ration cards, could imply that while absolute consumption may have risen, the expenditure incurred by the household fell, due to the presence of state aid or excess supply of foodgrain in an environment of higher temperatures. However, this explanation does not seem convincing if we truly interpret consumption expenditures in real terms as proxies for levels of consumption. The alternative explanation, thence, is that the dummy variable for ration cards simply divides the population into the poor and the relatively well off segments, in terms of their baseline consumption levels. In that case, the interaction term of the temperature shock and the possession of ration cards by the household reflects the differential effect of the temperature shock on low-income households relative to the average household. Therefore, while the average household experiences an increase in overall consumption, the ration-card holders, which constitute the lower tail of the distribution, are adversely affected by the temperature shock. In conclusion, the negative coefficients on the interaction terms clearly show the lack of state protection and insurance mechanisms against the potentially adverse effects of climate shocks, particularly at the lower end of the consumption distribution.

9 Mechanisms

To understand the causes of the rise in MPCE in response to temperature shocks, it is important to test different mechanisms. In this section, I test two key channels through which consumption may rise in response to unanticipated temperature shocks. First, a rise in household-level energy consumption (proxied by expenditure on electricity) may be driving the increase in total consumption expenditure. Second, households residing in relatively warmer districts may experience smaller increases in consumption expenditure compared to those in colder districts. This reflects both adaptation by households to climate change through long-term exposure to higher temperature, as is analysed in Taraz (2018a), as well as potential increases in productivity and hence income of households in colder districts.

The analysis for the responsiveness of energy (electricity) consumption to temperature variability is conducted as follows. I first test for the effect of climate shocks on *log* real MPCE by sub-round of the NSS survey, which broadly map to different seasons. Results obtained from these regressions, displayed in Table 19, show a rise in consumption expenditure in sub rounds 2 and 4, by approximately 1.5 - 3.3 per cent due to temperature shocks across various specifications. These rounds correspond to the months of October to December and April to June, i.e. the winter and summer months respectively, for most of the country, except for the southern states of Kerala, Tamil Nadu and Karnataka, which receive most of their rainfall in the months of October-December through the North-East monsoon (the rest of the country receives most of its rainfall over June-October through the South-West monsoon).

Next, I examine the effects of climate shocks on *log* household electricity consumption. It is important to note that electricity is not the primary source of energy for majority of households and the NSS records various forms of energy use such as firewood, dung cakes, matches, coke, kerosene etc. Given that households would adapt their energy use differently depending on their primary source of energy, I investigate the effects on electricity usage as it more clearly reflects the potentially increased use of climate control equipment such as air conditioners and coolers in response to hotter weather. Higher temperature and higher deviations of temperature from its long-term mean raises electricity consumption on average by 0.2 and 1.6 per cent respectively (Table 20). However, electricity consumption does not appear responsive to standardized shocks, i.e. either those averaged over the sub-round or those corresponding to the first month of the sub-round. Heterogeneity across sub-rounds shows that electricity consumption rises by 2.5 - 4.2 per cent across sub-rounds 1,2 and 4 (although the coefficient for sub-round 1 is only significant at the 10 per cent level), due to higher fluctuations of temperature relative to its long-run normal (Table 21, Column 2). The increase in electricity consumption in sub-rounds 2 and 4 can help explain the overall rise in consumption expenditure, as the magnitudes of the rise are comparable to the total rise in consumption in these sub-rounds (Table 19). Lastly, the differential response of electricity consumption across deciles of the initial consumption distribution is examined (results presented in Table 22).

The heterogeneous response of electricity consumption parallels the overall rise in consumption due to temperature shocks. Electricity consumption of households in the bottom eight deciles, i.e. 80 per cent of the population, declines due to higher temperatures relative to their long run means, while that for the top 20 per cent individuals rises. The median consumption decline is 14.2 per cent, based on absolute deviations of temperature from its long run mean and this decline progressively rises in absolute value at the lower tail of the distribution, with the bottom 10 per cent individuals witnessing a drop in electricity consumption of 42.7 per cent. At the upper tail, electricity consumption rises by 5.7 per cent and 21 per cent for the ninth and the top decile respectively. This significant rise in energy use by richer individuals may be driving the increase in overall consumption due to temperature shocks. The fall in energy consumption at the bottom of the distribution can be explained by the fact that the share of a household's total expenditure on energy is low among low-income households and it rises steadily with per capita income or per capita expenditure, until a turning point of approximately USD 8,000-10,000, beyond which the share declines (Dorband *et al.* 2019). Consequently, households may substitute away from energy consumption in an environment of unexpected temperature shocks and redirect resources to greater food intake in order to smooth consumption and minimise any loss of productivity and decline of health.

Another important mechanism examined is potential adaptation by households residing in districts which have experienced historically higher temperatures relative to the all-India median, compared with those districts which have experienced historically lower average temperatures. The results (presented in Table 23) show that while relatively hotter districts, i.e. those with long run mean temperatures above 25.6 °C, which is the country-level median, exhibit higher consumption expenditures in response to climate shocks (columns 2 and 3), hot districts do not exhibit systematically different consumption responses relative to colder districts, as revealed by the interaction term between the 'Hot District' dummy and the temperature variable. This evidence contrasts with that of Taraz (2018a), who finds smaller effects on historically hotter districts compared to colder ones, although the negative effects start to rise beyond 30 °C, even in hot districts. While temperature does not seem to impact districts differently, higher precipitation raises consumption expenditure by 0.008 per cent in hotter districts relative to colder ones.

To further test this mechanism, a dummy variable is now created for three temperature ranges: < 15 °C, 15-29 °C and > 29 °C, and interacted with the temperature shock. Results from this set of regressions (displayed in Table 24) fail to find a significant difference in consumption expenditures in response to temperature shocks across the different temperature ranges, although in column (4) consumption expenditures appear to be 1.9 per cent lower among households facing mean temperatures above 29 °C, relative to those living in colder conditions, i.e. < 15 °C. In addition, consumption expenditures of households in the middle range, i.e. 15-29 °C, appear to be 1.2 per cent lower due to temperature shocks, relative to households living in sub 15 °C conditions. This effect is statistically significant at the 10 per cent level. The temperature shock in the first month of the sub-round (Std. Temp. (1mo)) raises per capita consumption by 1.9 per cent on average and therefore, corresponds to the first temperature range. This helps to test the channel of productivity increases as being potential drivers of the observed rise in consumption due to temperature shocks. Indeed, Burke, Hsiang and Miguel (2015) find 13 °C to be the optimum temperature for maximum productivity, beyond which it declines rapidly. Therefore, the rise in consumption of households facing long run mean temperatures below 15 °C, may be partly explained by an increase in productivity and therefore, income and consumption.

The existence of productivity effects is further tested by regressing *log* consumption on temperature and temperature-squared to estimate a turning point level of temperature which optimises consumption. Calculations in the Appendix show that the consumption minima is obtained at a temperature of 7.9 °C and the consumption-temperature relationship does not follow an inverted-U curve. In fact, with the inclusion of year and district dummy variables, neither coefficients on the temperature or temperature-squared variables are statistically significant, indicating the lack of a temperature-productivity relationship for Indian households, insofar as consumption expenditures proxy income or productivity.

10 Limitations

The limitations of the dissertation are now discussed. The primary drawback of the analysis in this paper is that none of the four measures utilised for the climate variables, temperature and precipitation, fulfill the criterion of a normal distribution, as confirmed by the Shapiro-Wilk W test for normality (Table 9) and as can be inferred from the kernel density plots in Figure 4. The lack of normality is potentially due to spatial and temporal dependence of the climate data, which can typically be corrected by using Conley (2008)'s Heteroscedasticity and Autocorrelation Consistent (HAC) estimation technique, which corrects the standard errors for the spatial dependence among geographically concentrated districts. However, the large sample size employed in the estimation precluded efficient usage of Conley's technique and proved computationally costly. Further, this technique corrects the standard errors, thereby making the estimates more precise but does not affect the coefficient values. Therefore, the regression coefficients obtained in the preceding sections can be interpreted as they are, insofar as the coefficients are statistically significant at standard levels of significance.

Alternative measures of climate variables may be employed in future research to improve upon the estimates obtained in this paper. While mean temperature was tested through a number of alternative measures, the next step could be to study the effects of a rise in maximum temperature at a daily or monthly frequency on the local economy. It can plausibly be expected that household consumption patterns may react differently to unexpected increases in the maximum temperature, while the effects due to mean temperature may be less responsive, although the mechanisms are expected to be the same. In addition, rather than using precipitation levels, the Standardized Precipitation Index (SPI) could be utilised to capture the magnitude of drought and excess precipitation. This can be done by fitting a gamma distribution to the underlying precipitation data and subsequently normalising the data (Dallmann and Millock 2017). However, the program being computationally intensive prevents the use of this measure in this paper.

A third limitation of this dissertation is the use of the OLS estimation method rather than the quantile regression method for the evaluation of heterogeneous effects of climate shocks across the consumption distribution. The Quantile regression estimator minimises the asymmetric absolute loss function at different quantiles of the distribution, thereby estimating not the average effect but the effect on the data points closest to the τ^{th} quantile. While this method best approximates heterogeneous effects, a key issue in quantile regression is the non-differentiability of the absolute loss function at points where the error term is close to zero, i.e. $\mu_i = 0$. In large samples, this is typically not a concern as the probability of the estimator being non-differentiable declines with the sample size. However, this implies that the OLS and QR coefficients are not strictly comparable (Wooldridge 2002). The OLS estimation interacts the climate variables by the consumption decile to which the household belongs, thus estimating the differential effects across deciles in an efficient manner by utilising the entire dataset in the regression. This is an improvement upon alternative methods which estimate differential effects separately for each decile by restricting the observations to those pertaining to the relevant decile. Utilising only a subset of the data for estimation may not lead to normally distributed error terms, as a subset of the underlying population would not be normally distributed. This would raise concerns for hypothesis testing based on the regression estimates.

Lastly, the analysis raises some puzzles in terms of the mechanisms driving the increase in total consumption of the top 20 per cent individuals, beyond a rise in their energy consumption, which in part accounts for this increase. Therefore, it is important to test alternative mechanisms such as the income and productivity channels for the top deciles of the population. This could be done by utilising the India Human Development Survey (IHDS) which provides household-level data on income, consumption and wages, as well as other data sources such as the NSS Employment-Unemployment survey, the Annual Survey of Industries and the NSS firm-level surveys, which provide data on wages of workers and firm managers. Analysing differential impacts on sub-groups of the population such as production workers vis-à-vis firm managers may highlight important dimensions of the economic impacts of climate change and in particular, its consequences on inequality. Utilising alternative datasets could help answer these questions and may be interesting areas for further research.

11 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 lead to a reversal of the hitherto gains made in poverty reduction, lead to a loss of biodiversity and have adverse human health impacts. This paper examines the effects of climate shocks, measured as variability in temperature and precipitation, on monthly per capita consumption expenditure of Indian households over the 1988-2012 period. The analysis also delves into heterogeneity across households based on their consumption decile, sector of occupation, region of residence and access to state insurance through possession of ration cards.

Evidence for climatic impacts on the average household shows an increase in consumption expenditure in response to higher temperatures. 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). Heterogeneous impacts on households at various deciles of the consumption distribution highlight the mechanisms for this observed rise. While consumption of the top 20 per cent individuals rises, that of the bottom 50 per cent individuals (i.e. bottom five deciles) significantly declines due to equivalent heat shocks. Therefore, the observed positive impacts on the average household are being driven by the increase in consumption at the upper tail of the distribution. Two mechanisms are investigated for the observed rise in consumption. The evidence points to a rise in electricity consumption, presumably for the use of climate control such as electric coolers and air conditioners, due to unexpected higher temperatures. Differential responses of electricity expenditure across the initial consumption distribution shows a significant rise in electricity use for the top two deciles of the population and a decline for the remaining deciles, which mirrors the heterogeneous effects of climate shocks on total consumption. The decline in energy consumption of low-income households can be explained by their low energy expenditure shares (Dorband *et al.* 2019) which may lead to potential substitution of other types of consumption such as food and nutrition for energy in the wake of climate shocks and heat stress.

The second mechanism tested is a potential rise in productivity of households residing in relatively 'colder' districts, in response to higher temperatures, compared to households in historically 'warmer' districts. However, the empirical evidence fails to find differential economic impacts of climate shocks in 'hotter' vs 'colder' districts, thus ruling out the mechanism of a productivity increase on the average household. Further investigation is required to understand differential impacts across low- and upper-income households, in particular, whether the latter experience a rise in productivity perhaps due to increased energy consumption in response to temperature shocks.

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 agriculture and industrial sectors experience adverse climatic effects on their per capita monthly consumption, households in the services sector witness an overall increase in consumption, in both rural and urban areas. The rise in consumption of rural households relative to urban households due to equivalent temperature shocks seems counter-intuitive, as urban households may be expected to utilise more self-protection measures such as use of climate control against heat shocks. An interesting result is the rise in consumption of rural agricultural households, which is contrary to existing evidence on agricultural impacts of climate change. This rise in consumption may be driven by the increase in commodity prices due to lower crop yields, which may be reasonably expected on account of heat stress. Nonetheless, further assessment of the sector-specific mechanisms is needed to identify the channels resulting in these impacts. In addition, industrial households experience more adverse effects relative to agricultural ones on average across rural and urban regions, i.e. a loss of consumption by 6.5 per cent vs. 3.8 per cent, which highlights the importance of analyzing climatic impacts on this sector. Important questions for future research could be to understand the drivers of impacts by sector and their relative magnitudes, for example, whether a rise in energy consumption drives the aggregate increase in consumption of service sector households. Lastly, the possession of ration cards by households does not appear to moderate the adverse impacts of climate shocks on per capita consumption. Alternative measures of state insurance could be employed in future research to investigate the effects of social protection in mitigating potentially adverse climatic impacts.

The empirical analysis in this paper has important implications for economic and climate policy. The heterogeneous impacts of climate shocks reveal an increase in inequality of consumption, which would in turn lead to a slowed pace of poverty reduction and reflects the lack of inclusive growth. In this regard, an important policy question is whether market instruments such as carbon taxes can be employed for redistributive purposes, from high- to low-income households, in order to compensate the poor for reductions in their consumption due to climate change. A wholesome welfare analysis is required to evaluate the effects of such policies on various income groups of the population.

In addition, the rise in electricity consumption by richer individuals in response to temperature shocks has implications for national and international energy demand along with strategies for mitigation of climate change. In 2018, global energy demand rose by 2.3 per cent, 70 per cent of which was accounted for by China, the United States and India (IEA 2019). It is further forecast to grow by 25 per cent till 2040 (IEA 2018b). This increase in energy demand exerts pressure on existing sources of energy and would need to increasingly be met by renewable energy sources to combat rising emissions from fossil fuels. India's Nationally Determined Contribution to the Paris Climate Accord 2015 targets a 40 per cent share of renewable energy in the total installed power capacity by 2030, with 175 Gigawatts of solar power by 2022 (Press Information Bureau 2018 [PIB]). As of October 2018, the share of renewable energy from a mixture of sources including wind, solar, small-hydro and bio-power stood at 21.12 per cent (PIB 2018). Beyond existing national and global energy requirements and targets, the analysis in this paper highlights the unanticipated distributional consequences of existing global warming, such as rising inequality of total consumption as well as that of electricity or energy consumption. This helps identify an important dimension for effective policy action to serve the dual objectives of mitigating climate change and reducing socio-economic inequality, thereby promoting inclusive and sustainable growth.

12 References

Attanasio, O. P. and Pistaferri, L. 2016. Consumption Inequality. Journal of Economic Perspectives, 30 (2): 3-28.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M. and Shapiro, J. 2015. Convergence in Adaptation to Climate Change: Evidence from High Temperatures and Mortality, 1900-2004. American Economic Review, 105 (5): 247-51.

Bourguignon, F. and Morrisson, C. 2002. Inequality Among World Citizens: 1820-1992 . American Economic Review, 92 (4): 727-744.

Bourguignon, F. 2003. The Poverty-Growth-Inequality Triangle. World Bank.

Burke, M. and Emerick, K. 2016. Adaptation to Climate Change: Evidence from US Agriculture. American Economic Journal: Economic Policy, 8 (3): 106-40.

Burke, M., Hsiang, S. and Miguel, E. 2015. Global non-linear effect of temperature on economic production. Nature volume 527, pages 235–239 (12 November 2015).

Chancel, L. and Piketty, T. 2017. Indian income inequality, 1922-2015: From British Raj to Billionaire Raj? WID Working Paper Series No. 2017/11.

Chancel, L. and Piketty, T. 2015. Carbon and inequality: from Kyoto to Paris. Paris School of Economics and IDDRI, Sciences Po.

Conley, T. G. 2008. Spatial Econometrics. In: Palgrave Macmillan (eds) The New Palgrave Dictionary of Economics. Palgrave Macmillan, London.

Cubasch, U., D. Wuebbles, D. Chen, M.C. Facchini, D. Frame, N. Mahowald, and J.-G. Winther. 2013. Introduction. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Dallmann, I. and Millock, K. 2017. Climate Variability and Inter-State Migration in India. CESifo Economic Studies, Vol. 63, Issue 4, pp. 560–594.

Datta, K. L. 2006. The Debate on the Poverty Estimates of 1999–2000. ICRIER Working Paper No. 188.

Deaton, A. S. 1997. The Analysis of Household Surveys : A Microeconometric Approach to Development Policy. Washington, D.C. : The World Bank.

Dell, M., Jones, B., Olken, B. 2014. What Do We Learn from the Weather? The New Climate Economy Literature. Journal of Economic Literature, 52(3), 740-798.

Dell, M., Jones, B. F. and Olken, B. A. 2012. Temperature Shocks and Economic Growth: Evidence from the Last Half Century. American Economic Review, 4(3), 66-95.

Deryugina, T. and Hsiang, S. 2014. Does the Environment Still Matter? Daily Temperature and Income in the United States. NBER Working Paper No. 20750.

Deschênes, O. and Greenstone, M. 2011. Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. American Economic Journal: Applied Economics, 3 (4): 152-85.

Dorband, I., Jakob, M., Kalkuhl, M. and Steckel, J. 2019. Poverty and distributional effects of carbon pricing in low- and middle income countries – A global comparative analysis. World Development. Vol. 115, pp. 246-257.

FAO, IFAD, UNICEF, WFP and WHO. 2018. The State of Food Security and Nutrition in the World 2018. Building climate resilience for food security and nutrition. Rome, FAO.

Fleurbaey M., S. Kartha, S. Bolwig, Y. L. Chee, Y. Chen, E. Corbera, F. Lecocq, W. Lutz, M. S. Muylaert, R. B. Norgaard, C. Okereke and A. D. Sagar. 2014. Sustainable Development and Equity. In: Climate Change. 2014. Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlomer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Government of India. 2018a. Economic Survey of India, 2017-18, Climate, Climate Change and Agriculture (Chapter 6).

Government of India. 2018b. Economic Survey of India, 2017-18, State of the Economy: An Analytical Overview and Outlook for Policy (Chapter 1).

Greenstone, M. and Hanna, R. 2014. Environmental Regulations, Air and Water Pollution, and Infant Mortality in India. American Economic Review, 104 (10): 3038-72.

Guhathakurta, P., Sreejith, O. P. and Menon, P. A. 2011. Impact of climate change on extreme rainfall events and flood risk in India. Journal of Earth System Science. Vol. 120, No. 3, pp. 359-373.

Hsiang, S. and Meng, K. 2015. Tropical Economics. American Economic Review, 105 (5): 257-61.

International Energy Agency. 2019. Global Energy CO_2 Status Report.

International Energy Agency. 2018a. CO_2 Emissions Statistics, 2018.

International Energy Agency. 2018b. World Energy Outlook 2018.

Intergovernmental Panel on Climate Change (IPCC). 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Jacoby, H., Rabassa, M. and Skoufias, E. 2011. Distributional implications of climate change in India. Policy Research working paper ; no. WPS 5623. Washington, DC : World Bank Group.

Mani, M., Bandyopadhyay, S., Chonabayashi, S., Markandya, A. and Mosier, T. 2018. South Asia's Hotspots : Impacts of Temperature and Precipitation Changes on Living Standards. South Asia Development Matters. Washington, DC: World Bank. © World Bank.

National Sample Survey Organisation (NSSO). 2011-12. Key Indicators of Household Consumer Expenditure in India. NSS 68th Round.

National Sample Survey Organisation (NSSO). 2009-10. Level and Pattern of Consumer Expenditure. NSS 66th Round.

Olsson, L., M. Opondo, P. Tschakert, A. Agrawal, S.H. Eriksen, S. Ma, L.N. Perch, and S.A. Zakieldeen. 2014. Livelihoods and poverty. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 793-832.

Piketty, T. and Qian, N. 2015. Income Inequality and Progressive Income Taxation in China and India, 1986-2015. American Economic Journal: Applied Economics, 1 (2): 53-63.

Pindyck, R. 2013. Climate Change Policy: What do the models tell us? NBER Working Paper Series, Working Paper 19244.

Pischke, S. 2007. Lecture Notes on Measurement Error. London School of Economics and Political Science. Available here.

Press Information Bureau (PIB). 2018. Year End Review 2018 – MNRE. Available here.

Rose, E. 1999. Consumption Smoothing and Excess Female Mortality in Rural India. Review of Economics and Statistics, Vol. 81, Issue 1, pp. 41-49.

Skoufias, E., Rabassa, M. and Olivieri, S. 2011. The Poverty Impacts of Climate Change. A Review of the Evidence. World Bank Policy Research Working Paper 5622.

Somanathan, E., Somanathan, R., Sudarshan, A. and Tewari, M. 2015. The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing. Indian Statistical Institute, Delhi, Economics and Planning Unit, Discussion Paper 15-03.

Somanathan E., T. Sterner, T. Sugiyama, D. Chimanikire, N. K. Dubash, J. Essandoh-Yeddu, S. Fifita, L. Goulder, A. Jaffe, X. Labandeira, S. Managi, C. Mitchell, J. P. Montero, F. Teng, and T. Zylicz. 2014. National and Subnational Policies and Institutions. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlomer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Taraz, V. 2018a. Can farmers adapt to higher temperatures? Evidence from India. World Development, Vol(112), pp. 2015-219.

Taraz, V. 2018b. Climate change, social protection, and crop yields: Evidence from India. Available at SSRN.

Taraz, V. 2017. Adaptation to climate change: Historical evidence from the Indian monsoon. Environment and Development Economics, 22(5), 517-545.

Walthall, C.L., J. Hatfield, P. Backlund, L. Lengnick, E. Marshall, M. Walsh, S. Adkins, M. Aillery, E.A. Ainsworth,C. Ammann, C.J. Anderson, I. Bartomeus, L.H. Baumgard, F. Booker, B. Bradley, D.M. Blumenthal, J. Bunce, K. Burkey, S.M. Dabney, J.A. Delgado, J. Dukes, A. Funk, K. Garrett, M. Glenn, D.A. Grantz, D. Goodrich, S. Hu, R.C. Izaurralde, R.A.C. Jones, S-H. Kim, A.D.B. Leaky, K. Lewers, T.L. Mader, A. McClung, J. Morgan, D.J. Muth, M. Nearing, D.M. Oosterhuis, D. Ort, C. Parmesan, W.T. Pettigrew, W. Polley, R. Rader, C. Rice, M. Rivington, E. Rosskopf, W.A. Salas, L.E. Sollenberger, R. Srygley, C. Stöckle, E.S. Takle, D. Timlin, J.W. White, R. Winfree, L. Wright-Morton, L.H. Ziska. 2012. Climate Change and Agriculture in the United States: Effects and Adaptation. USDA Technical Bulletin 1935. Washington, DC. 186 pages.

Wooldridge, J. 2002. Econometric Analysis of Cross-Section and Panel Data. MIT Press.

World Bank. 2019. Poverty and Equity Brief, South Asia, India.

World Bank, World Development Indicators. 2017. GDP Ranking. Accessed on 11th April, 2019.

World Meteorological Organization (WMO). 2019. WMO Statement on the State of the Global Climate in 2018. WMO-No. 1233.

13 Appendix

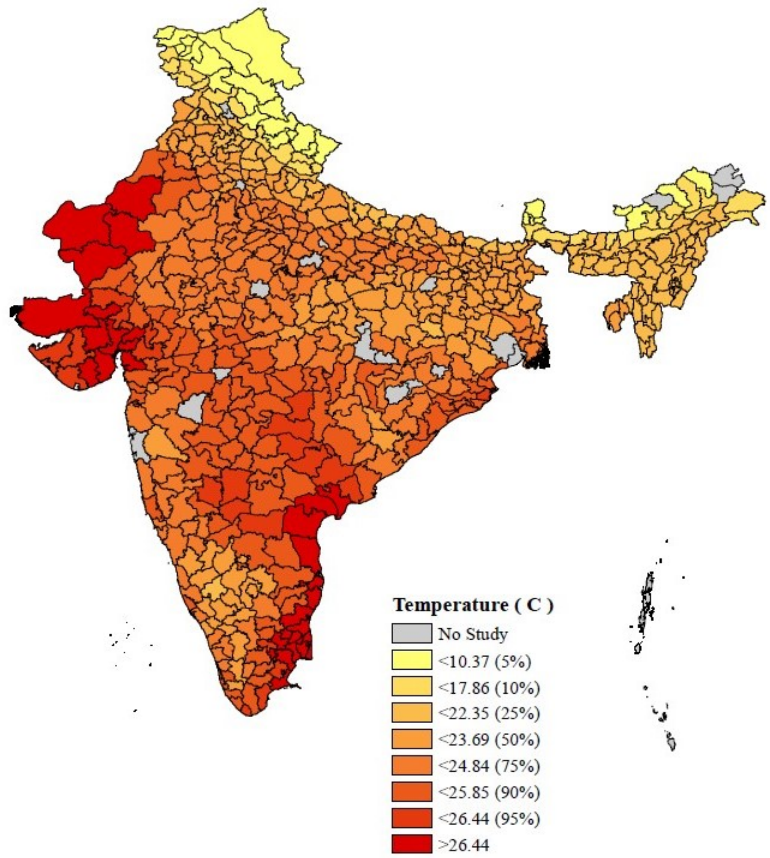

Figure 4: Spatial distribution of mean temperature across Indian districts, 1979-2015. Source: Taraz (2018a)

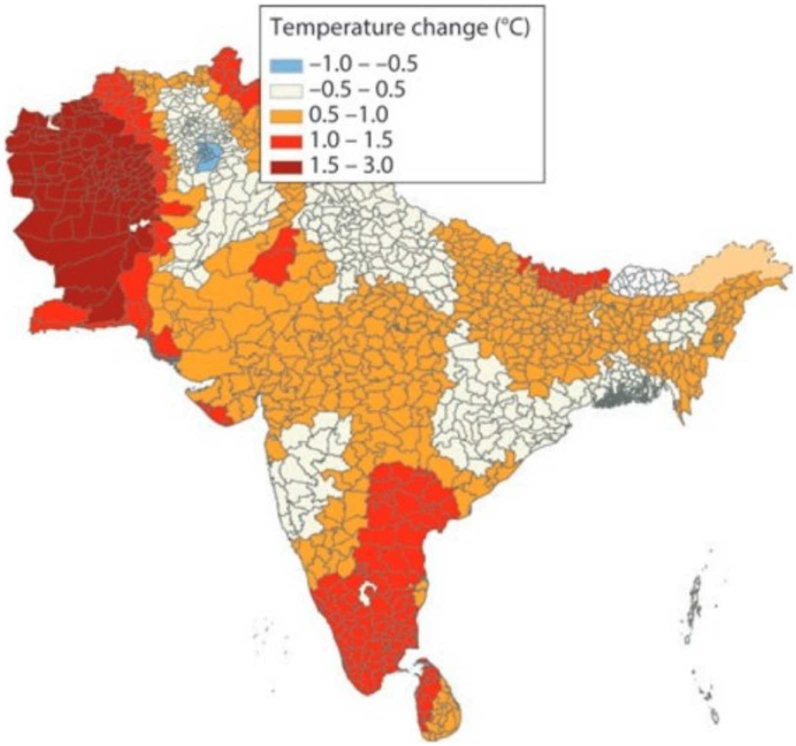

Figure 5: Temporal change in mean temperature across Indian districts, 1951-2010. Source: Mani *et al.* (2018)

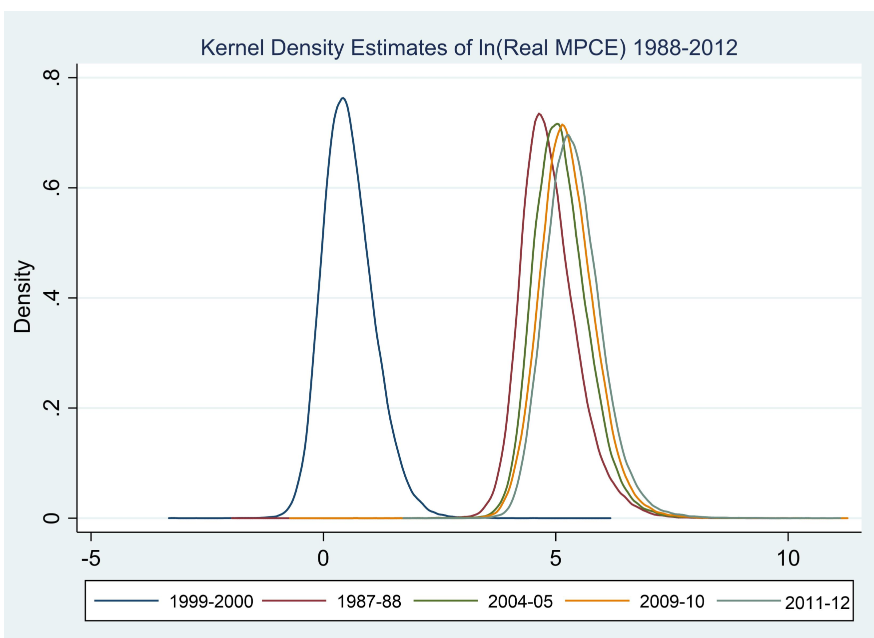

Figure 6: Kernel Density Plots of ln(Real MPCE), 1988-2012

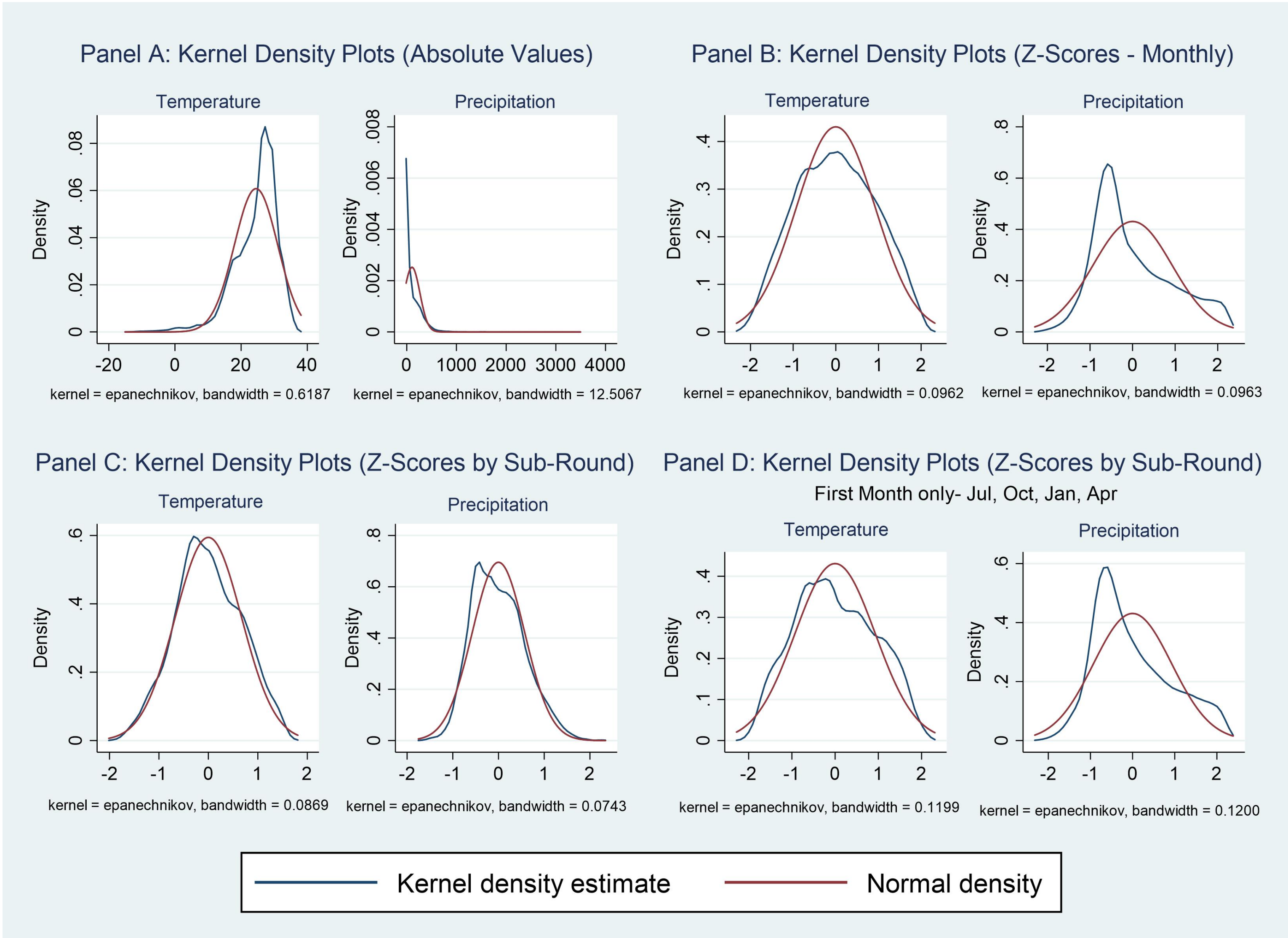

Figure 7: Kernel Density Plots of Temperature and Precipitation (all measures)

Variables	Observations	W	V	Z	Prob>z
Std. Temp.	545,833	0.99014	825.988	19.072	0.00000
Std. Pre.	545,683	0.98439	1307.920	20.378	0.00000
ln(Real MPCE) - 1988	114,291	0.97146	955.532	6.988	0.00000
ln(Real MPCE) - 2000	111,440	0.98385	531.462	6.594	0.00000
ln(Real MPCE) - 2005	123,211	0.97794	776.882	6.651	0.00000
ln(Real MPCE) - 2010	98,354	0.98125	566.193	6.930	0.00000
ln(Real MPCE) - 2012	98,535	0.97670	704.468	7.110	0.00000

Table 9: Shapiro-Wilk W test for normal data

Decile	Mean	Min.	Max.
1	71.27	49.03	84.50
2	93.70	84.50	102
3	109.6	102.0	117.2
4	125.0	117.2	133.2
5	142.3	133.2	151.6
6	162.6	151.7	174.5
7	189.2	174.5	205.9
8	227.8	205.9	253.8
9	295.9	253.8	351.9
10	583.8	351.9	102185.1
Average	200.1	49.03	102185.1
N	432928		

Table 10: Summary Statistics of Real MPCE by Quantile Categories (Rs.)

ln(Real MPCE)	(1)	(2)	(3)	(4)	(5)	(6)
Temp.	-0.00633***	0.000962**				
	(-5.7528)	(3.0702)				
Pre.	0.000199***	-0.0000219				
	(4.2638)	(-1.7300)				
Dev. Temp.			0.0113**			
			(3.1688)			
Dev. Pre.			-0.0000159			
			(-0.4263)			
Std. Temp.				0.0122***	0.0117***	
				(4.1070)	(3.6291)	
Std. Pre.					-0.00218	
					(-0.6145)	
Std. Temp. (1mo)						0.00645**
						(2.8552)
Std. Pre. (1mo)						-0.00363
						(-1.7315)
Constant	5.001***	5.419***	5.439***	5.439***	5.440***	5.439***
	(174.1499)	(510.7805)	(779.8587)	(772.6421)	(774.7374)	(768.7406)
N	545831	545831	545831	545831	545681	542765
R^2	0.907	0.921	0.921	0.921	0.921	0.921
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
District Dummies	No	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Pooled Cross-Section Regression Results (1988-2012)

ln(Real MPCE)	(1)	(2)	(3)	(4)
Temp.	0.00585			
	(0.80)			
Pre.	-0.0005***			
	(-3.86)			
Dev. Temp.		0.0468***		
		(3.53)		
Dev. Pre.		-0.000432**		
		(-3.09)		
Std. Temp.			0.0483***	
			(4.25)	
Std. Pre.			-0.0270*	
			(-2.07)	
Std. Temp. (1mo)				0.0290***
				(3.40)
Std. Pre. (1mo)				-0.0234**
				(-2.92)
Constant	4.667***	4.752***	4.752***	4.752***
	(25.23)	(532.73)	(517.89)	(549.92)
N	2588	2588	2588	2588
R^2	0.995	0.995	0.995	0.995
Year Fixed-Effects	Yes	Yes	Yes	Yes
District Fixed-Effects	Yes	Yes	Yes	Yes

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Panel Fixed-Effects Regression Results (1988-2012)

Deciles (Mean Value)	(1a) Temp.	(1b) Pre.	(2a) Dev. Temp.	(2b) Dev. Pre.	**(3a) Std. Temp.**	(3b) Std. Pre.	(4a) Std. Temp. (1mo)	(4b) Std. Pre. (1mo)
1 (Rs. 71)	-0.0403***	0.000203***	-0.616***	-0.00239***	**-0.493*** **	-0.275***	-0.0560***	-0.0570***
	(-63.68)	(7.29)	(-27.58)	(-6.15)	(-21.71)	(-10.35)	(-3.77)	(-3.49)
2 (Rs. 94)	-0.0303***	0.000126***	-0.463***	-0.00176***	**-0.376*** **	-0.182***	-0.0714***	-0.0432***
	(-48.12)	(6.50)	(-34.32)	(-7.79)	(-28.32)	(-11.71)	(-8.12)	(-4.18)
3 (Rs. 110)	-0.0245***	0.0000719***	-0.346***	-0.00114***	**-0.279*** **	-0.100***	-0.0543***	-0.0298***
	(-38.81)	(3.85)	(-31.02)	(-6.68)	(-24.20)	(-8.12)	(-7.57)	(-3.81)
4 (Rs. 125)	-0.0197***	0.0000233	-0.261***	-0.000835***	**-0.209*** **	-0.0634***	-0.0430***	-0.0233***
	(-30.85)	(1.30)	(-25.23)	(-6.73)	(-20.55)	(-6.42)	(-7.19)	(-3.40)
5 (Rs. 142)	-0.0150***	0.00000372	-0.197***	-0.000525***	**-0.159*** **	-0.0307***	-0.0375***	-0.0143*
	(-23.42)	(0.23)	(-22.94)	(-4.49)	(-19.22)	(-3.37)	(-7.40)	(-2.36)
6 (Rs. 163)	-0.00991***	-0.0000185	-0.130***	-0.000218*	**-0.108*** **	-0.00211	-0.0325***	-0.00446
	(-15.43)	(-1.29)	(-16.64)	(-2.57)	(-13.87)	(-0.30)	(-6.92)	(-0.82)
7 (Rs. 189)	-0.00442***	-0.0000239*	-0.0586***	-0.0000242	**-0.0477*** **	0.0152**	-0.0207***	-0.00197
	(-6.85)	(-2.05)	(-7.23)	(-0.37)	(-6.45)	(2.62)	(-5.01)	(-0.41)
8 (Rs. 228)	0.00214***	-0.0000156	0.0273**	0.000231**	**0.0236** **	0.0412***	-0.00251	0.00621
	(3.38)	(-1.75)	(3.07)	(2.78)	(2.88)	(7.80)	(-0.58)	(1.50)
9 (Rs. 296)	0.0110***	-0.0000170	0.138***	0.000524***	**0.118*** **	0.0686***	0.0232***	0.0117**
	(18.10)	(-1.87)	(11.56)	(5.69)	(11.19)	(10.04)	(4.96)	(2.59)
10 (Rs. 584)	0.0328***	-0.0000123	0.444***	0.000670**	**0.383*** **	0.0881***	0.114***	0.0138
	(63.15)	(-0.50)	(18.93)	(3.06)	(18.66)	(5.20)	(12.88)	(0.94)
N	432928	432928	432928	432928	432850	432850	430417	430417
R^2	0.821	0.821	0.285	0.285	0.286	0.286	0.233	0.233

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Constant term omitted from table to conserve space.
Inclusion of year and district dummy variables. 'Std. Temp. (1mo)' and 'Std. Pre. (1mo)' refer to the first month of each sub-round.

Table 13: Impact of climate shocks on ln(Real MPCE) by Consumption Deciles, 1988-2012 (excluding 2000)

ln(Real MPCE)	(1)	(2)	(3)	(4)
Temp.	0.000770*			
	(2.31)			
Pre.	-0.0000183			
	(-1.31)			
Dev. Temp.		0.0122*		
		(2.54)		
Dev. Pre.		-0.0000338		
		(-0.82)		
Std. Temp.			0.0146***	
			(3.52)	
Std. Pre.			-0.00437	
			(-1.09)	
Std. Temp. (1mo)				0.00719**
				(2.97)
Std. Pre. (1mo)				-0.00606**
				(-2.66)
Constant	5.435***	5.451***	5.452***	5.450***
	(486.51)	(794.99)	(787.36)	(784.00)
N	434391	434391	434313	431877
R^2	0.226	0.226	0.226	0.226

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Inclusion of year and district dummies.

Table 14: Robustness Check for Pooled OLS Regressions (All years except 1999-2000)

ln(Real MPCE)	(1)	(2)	(3)	(4)
Temp.	0.000574			
	(1.49)			
Pre.	-0.0000152			
	(-0.93)			
Dev. Temp.		0.0117**		
		(2.64)		
Dev. Pre.		-0.000143***		
		(-3.63)		
Std. Temp.			0.0120**	
			(3.01)	
Std. Pre.			-0.0137***	
			(-3.94)	
Std. Temp. (1mo)				0.00446
				(1.81)
Std. Pre. (1mo)				-0.0123***
				(-5.01)
Constant	5.716***	5.724***	5.722***	5.726***
	(541.36)	(1239.18)	(1246.69)	(1364.54)
N	320100	320100	320032	318145
R^2	0.186	0.187	0.187	0.187

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Inclusion of year and district dummies.

Table 15: Robustness Check for Pooled OLS Regressions (All years except 1987-88 and 1999-2000)

ln(Real MPCE)	(1) Temp.	(2) Std. Temp.	(3) Temp.	(4) Std. Temp.
NIC Code 1 (Agriculture)	-0.00360***	-0.0383***		
	(-9.23)	(-6.47)		
NIC Code 2 (Industry)	-0.00438***	-0.0647***		
	(-9.48)	(-9.48)		
NIC Code 3 (Services)	0.00350***	0.0306***		
	(-9.21)	(-6.22)		
Region (1 = Rural, 0 = Urban)	0.00324***	0.0470***		
	(-11.31)	(-7.6)		
Rural Agriculture			-0.0000665	0.0140**
(NIC Code - 1, Region - 1)			(-0.18)	(-2.96)
Urban Agriculture			-0.00767***	-0.0973***
(NIC Code - 1, Region - 2)			(-15.77)	(-8.28)
Rural Industry			-0.00235***	-0.0290***
(NIC Code - 2, Region - 1)			(-5.95)	(-4.71)
Urban Industry			-0.00329***	-0.0535***
(NIC Code - 2, Region - 2)			(-6.69)	(-6.73)
Rural Services			0.00679***	0.0744***
(NIC Code - 3, Region - 1)			-19.39	-14.64
Urban Services			0.00344***	0.0325***
(NIC Code - 3, Region - 2)			-8.96	-6.61
Constant	5.417***	5.444***	5.417***	5.443***
	(-507.97)	(-779.03)	(-504.78)	(-779.3)
N	512020	511877	512020	511877
R^2	0.925	0.923	0.925	0.923

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Inclusion of precipitation controls, year dummies and district dummies.

Table 16: Heterogeneous effects of climate shocks by a household's primary occupation and region of residence.

ln(Real MPCE)	(1a)	(1b)	(2a)	(2b)
	(All years except 2000)		(All years except 1988 & 2000)	
	Temp.	Std. Temp.	Temp.	Std. Temp.
Rural Agriculture	-0.0000302	0.00734	0.00167***	0.0178**
(NIC Code - 1, Region - 1)	(-0.08)	(-1.21)	(-3.74)	(-2.98)
Urban Agriculture	-0.00787***	-0.144***	-0.00906***	-0.164***
(NIC Code - 1, Region - 2)	(-15.19)	(-10.84)	(-15.20)	(-11.72)
Rural Industry	-0.00285***	-0.0347***	-0.00278***	-0.0314***
(NIC Code - 2, Region - 1)	(-7.08)	(-4.98)	(-6.40)	(-4.71)
Urban Industry	-0.00382***	-0.0624***	-0.00659***	-0.0896***
(NIC Code - 2, Region - 2)	(-7.50)	(-6.57)	(-12.08)	(-9.01)
Rural Services	0.00658***	0.0965***	0.00659***	0.0968***
(NIC Code - 3, Region - 1)	(-17.7)	(-16.06)	(-15.37)	(-15.39)
Urban Services	0.00307***	0.0504***	0.00110*	0.0390***
(NIC Code - 3, Region - 2)	(-7.63)	(-8.05)	(-2.39)	(-5.97)
Constant	5.434***	5.454***	5.725***	5.724***
	(477.96)	(795.67)	(512.80)	(1169.95)
N	407471	407395	298444	298378
R^2	0.249	0.230	0.218	0.192

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Inclusion of precipitation controls, year dummies and district dummies.

Table 17: Robustness Checks for heterogeneous effects of climate shocks by a household's primary occupation and region of residence.

	(1) ln(Real MPCE)	(2) ln(Real MPCE)	(3) ln(Real MPCE)	(4) ln(Real MCE)
Ration (= 1)	-0.118***	-0.101***	-0.117***	0.147***
	(-14.32)	(-3.60)	(-14.17)	(11.63)
Temperature		0.00185		
		(1.86)		
Temperature * (Ration = 1)		-0.000690		
		(-0.64)		
Std. Temp.			0.0400***	0.0310*
			(3.73)	(2.56)
Std. Temp. * (Ration Card = 1)			-0.0318**	-0.0339**
			(-2.87)	(-2.67)
Constant	5.810***	5.772***	5.804***	7.128***
	(803.91)	(223.05)	(765.86)	(651.87)
N	221746	221746	221702	221702
R^2	0.206	0.206	0.207	0.168

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Inclusion of precipitation controls, year and district dummies.
MCE - Monthly consumer expenditure for a household.

Table 18: Effects of temperature shocks on consumption in the presence of ration cards (2004-05 and 2011-12)

ln(Real MPCE) Sub-Round	(1) Temp.	(2) Dev. Temp.	(3) Std. Temp.	(4) Std. Temp. (1mo)
1 (Jul-Sep)	0.000899	0.0119	0.0103	-0.000691
	(1.29)	(0.87)	(1.57)	(-0.12)
2 (Oct-Dec)	0.000916	0.0332***	0.0202***	0.00539
	(1.05)	(3.89)	(3.36)	(1.15)
3 (Jan-Mar)	0.000136	0.00526	0.00535	0.00680
	(0.16)	(0.96)	(0.96)	(1.66)
4 (Apr-Jun)	0.000492	0.00696	0.0237**	0.0154***
	(0.80)	(1.09)	(3.16)	(3.63)
Constant	5.444***	5.456***	5.455***	5.456***
	(239.58)	(810.86)	(785.46)	(797.12)
N	433067	433067	432989	430556
R^2	0.225	0.225	0.225	0.225

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Inclusion of precipitation controls, year and district dummies.

Table 19: The impact of climate shocks on ln(Real MPCE) by sub-round of the NSS survey

ln(Electricity Exp.)	(1)	(2)	(3)	(4)
Temp.	0.00244***			
	(4.06)			
Dev. Temp.		0.0157*		
		(2.32)		
Std. Temp.			-0.00326	
			(-0.49)	
Std. Temp. (1mo)				-0.00393
				(-1.02)
Constant	2.825***	2.879***	2.885***	2.882***
	(140.61)	(193.53)	(190.82)	(190.27)
N	303904	303904	303832	301690
R^2	0.911	0.911	0.911	0.911

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Inclusion of precipitation controls, year and district dummies.

Table 20: The impact of climate shocks on *log* electricity consumption, 1988-2012 (excluding 2000)

ln(Electricity Exp.)	(1)	(2)	(3)	(4)
Sub-Round	Temp.	Dev. Temp.	Std. Temp.	Std. Temp. (1mo)
1 (Jul-Sep)	-0.00189	0.0421	0.0114	0.00539
	(-1.73)	(1.96)	(1.09)	(0.68)
2 (Oct-Dec)	-0.00101	0.0327**	0.00775	0.0102
	(-0.78)	(2.86)	(0.90)	(1.50)
3 (Jan-Mar)	-0.00308*	-0.00325	-0.0210*	-0.0127*
	(-2.53)	(-0.39)	(-2.35)	(-1.98)
4 (Apr-Jun)	-0.000172	0.0250**	0.00833	-0.00478
	(-0.19)	(2.91)	(0.71)	(-0.74)
Constant	2.930***	2.881***	2.885***	2.884***
	(79.58)	(194.12)	(189.34)	(191.80)
N	303904	303904	303832	301690
R^2	0.911	0.911	0.911	0.911

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Inclusion of precipitation controls, year and district dummies.

Table 21: The impact of climate shocks on *log* electricity consumption by sub-round

ln(Electricity Exp.)	(1)	(2)	(3)	(4)
Decile	Temp.	Dev. Temp.	Std. Temp.	Std. Temp. (1mo)
1	-0.0236***	-0.427***	-0.385***	-0.0991***
	(-22.48)	(-10.14)	(-10.12)	(-4.95)
2	-0.0174***	-0.293***	-0.265***	-0.0661***
	(-19.44)	(-13.46)	(-13.43)	(-5.71)
3	-0.0135***	-0.241***	-0.219***	-0.0560***
	(-17.08)	(-15.61)	(-15.20)	(-5.92)
4	-0.0111***	-0.170***	-0.157***	-0.0409***
	(-15.20)	(-12.21)	(-12.26)	(-5.25)
5	-0.00881***	-0.142***	-0.134***	-0.0398***
	(-12.58)	(-12.04)	(-12.01)	(-5.56)
6	-0.00600***	-0.0971***	-0.0976***	-0.0325***
	(-8.65)	(-9.21)	(-9.74)	(-5.34)
7	-0.00315***	-0.0619***	-0.0764***	-0.0322***
	(-4.66)	(-6.59)	(-8.31)	(-5.58)
8	0.000565	-0.0138	-0.0280**	-0.0156**
	(0.85)	(-1.51)	(-3.14)	(-2.94)
9	0.00568***	0.0568***	0.0288**	0.00286
	(8.34)	(5.81)	(3.14)	(0.54)
10	0.0168***	0.208***	0.164***	0.0547***
	(25.42)	(15.62)	(13.45)	(7.28)
Constant	2.625***	2.845***	2.849***	2.869***
	(135.98)	(197.03)	(191.16)	(187.75)
N	303900	303900	303828	301686
R^2	0.922	0.912	0.912	0.911

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Inclusion of precipitation controls, year and district dummies.

Table 22: Heterogeneous impacts of climate shocks on *log* electricity consumption by decile

ln(Real MPCE)	(1) Temp.	(2) Dev. Temp.	(3) Std. Temp.	(4) Std. Temp. (1mo)
Hot District (= 1)	-0.0439	0.00651*	0.00617*	0.00544
	(-1.24)	(2.27)	(2.16)	(1.94)
Temp.	0.00109			
	(1.51)			
Dev. Temp.		0.0133**		
		(3.28)		
Std. Temp.			0.0124**	
			(3.17)	
Std. Temp. (1mo)				0.00587*
				(2.00)
Hot District (= 1) * Temp. Variable	0.00125 (1.01)	-0.00548 (-0.83)	-0.00163 (-0.28)	0.00135 (0.31)
Pre.	-0.0000723***			
	(-4.03)			
Hot District (= 1) * Pre.	0.0000833*** (3.36)			
Constant	5.416***	5.433***	5.434***	5.434***
	(330.14)	(707.51)	(711.61)	(692.56)
N	545831	545831	545681	542765
R^2	0.921	0.921	0.921	0.921

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Inclusion of precipitation controls, year and district dummies.

Table 23: Differential impacts of climate shocks across 'Hot' and 'Cold' Districts (1988-2012)

ln(Real MPCE)	(1)	(2)	(3)	(4)
Temp.	-0.0000321			
	(-0.02)			
Dev. Temp.		0.00690		
		(0.77)		
Std. Temp.			0.00669	
			(0.71)	
Std. Temp. (1mo)				0.0189**
				(3.15)
Temp. Range 1 (15-29 °C)	-0.0456	-0.00938	-0.00983	-0.00988
	(-1.93)	(-1.12)	(-1.16)	(-1.16)
Temp. Range 2 ($>$ 29 °C)	0.0446	0.000415	-0.000655	-0.00215
	(0.50)	(0.05)	(-0.07)	(-0.23)
Temp. Range 1 * Temp. Variable	0.00211	0.0111	0.00800	-0.0121
	(1.31)	(1.11)	(0.79)	(-1.89)
Temp. Range 2 * Temp. Variable	-0.00108	-0.00998	-0.00730	-0.0191*
	(-0.36)	(-0.88)	(-0.60)	(-2.49)
Std. Pre. (1mo)				0.0161*
				(2.14)
Temp. Range 1 * Std. Pre. (1mo)				-0.0199*
				(-2.46)
Temp. Range 2 * Std. Pre. (1mo)				-0.0263**
				(-3.00)
Constant	5.438***	5.448***	5.450***	5.450***
	(258.16)	(511.20)	(507.91)	(501.69)
N	545831	545831	545681	542765
R^2	0.921	0.921	0.921	0.921

t statistics in parentheses ; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Inclusion of precipitation controls, year and district dummies.

Table 24: Differential impacts of climate shocks by temperature ranges (1988-2012)

Calculation of Temperature Inflection Points

A quadratic equation can be written as:

$$y = ax^2 + bx + c \tag{7}$$

The first-order condition w.r.t. x for global optimum is:

$$\frac{dy}{dx} = 2ax + b = 0 \tag{8}$$

$$\implies x^* = -\frac{b}{2a} \tag{9}$$

is the solution to the global optimum. Based on the second order derivative, $a < 0$ implies the function is concave and x^* is the point of global maxima, whereas $a > 0$ implies a convex function, with x^* being the point of global minima.

Calculation of the temperature threshold to optimise consumption is a parallel exercise. Given a = 0.0000178 and b = - 0.0002829 (regression not shown), yields an optimum temperature, T^* = 7.9 °C. Further, $a > 0$ implies that consumption increases with temperature and does not peak at the optimum of 7.9 °C.