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Adverse Impacts

An Empirical Examination of the Impact of Climate Extremes on Inequality in India

by

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Abstract: Climate change is receiving more attention; the public debate has started to note its significance, and the consequences have started to show. How societies are interlinked with their environment is as evident in the 21st century as ever before. This study is an attempt to examine the relationship between climate change and inequality in India. Climate change is quantified by investigating climate extremes, defined as excessive and insufficient precipitation and abnormal hot or cold temperatures. Distributions include consumption expenditure, food expenditure, land ownership and land cultivated, this being necessary to fully understand inequality of wealth and livelihoods. By utilizing five rounds of NSSO, between 1999-2012, and University of Delaware climate data in a fixed-effect regression, this thesis is calculating the impact of climate extremes on inequality at the district level in India. The most prominent finding is the non-uniform impact of climate extremes on inequality in India. The type of shock impacts distributional indicators differently and each distribution receive dissimilar impacts. To understand mediating factors on the impact of climate extremes, this thesis takes an interdisciplinary approach and utilizes a Vulnerability-Resilience framework, showing the importance of a societies' coping and adaptivity capacity.

Keywords: India, Inequality, Climate change, Climate extremes, Fixed-Effects model.

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1 Introduction

Climate change has increased in awareness; the public debate has started to note its significance, and its consequences have started to show. Global warming implies both gradual changes in the climate as well as an increase in the probability of events that occur seldomly (Hamann et al., 2018). Estimates suggest that richer countries experience more limited economic consequences of climate change than poorer (Acevedo, Mrkaic, Novta, Pugacheva & Topalova, 2018, 2018; Diffenbaugh & Burke, 2019; Mendelsohn, Dinar & Williams, 2006) and inequality increases for countries that experience natural disasters (Yamamura, 2015). Due to the convergence of countries' incomes has global inequality decreased in the last decades (Niño-Zarazúa, Roope & Tarp, 2017; Sala-i-Martin, 2006). However, individually almost all countries have experienced increased inequalities (Alvaredo, Chancel, Piketty, Saez & Zucman, 2017). With the increased presence of climate change which adversely impacts the poorest countries, the trend of convergence of countries’ incomes is counteracted. Whether climate change counteracts or support the trend of increasing inequality for countries is more contested, and something that this study will attempt to analyze.

Natural disasters and climate variability have always impacted human settlements and societies, yet global warming lead to increased intensity and frequency of climate extremes (IPCC, 2019). Through land degradation processes including larger rainfall intensities, flooding, droughts in both severity and frequency, heat stress, wind, dry spells, sea-level wave action and rise, and permafrost, are livelihoods altered (IPCC, 2019). Climate change adjust precipitation patterns with increased occurrence of abnormal rainfall levels as well as droughts. Consequently, some areas will be flood-prone while others will have severe lack of basic drinking water (UNFCCC, 2007). Further, IPCC (2019) states that climate change leads to gradual changing climate zones in the world, which includes increased areas of arid land. Naturally, this leads to plants and species experiencing changing habitats, which modifies their abundance and seasonal activities. Desertification leads to a reduction in livestock and crop productivity and changes the composition of preferred plant species that reduce biological diversity across dryland (IPCC, 2019). Studies find that climate change has already lowered yields in areas closer to the equator while has increased yields in regions far off, hence portraying adverse effects (IPCC, 2019). Together with changing precipitation, changed temperatures implies changing growing seasons which leads to reductions in regional yields, reduced freshwater availability, harmed biodiversity and increased tree mortality (IPCC, 2019). Climate change, thus, leads to stresses on food value chains and decreased agricultural productivity, implying food insecurity and increased food prices (IPCC, 2019).

India is and will be deeply impacted by climate change. The country was the fifth most affected country by climate change in 2018 and is placed 17th when measuring the last two decades (Eckstein, Winges, Künzel & Schäfer, 2020). Existing trends show increased extreme temperatures in India with less extreme cold days during winter and more heat waves during summer (Dash & Mamgain, 2011). Decertification, land degradation in arid, semi-arid and dry sub-humid areas is a continuous process in India (IPCC, 2019). All types of major cereals, vital for livelihoods, are negatively impacted by the gradual changes that climate changes contribute to (IPCC, 2019). Evidence suggests that climate change, in India, will lead to increased intensity and frequency of climate extremes such as drought, heatwaves and intense rainfall (Nagaveni & Anand, 2017). India, together with Pakistan, will be at the forefront by some climate extremes, projections estimate that the countries will be the first which systematically experiences lethal heatwaves (Woetzel, Pinner, Samandari, Engel, Krishnan, Boland, & Powis, 2020).

Inequality has received increased attention in the last decade and is now at the center of political and economic debate (Atkinson & Bourguignon, 2015). The liberal economic reforms of early 1990, which has increased growth and decreased poverty, has amplified economic inequality in India, disregarding the type of measurement and the type of group investigated (Chancel & Piketty, 2019; Jayadev, Motiram & Vakulabharanam, 2007; Kundu & Mohanan, 2009; Motiram & Vakulabharanam, 2013). Chancel & Piketty (2019) investigates India's income inequality between 1922 and 2015, finding that the recent inequality increase is due to the growth of top income earners. Consequently, the lowest 50 % and the 50th-90th percentiles have decreased their relative shares. Chancel & Piketty (2019) show that India's middle class receive a considerably smaller share of total national output than China's, Europe's and US's counterpart.

India is a federalist country and considerable share of the researchers are focusing on states and districts. Evidence portraits growing inequality between India's states, with the already wealthier states being drivers of economic growth (Kundu & Mohanan, 2009). For states, the effect is not uniform, some states experiencing decreased inequality while other increased. Motiram & Vakulabharanam (2013) highlight the non-inclusive growth pattern in India, states who have achieved the most significant growth rates have also seen the most substantial increases in inequality. Azam & Bhatt (2016) decompose income inequality by the district level, finding that inequality in India is to four fifth, both for rural and urban areas, dependent on within-district inequality. For the between-district inequality, between-state inequality is the major determinant of for rural areas, while within-state inequality is the major determinant for urban. The increased inequality, between 1993-2011, is to a majority driven by characteristics within districts.

In India is most of the population residing in the rural sector, and substantial differences exist between urban and its counterpart. Urban income inequality is more significant than rural, and both rural and urban inequality has increased since the economic reforms in the early 1990s (Motiram & Vakulabharanam, 2013). Individually, both food and non-food expenditure inequality have decreased between 1987-2012 (Basole & Basu, 2015). However, overall expenditure inequality has increased due to a shift towards more non-food expenditures which is more unequal distributed. In contrast, Singh, Kumar & Singh (2016) argue that the post-reform period has led to increased food-expenditure inequality in India, both in rural and urban sectors and in most states, yet there has been a decrease of inequality in caloric intake. Tripathi (2016) find that number of household members, education and the land possession are major determinants of inequality in India.

Wealth inequality has also increased in India and Bharti (2018) states that the top 10 %- and 1%-wealth owners are the driver of the change. The middle-income group and the lowest half of the population have seen their shares decline. Further, urban wealth inequality is more extensive than rural, and the wealth ratio, urban wealth divided by rural, has increased (Bharti, 2018). Jayadev, Motiram & Vakulabharanam (2007) find that the rich- and medium-rich states have experienced greater wealth increases than poorer states, arguing for increased between-state inequality. States which has seen the relative largest growth in wealth has also experienced the largest growth in wealth inequality, arguing for non-inclusive growth. Land ownership constitutes the most crucial wealth asset, being 65 % of rural wealth and 45 % of urban (Bharti, 2018). Landholdings, as a determinant of wealth, has since 1960 become more critical in both rural and urban areas separately. Although, due to urbanization have the overall importance declined to be more than 55 % in total.

No study found has investigated the impact of climate variability on inequality in India, and whether it has contributed to the increased inequality. However, studies that exist may provide preliminary suggestions. Jayachandran (2006) find that agricultural wages are more responsive to adverse rainfall at the lower end of the distribution. Similarly, Mahajan (2017) discover that female agricultural wages increase more than male during favorable agricultural conditions. Other research suggests that adverse rainfall increases inequality of health and education (Mendiratta, 2015; Shah & Steinberg, 2017) and case studies on the city- and district-level finds that inequality increases due to climate shocks (Hallegatte et al., 2010; Narayanan & Sahu, 2011).

Turning to general findings of the relationship between the environment and inequality. A rapidly expanding field of research is investigating how climate change, climate extremes and natural disasters impact socio-economic outcomes. Based on country findings, surveys argue that there is a consensus for a short-term negative economic impact of natural disasters, but that the distributional effects are more contested (Cavallo & Noy, 2011; Karim & Noy, 2016). How climate variability impacts the economy is less discussed. The impact of adverse temperature and global warming is receiving a bourgeoning interest. Studies have found that there are non-linear effects of temperatures on economic activity (Burke, Hsiang & Miguel, 2015) and that developing countries experience a decrease in GDP due to temperature shocks and global warming (Dell, Jones & Olken, 2012; Lee & Villaruel, 2016; Zhao, 2018). However, these findings disregard the distributional outcome.

Studies that have incorporated socio-economic factors have instead investigated the impact of droughts and floods. Detailed examinations have noted differences between the short- and long-run inequality impacts of floods (Banerjee, 2007; McSweeney & Coomes, 2011). Nevertheless, floods are not the only way which above-normal water impact societies. A study on Mozambique finds that more-than-average precipitation decreases inequality due its positive effect on agriculture (Silva, Matyas & Cunguara, 2015). Additionally, research on draughts describe that the impact on different economic distributions may differ (Carter, Little, Mogues & Negatu, 2007; Keerthiratne & Tol, 2018). Altogether, to my knowledge, only one study has been investigated both the impact of temperatures and precipitation and the study disregards the distributional aspects (Skoufias & Vinha, 2012).

Consequently, the purpose of this study is to investigate the impact of a climate change on economic inequality in India. By utilizing previous impacts of climate extremes, it is possible to understand the distributional consequences in a world where shocks occur more often. By utilizing five survey years of NSSO data, spanning 1999-2012, this thesis disentangle inequality by investigating four different economic distributions; consumption expenditure, food expenditure, land ownership, and land cultivated. Climate change is measured by investigating the impact of climate extremes on the aforementioned distributions. Climate extremes is defined as a positive or negative shock for precipitation and temperatures. By investigating the effect of climate extremes up to five years by utilizing the fixed-effect panel model, the thesis takes into consideration both the short- and medium-term distributional impacts.

The most prominent finding is the non-uniform impact of climate extremes on inequality in India. Different shocks have different impacts on the distribution investigated. Further, the same shock has different impacts on the four indicators. For understanding mediating factors of the impact of climate extremes, this thesis takes an interdisciplinary approach and utilizes a Vulnerability-Resilience framework, showing the importance of the coping and adaptive capacity, rather than the sensitivity of the society. Economic capacity, measured by the district mean income and the initial inequality level, is the single most vital feature for limiting the impact of the climate shock, describing the need to address inclusive economic growth to cope with the impact of climate change.

1.1 Scope, Aim and Research Questions

1.1.1 Scope of Climate Change

This aim of this thesis is to empirically investigate socio-economic consequences of climate change. Altogether, climate change is large in scope and including all dimensions is not possible, leading to a need of clarifying and define what aspects of climate change that is of interest.

IPCC (2019, p.808) defines climate change as:

> A change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/ or the variability of its properties and that persists for an extended period, typically decades or longer.

The definition describes that the variability and mean of the climate is of interest. Accordingly, climate extreme is introduced to understand the impact of climate change. Climate extreme is defined as:

> Climate extreme (extreme weather or climate event) The occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable. For simplicity, both extreme weather events and extreme climate events are referred to collectively as 'climate extremes'. (IPCC, 2019, p.808)

To understand what to measure when understanding climate, the definition of climate is used "The relevant quantities [for climate] are most often surface variables such as temperature, precipitation and wind” (IPCC, 2019, p.807-808). To limit the thesis and align with the literature is wind variation excluded (wind data is also more difficult to obtain), and precipitation and temperature of focus. Positive (warmer) and negative (colder) temperature is referred to as ‘temperature shocks’. Positive (excessive) and negative (drought) rainfall is referred to as ‘precipitation shocks’. In line with pioneering studies including Schlenker, Hanemann & Fisher (2006), Deschênes & Greenstone (2007) and Dell, Jones & Olken (2012), does this thesis utilize previous variation to understand the future consequences of climate change.

1.1.2 Aim and Research Questions

Climate change will and already is impacting livelihoods worldwide. Low-income countries are adversely affected (Acevedo et al., 2018: Mendelsohn, Dinar & Williams, 2006) and poor people within countries to an even greater extent (Karim & Noy, 2016). With a trend of increasing inequality within countries in the world (Alvaredo et al. 2017), climate change may further exaggerate the problem as studies suggest. An examination on India is important due to several reasons. Firstly, understanding how countries and distributions are affected by climate change is necessary for assessing its consequences. Secondly, India is the second-most populous country in the world; inequality within the country is an essential feature for determining global inequality. Thirdly, due to India's increasing inequality, whether extreme weather has contributed to this development is an avenue not previously investigated to my knowledge.

With the increasing presence of climate change, precipitation and temperatures will change. Since poorer people have lower coping capacities, they are more vulnerable and inclined to be negatively impacted by even small variations in weather. The rich, on the other hand, have more to lose and, hence, a vast impact could decrease inequality within a society. This thesis aims at investigating how climate extremes impacts inequality in India. Accordingly, the research questions are as follow:

How does climate extremes impact inequality in India?

- How do extreme temperature affect inequality in India?
- How do extreme precipitation impact inequality in India?

Limitations do naturally exist. Based on the scientific evidence that climate change will increase the occurrence of climate extremes (IPCC, 2019), does this thesis provides a limited estimation of how climate change impact inequality. ‘Limited’ implies that climate change impact inequality in other forms than this thesis covers. Further, this thesis only investigates inequality within districts and not between them. As noted, climate change will adversely impact poorer countries, how climate change impact the mean district income is not investigated, thus, the impact on the all Indian inequality may react differently to the impact on district inequality. Lastly, the generalizability of the findings could be limited because of India’s heterogeneity.

1.2 Outline of the Thesis

The outline of the thesis will be as follows. The following chapter provide a review of the existing literature on how climate change and natural disasters impact socio-economic outcomes. Chapter three introduce the Vulnerability-Resilience Indicator Prototype which is the framework to understand the mechanisms behind the impact of climate change on inequality. Chapter four presents the methodology and data. Chapter five provides the results and a discussion of the empirical relationship between climate extremes and inequality. Finally, chapter six concludes with summing up the findings and provides policy suggestions.

2 Literature Review

The economic consequences of climate change are large and heterogenous. Diffenbaugh & Burke (2019) show that global warming has adverse macroeconomic effects, countries with hot climates, often low-income countries, are most hardly affected and will experience decreased output. The result is mediated through reduced agriculture production, reduced productivity for workers exposed, poorer general health, and slower investments (Acevedo et al., 2018). Mendelsohn, Dinar & Williams (2006) support the finding with their examination of economic impacts in climate-sensitive sectors. Low-income countries will be adversely affected since their location is unfavorable to weather shocks. Adaptation, wealth and technology can impact the effect; however, the location is the premier problem, leading to global divergence of incomes.

Moreover, the introduction showed that climate change will increase climate variability and the occurrence of extreme weather events. However, how societies are impacted by the environment dependent on their characteristics have received notable interest. Evidence from the US argues that there is underinvestment in mitigation efforts since voters do not reward politicians who are risk avert (Healy & Malhotra, 2009). However, Besley & Burgess (2002) finds in India that newspaper distribution is negatively correlated to flood impacts. The researchers argue that newspaper cause accountability which in turn mobilize risk preventing resources that limits the effects of floods. Similarly, stable democratic governments and property rights reduce the consequences of disasters (Kahn, 2005; Raschky, 2008) as well as lower corruption levels (Escaleras, Anbarci & Register, 2007). Anbarci, Escaleras & Register (2005) find that inequality increases the impact of disasters since inequality is a significant determinant of prevention efforts. More unequal societies spend less resources on prevention, making them generate a lower capability of tackling the consequences.

2.1.1 Impacts of the Environmental Variation on Inequality

Studies synthetizing empirical results suggest that distributions within countries are impacted of climate extremes and natural disasters. Cavallo & Noy (2011) conclude, in their systematic literature review of how natural events impacts economies, that there is an agreement regarding a negative short-run economic output effect; however, the distributional effects within countries are more contested. In a meta-regression study, Karim & Noy (2016) find that incomes within countries are impacted adversely and incomes are more impacted than consumption due to natural disasters. Additionally, non-food consumption is more sensitive than food. Nevertheless, the authors stress that there is no uniform impact in the consequences of natural disasters. A survey from Latin America describes that those with the least assets are seeing larger relative decline of wealth compared to wealthier individuals due to natural disasters (Lopez-Calva & Ortiz-Juarez, 2009).

Yamamura (2015) conducts a cross-country investigation, finding that natural disasters have a short- and medium-term inequality increasing impact while the long-term effect is insignificant. Hence, the researcher concludes, disaster does not provide a structural shift in inequalities. The poor are more inclined to experience income losses due to climate shock, generating an unequal income distribution. A reason explaining why inequality is increased could be due to poor are more vulnerable. Kim (2012) finds that for large and unexpected events are poor twice as likely to live in disaster-prone areas globally. Also, Bui et al. (2014) notes that inequality increases due to self-reported climate shocks in Vietnam. Consequently, inequality is increased, in the short-run, due to natural disasters, this for both income and consumption-based inequality estimates.

The threat of disasters does also induce poverty. Barnett & Mahul (2007) state that weather-risks facing rural households contribute both directly and indirectly to chronicle poverty. Extreme weather events destroy assets vital for productivity that has been accumulated for years, suggesting long-term impacts on the possibilities to gain income. Additionally, the ex-ante risk of extreme weather events creates a risk avert behavior that limits investments. Baez & Mason (2008) state that rural households in Latin America experience negative incomes due to weather-related risks. Weather risks impact investment behavior that limit incomes and decrease food and non-food consumption, yet non-food more. Simultaneously, poor experience low investments in human capital, health, nutrition and productive assets leading to low coping capacity.

The literature describe that coping mechanisms are vital for limiting the impact of a shock. In Jamaica, where remittances are vital for the poorest, did Hurricane Gilbert in 1988 increase remittances and migration (Attzs, 2008; Clarke & Wallsten, 2003). However, the family may need to increase its labor force at the household, this was found by Halliday (2012). In El Salvador, the 2001 earthquake caused decreased female migration while nothing happened to the male, this since the expected outcome of female migration is lower. Carter et al. (2007) performs a comparative study of climate shocks on inequality Ethiopia and Honduras. For Honduras in the wake of a hurricane, the coping capacity was better for wealthier households during the medium-term which increased wealth inequality. The case of Ethiopia show that wealth is an asset worth to protect. During the prolonged drought in 1998-2000 was consumption used to decrease the impact of wealth, thus consumption inequality increased while the distribution of wealth remained intact.

2.1.2 Impacts of Droughts, Floods and Temperature

A significant share of the literature has investigated the effect of draughts on distributional aspects. Reardon & Taylor (1996) research highlight the different impact along the distribution of incomes and the importance of diversified incomes. In Burkina Faso, they find that income diversification had a U-shaped pattern. Where the poorest had the most diversified incomes, the drought lead to decreased inequality but increased poverty. More evidence from Ethiopia portraits that a major drought in late 1990s had a short-term poverty increasing impact, yet it did not increase poverty in the medium- and long-term since droughts improved income diversification with less focus on rain-fed agriculture (Little, Stone, Mogues, Castro & Negatu

, 2006). The evidence describes the importance of short- and medium-term impact of climate shocks.

Studies investigating floods have also noted that the time after impact is crucial in understanding the consequences on inequality. Banerjee (2007) investigate Bangladesh, finding ambiguous wage effects due to floods. Floods have a short-term income inequality increasing impact while lead to a more egalitarian medium-run outcome. In the end, floods generate abnormal production of agricultural goods that increases wages more at the lower end. Similarly, a mixed-methods investigation at the local level in Honduras find that a climate shock led to systematic lower inequalities levels (McSweeney & Coomes, 2011). The outbreak of a flood, which did hit the poor hardest, lead to a window of opportunity of institutional change in landholdings benefiting the poor.

All studies do not isolate drought and flood impacts. Silva, Matyas & Cunguara (2015) performs a pioneering study when investigating the impact of precipitation shocks on income inequality on the regional level in Mozambique. The researchers compare climate shocks with economic, finding that the same weather event may both increase and decrease inequality. A climate shock increase inequality in five out of eight cases which is exaggerated with economic downturns, if weather conditions are beneficial, income inequality decreases. Keerthiratne & Tol (2018) studies Sri Lanka and finds an unambiguous decrease in income inequality due to different types of climate impacts, which is to 90 % floods and draughts. However, consumption expenditure inequality does not decrease.

A limited amount of literature investigates the impacts of temperature. A pioneering study by Burke, Hsiang & Miguel (2015) show that there are non-linear effects of temperature on global economic activity, peaking at 13°C. Above 13°C does increasing temperature decrease productivity. In line with the finding does Dell, Jones & Olken (2012) show that temperatures shock decrease growth in developing countries, a 1°C increase in temperatures for a year lowers economic growth by 1.3 %. Recent literature has estimated the cost and consequences of global warming. Zhao (2018) suggest that if global warming exceeds the 1.5°C limit, it will lead to almost 3 % decreased growth for India up till 2050. Lee & Villaruel (2016) argue that the economic consequences of global warming are best mediated via financial inclusion and governments prevention efforts. These studies provide novel research on the economic consequences but disregards the distributional aspects within societies.

Skoufias & Vinha (2012) investigate the impact of extreme temperatures and precipitation on household welfare in Mexico, finding that the household reacts differently according to the type of shock and when in the year that the shock occurs. Additionally, the type of climate zone is of importance, those in arid zones experience lower expenditures, leading to increased inequality, due to colder or drought years compared to other regions which did not see a small declined during such years. In Nigeria does Dillon, Mueller & Salau (2011) find that male migration is working as a coping mechanism for extreme temperature variation. The researchers argue that the expected labor market outcomes for males are more significant than for females which generates the gendered effect. Thus, migration becomes a way to stabilize incomes and consumption. The scant research on temperature shocks need to be extended, and the existing results provide limited suggestions for India.

2.1.3 Limited Research Covering India

While no study has investigated the impact of natural disasters or extreme weather event on economic inequality in India, studies have examined the impact of adverse precipitation on wages. Jayachandran (2006) investigate how agricultural wages on the district level in India is impacted by productivity shocks, calculated by rainfall anomalies with more-than-average implying a positive shock while a drought is a negative productivity shock. He finds that the closer workers are to subsistence levels, the more inelastic is the supply, and the more are wages fluctuating. Banking services and physical infrastructure are important determinants of vulnerability. Further, the distribution of wealth is an important determinant of how vulnerable individuals are. Lastly, rich, who are labor hirers, may be better off when wages are decreasing. Mahajan (2017) builds from Jayachandran (2006) and provides an examination of how rainfall variability impacts the gender wage gap for the agricultural population at the district level, finding that both female and male wages respond positively to increased rainfall, while decrease when there is a drought. During more than average precipitation in rice-cultivated areas is the female-to-male wage ratio increased, implying a more equal outcome. Female labor can more easily adjust due to shocks, and the demand is larger during good agricultural conditions. The studies provide novel information; however other distributions could be impacted differently than wages.

Two significant studies have investigated how precipitation shocks impact health outcomes on rural households in India. Shah & Steinberg (2017) finds that both parents and children are sensitive to droughts and work less during drought years, generating lower incomes. Simultaneously, both parents and children work more during years with increased rainfall which increase incomes. Children in pre-school years scores significantly worse during years with drought while children in school age score better. The researcher argues that undernutrition in pre-school years decrease ability while school-aged children substitute on-field time for education. In the same vein, Mendiratta, (2015) investigate the impact of adverse rainfall on infants' health, finding that negative rainfall decreases height and weight for both boys and girls. The decreased height is mediated through the negative effect of droughts on incomes, indicating that increased inequality of health is an outcomes of climate extremes in India. The studies suggest increasing income inequality due to precipitations shocks, however, they do not estimate it systematically for a population with multiple occupations.

Lastly, finishing with case research which investigate the distributional effects. Hallegatte et al. (2010) find that the great floods of Mumbai in 2005 did impact the population at the lower end of the income distribution mostly. The authors note that the cost is limited for the poorest, however, the relative impact is larger. A study based on the 2004 Indian ocean tsunami's impact on India show that females had a death toll three times the male and recovered significantly slower (Hines, 2007). Narayanan & Sahu (2011) investigate the impact of natural disasters, in a district in the state Orissa, on health and income. They find that higher casts are less vulnerable, that the larger the shock, the more considerable expenditure on health insurance and that households are selling assets as a coping mechanism. The case studies suggest increasing inequality due to natural disasters, however, they do not estimate the entire India or include temperature variation.

3 Theoretical Perspective: Vulnerability and Resilience

Inequality within countries are increasing worldwide (Alvaredo et al., 2017). Thus, finding drivers of inequality must be regarded as important. Although, theoretically, the topic has received relative limited interest in economics. Most famously, the hypothesis of the Kuznets (1955) curve argues for increasing inequality at the beginning of economic growth, followed by a decrease when a majority of the population is working in the urban sector. In his influential book, Piketty (2014) argues that interest rates are rising faster than growth rates which accelerates incomes at the top of the distribution. Additionally, on a historical and empirical note, Scheidel (2017) show that revolution, mass-wars, pandemics and state collapse has been the greatest levelers of inequality. Altogether, these propositions generate limited theoretical answers of how climate extremes impact inequality. Thus, incorporating an interdisciplinary theoretical perspective of how climate change impact societies is a more potent avenue.

Disaster risk, implying the consequences of an environmental hazard, is dependent on four features; hazard, exposure, vulnerability and capacity (United Nations, 2016). Decades ago, the impact of natural hazards on societies where understood as a natural consequence, unrelated to human societies and impacts could only be reduced by improving physical infrastructure, leading to a focus on the hazard itself (Noy & Yonson, 2018). However, this paradigm has been overthrown by increased attention on how societies cope with disasters, focusing on how hazards becomes disasters rather than how natural hazards develop. Increased attention of the underlying mechanisms that generate the disastrous impacts has led to vulnerability and resilience research, which emphasize on exposure, vulnerability and capacity. Kelman, Gaillard, Lewis & Mercer (2016) argue that vulnerability and resilience is of chief importance to understand who are impacted by climate variability and climate change. Further, it provides a common concept regarding societal consequences of climate related impacts.

Vulnerability is defined as:

> The conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards. (United Nations, 2016, p.23)

The damages can be of direct impact; lives, material damages etc. and indirect impacts which is loss of production, employment, and vital services (Proag, 2014). Thus, potentially impacting livelihoods and consumption in the short-, medium- and long-run. IPCC (2012) argue that vulnerability is of multi-dimensional scope and simultaneously differential, implying that it changes across physical space with and among groups. Additionally, vulnerability is scale-dependent, suggesting that the unit of analysis is of concern, and dynamic, implying its characteristics and driving features are changing over time. A vulnerability investigation helps in understanding who gets affected, and the consequences for economic distributions.

Resilience is defined as:

> The ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management. (United Nations, 2016, p.23).

Resilience describes how a system can deal with a change while simultaneously change over time (Folke, Rockström, Österblom, Walker, & Hahn, 2009). Thus, it designates the coping capabilities in both the short- and long-run. Resilience has three dimensions: persistence or buffer capacity implies how the system copes with a shock; adaptability indicates the capacity for collective action to safeguard the current system and uphold livelihoods; and transformability identifies the possibility to innovate and transform the system (Folke et al. 2009). Thus, resilience describes both how severe the system will be impacted and how it may be transformed over time. Consequently, a climate extreme may provide a "window of opportunity" for change, since it generates possibilities to rebuild infrastructure and rethink behavioral patterns.

3.1 The VRIP Framework

To make use of the insights from climate change research will this thesis utilize Brenkert & Malone's (2005) Vulnerability-Resilience Indicator Prototype (henceforth VRIP). The VRIP framework introduces indicators and variables for analyzing vulnerability- and resilience levels for understanding how societies are impacted by environmental shocks. Brenkert & Malone (2005) introduce the VRIP to study countries and Indian states. In this thesis will a slightly modified India version be used (see table 3.1 for an overview of the indicators used and subchapter 4.3.3 for how the indicators are transformed into variables and corresponding summary statistics).

The VRIP framework indicates whether the society, which experience a climate shock, can safeguard itself from large socio-economic consequences. Therefore, a society which is vulnerable and not resilient, will more starkly be impacted by climate variability than a society which is not vulnerable and is resilient. Hence, the VRIP framework provides understanding of mediating factors for the impact of climates extremes on inequality.

3.1.1 Description of Indicators

The VRIP framework is divided into two parts; coping and adaptive capacity, and sensitivity, with the former referring to resilience and the second to vulnerability. Coping and adaptive capacity describe societies possibility to react, which is dependent on human resources, economic capacity and social capital. Sensitivity focus on societies' fragility and existing resources within infrastructure, food security, ecosystems, health and water resources.

Starting with indicators for coping and adaptive capacity. *Economic capacity* generate access through markets and technology to resources that support adaptation to climate variability. Hence, it may both help in managing the direct impacts of the climate extremes as well as the possibility to react. The mean income level is the variable to measure the wealth and total output. However, if the resources are not equally distributed, people will still be vulnerable. Thus, is inequality also applied. *Human resources* are important for coping and adaptive capacity. The indicator is used to understand the flexibility of individuals and their ability to find and make use of new opportunities. The dependency ratio, working age in relation to non-working age, describe the proportion of fully economically active compared to less active. Further, education is important for being able to adapt to new opportunities and have the skills required. *Environmental capacity* describes the current stresses on the ecosystems and the possibility of the ecosystem to adapt to changes. People living in environments with a better buffer capacity will not be as severely affected as those living in with a constrained environment. Population density describe the population pressure and the stresses on ecosystem. Sulphur dioxide (SO_2) describe the air quality which contributes to land stresses. Land unmanaged describe landscape fragmentation and the ease of ecosystem migration.

As earlier described, 'Sensitivity' measures how vulnerable societies are and describe the possibility to limit the impact of the extreme events. *Settlement and infrastructure sensitivity* describe the effects and threats on economic activities. Climate change and climate related shocks put stress on ecosystem services, if ecosystems are already under pressure, devasting consequence may follow. The populations access to basic services works as a buffer for a shock and is necessary for basic hygiene. *Food security* is incorporated as the potential for changes in the availability of food for a district. The pressure on current system, the amount of available resources and the degree of self-sufficiency determines the effect of a catastrophe. Food production measure the available food production in the area that may supply the local population. *Human health sensitivity* describes how humans are impacted by climate variability. Fertility rates is a proxy for general health circumstances and medical services. The indicators describe conditions that impact human health, this includes nutrition and exposure to diseases. *Water resource sensitivity* describe potential stresses on water systems. It provides information that describe how vulnerable fundamental factors for livelihood are functioning. Water use describe potential stresses on resources that are crucial for livelihoods, with low amount of water, the sensitivity for a shock is low and health is impacted. The level of ground water is used as proxy for the water use and water availability.

Table 3-1 Vulnerability-Resilience Indicator Prototype adopted from Brenkert and Malone (2005).

Type	Indicator	Variable	What does it measure?
Coping and adaptive capacity	**Economic capacity**	GDP per capita	Distribution of access to markets, technology, and other resources useful for adaptation
		Inequality	Realization of the potential contribution of all people
	Human and civic resources	Dependency ratio	Provide a proxy for social and economic resources available for adaption after meeting the present needs
		Education: Below primary schooling	Provide a proxy for Human Capital and possibility for labour force to adopt
	Environmental capacity	Population density	Describe how population pressure and stresses ecosystems
		SO_2	Air quality and other stresses on ecosystems
		% Land unmanaged	Landscape fragmentation and ease of ecosystem migration
Sensitivity	**Settlement/ infrastructure sensitivity**	Population with no access clean water/sanitation	The populations access to basic services as a buffer for variability of climate and changed
	Food Security	Cereals production/crop land area	Productivity and modernization of the agricultural sector, access to inputs to buffer against climate variability
	Ecosystem sensitivity	% Land managed	Degree of human intrusion into the natural landscape and land fragmentation
		Fertilizer use per cropland area	Fertilizers loads ecosystems and generates stresses from pollution
	Human health sensitivity	Reproduction	Describe conditions that impact human health which includes nutrition, exposure to disease risks as well as health access
	Water resource sensitivity	Water availability	Withdrawals to meet current or projected needs

4 Method and Data

The following chapter presents the methodological approach taken and the data sourced used. The outline of the chapter is as following. How climate extremes are quantified into precipitation and temperature shocks is firstly examined. Secondly, an introduction to inequality and the procedures to calculate the inequality rates. Thirdly, a presentation regarding the econometrical method applied. Fourthly, presentation of the variables used in the regression and the VRIP analysis.

4.1 Quantifying Climate Change

The scope outlined how climate change implies increased climate extremes, and that the precipitations and temperatures are the most vital features of climate. Thus, quantifying the effect of climate change will be through the impact of occurred climate extremes.

Center of Climatic Research at the University of Delaware provides data on temperatures and precipitation (Willmott & Matsuura, 2001). Both precipitation and temperature are interpolated to a 0.5 degree by 0.5-degree latitude-longitude grid, where the grid nodes are centered on the 0.25 degree (for a full description of air temperature see Matsuura & Willmott, (2012a) and for precipitation see Matsuura & Willmott (2012b)). Temperature is measured as monthly averages of station air temperature in Celsius degrees (°C). Precipitation is measured as monthly total rain-measured precipitation in centimeter a month (cm/month). Both precipitation and temperatures are aggregated to yearly means.

Temperatures and precipitation on the district level are derived by estimating the average of all grid points lying within the geographical boundaries by utilizing the QGIS software (see Mahajan (2017)). A limitation exist since the population of the district does not always experience the average climate in the district. As an example, in the Himalayas do people reside in the warmer valleys while the weather is dependent on the entire district and, thus, partly on the high mountains. The Kargil district which is the coldest district has a mean temperature of -17 °C, the mean temperature of the districts headquarters is 8 °C (Climate-Data.org, 2020).

The WMO (2017) states that 30 years is the standard for calculating averages for climatological standard, yet the length may not capture extreme events and precipitation need a more extended recording period. Thus, in line Mahajan (2017), is 40 years chosen. The mean and standard deviation are calculated based on yearly means between the years 1954-1993, providing a 40-year base for understanding how weather between 1994-2012 (my observation period starts in 1999, see next subchapter) has deviated from the trend.

Shocks are defined in line with Mahajan (2017), an extreme positive weather shock is when the annual average of precipitation/temperature is more than the mean precipitation/temperature plus a standard deviation calculated between 1954-1993. Similarly, a negative shock is when a year's mean temperature/precipitation is below the mean minus one standard deviation. By following the methodology and understand how adverse precipitation impacts inequality are two precipitation variables generated. Firstly, if there is less rainfall than the average, implying that there is a drought, there is a negative precipitation shock. Secondly, if there is more rainfall than average, there is a positive rainfall shock. Research has noted that positive rainfall shocks have a positive impact on productivity in India (Jayachandran, 2006; Mahajan, 2017). However, a positive rainfall shock could also lead to floods, implying that the strength of a positive rainfall shock could have a non-linear impact. Similarly, the extreme temperature shocks are calculated with the same approach with a positive temperature shock being a year where the temperature is warmer than the long-term mean plus a standard deviation. A negative temperature shock is occurring a year when the temperature is less than the mean minus one standard deviation.

The literature showed the importance of short- and medium-run impacts and that these may be differential (Banerjee, 2007; Little et al., 2006; Yamamura, 2015). The thesis follow Yamamura (2015) and uses time-lags up to five years. Since the year when the distribution is measured is six years of shocks included, implying that these shocks are included: t-5 (for the five-year lag), t-4, t-3, t-2, t-1 and t-0.

In summary, this thesis disentangles between precipitation and temperature shocks, with their positive and negative impacts and treat them as dummy variables if the years observed value is above/below the mean plus/minus a standard deviation. Additionally, to introduce robustness and investigate whether larger shocks has another effect, an additionally classification is introduced in table 5.4 with two standard deviations from the mean (the analysis focus on the 1 std deviation unless anything else stated).

4.1.1 The Indian Climate and the Occurrence of Climate Extremes

Figure 4.1 and 4.2 show the long-term means of temperature and precipitation. Figure 4.1 shows a distinct pattern that southern districts are in general warmer. Districts that borders the ocean is warmer than inland districts. The northern districts, located in the Himalayas, are the coldest. The difference in mean temperature is significant in India. The state of Ladak has the coldest districts, with Kargil and Leh experiencing a mean temperature of -17 °C. The warmest districts, averaging 26°C, are in the southern states of Kerala, Karnataka and Tamil Nadu.

Figure 4.2 shows the mean precipitation in India. Comparing to temperatures, the districts experiencing most precipitations are spread out. Districts located in the north, east and south-east are those experiencing most rainfall. The wettest districts are in the Himalayas in the states

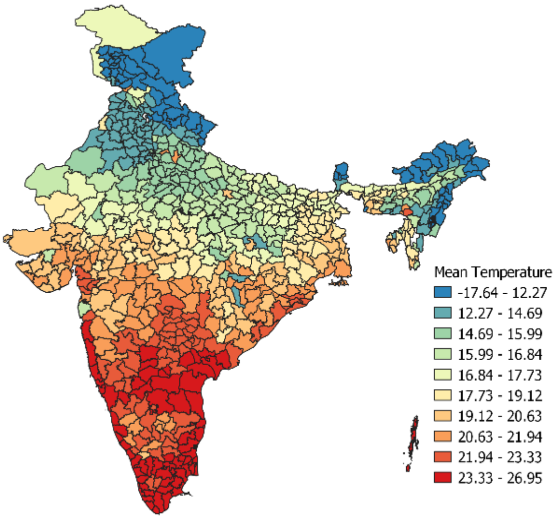

Figure 4-1 Mean temperature (in °C) in India between the years 1954–1993. Own calculations.

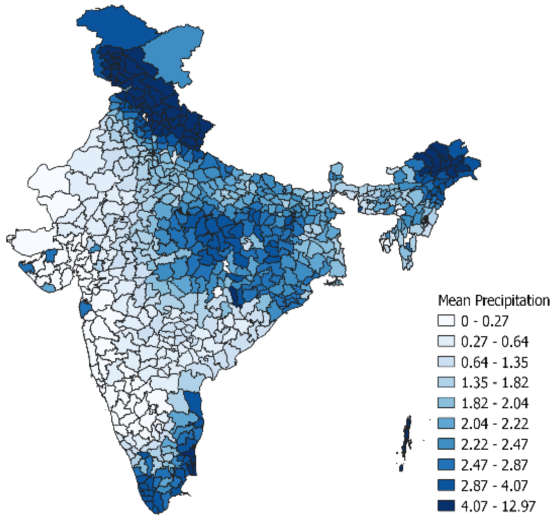

Figure 4-2 Mean precipitation (in cm/month) in Indian states between 1954-1993. Own calculations.

of Jammu & Kashmir and Himachal Pradesh who experience more than 12 cm of rain every month. The driest states are in the west with some states averaging less than 0.1 cm of rain.

Figure 4.3 and 4.4 depict the amount of positive and negative precipitation shocks in India for each district for the period 1994-2012. The increasing intensity describes that more shocks (more years with adverse precipitation) have occurred in the district. There are in general, more positive rainfall shocks than negative with the average district experiencing 3.2 positive shocks over the 18 years while the number for negative shocks is 1.1. While the positive shocks are spread out across the county, the negative shocks are clustered in the north and northeast.

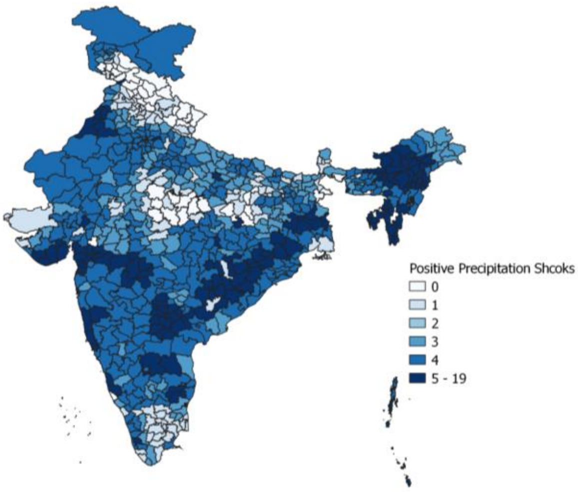

Figure 4-3 Number of years with positive precipitation shocks. Own calculations.

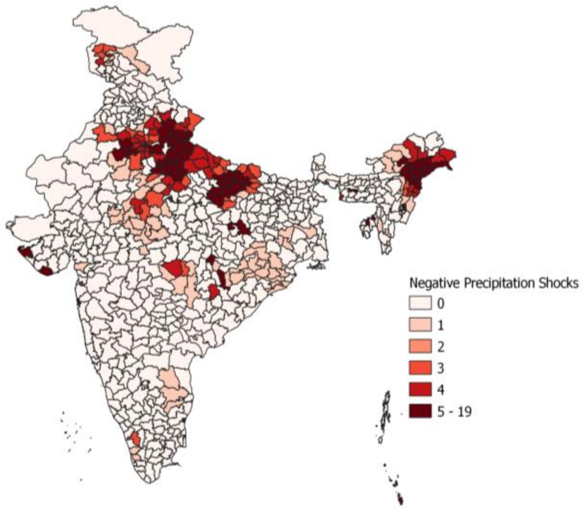

Figure 4-4 Number of years with negative precipitation shocks. Own calculations.

Figure 4.5 and 4.6 display the location of positive and negative temperature shocks, the amount of shocks refers to the period 1994-2012. Both positive and negative shocks have a distinct pattern. Districts are, on average, experiencing 2.2 positive shocks while 3.4 negative temperature shocks during the period of 1994-2012. Most states are experiencing one positive temperature shock or less during the observation period, while this is the case for 30 % of the districts with the negative shock. The positive shocks are mainly located in the south, however, districts with several years experiencing positive temperature shocks are located around the country. Similarly, districts receiving negative temperature shocks are found in almost all regions except the very south part of India. Northeast districts are in general the districts experience negative temperature shocks.

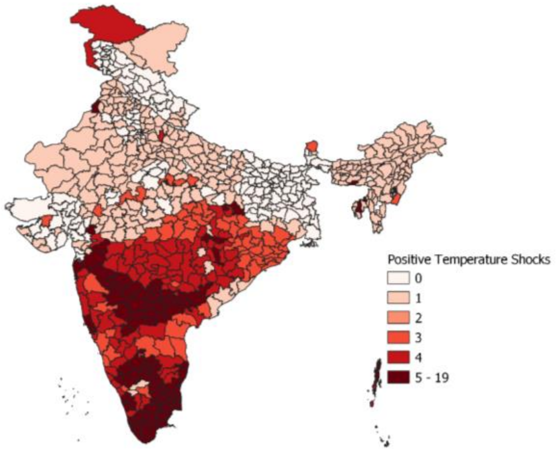

Figure 4-5 Number of years with positive temperature shocks. Own calculations.

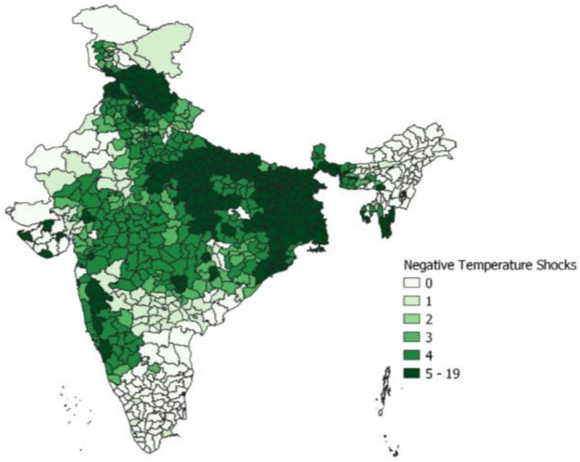

Figure 4-6 Number of years with negative temperature shocks. Own calculations.

The average number of shocks between the period of 1994-2012 is more than nine per district, implying that the districts, in general, are experiencing a shock, positive or negative, precipitation or rainfall, every second year. The districts experiencing the shocks are spread out, although there are some clustering effects for each type of shock. All regions are covered extensively by at least one type of shock. Additionally, the maps 5.3-5.6 act as a robustness check, if the chocks would be clustered in a particular district, then the effect of a climate shock could be significant to that region rather than the case for all of India. Appendix C describe the amount of shocks for each type and time-lag with both classifications of shocks (1 and 2 std).

4.2 Inequality within Districts

Inequality is a hotly debated topic; however, unclear definitions and scopes implies that the meaning of inequality is diverse and non-precise (Atkinson & Bourguignon, 2015). Inequality is defined as "the state of not being equal" (UN, 2015, p.1), implying that inequality can be in terms of several different dimensions (see The World Social Science Report (UNESCO, 2016) for a thorough review).

Moreover, the unit of analyzing inequality is of importance. Several previous studies (Jayachandran, 2006; Mahajan, 2017) have motivated that districts in India, the level below state, is the best unit of analysis when understanding inequality. The authors argue that the district level constitutes a set labor market since it includes both rural and urban villages as well as poor and wealthier individuals and workers are not extensively migrating from its borders. Further, characteristics found within districts account for a majority of inequality in India (Azam & Bhatt, 2016). Hence, the district level is used to understand inequality.

From the definition of inequality may the inequality be calculated from two to more persons. An emerging research field has acknowledged the importance of intra-household inequality. Significant inequality may exist within households, power analysis and gender research show that the resources within families are driven towards men (Chiappori & Meghir, 2015). Research has found that the death tolls for females are more significant than men due natural disasters (Hines, 2007; Neumayer & Plümper, 2007). Problems arise with the NSSO data, which is used for inequality computation, since the least unit of analysis is on the household level, hence it is not possible to disaggregate between household members. Thus, when analyzing the household level, this study assumes perfect equality within the household members, an assumption that, as noted, is not correct but cannot be resolved. If it would be possible to include within-household inequality, there would be a significant increase in inequality rates; however, it is difficult to access the implications of excluding intra-household inequality from the impact from climate extremes.

4.2.1 Choice of Economic Distributions

Economic inequality can be described in both material outcomes and initial conditions with the former manifested in monetary outcomes and the latter in nonmonetary (UN, 2015). Non-monetary economic inequality is manifested in the debate regarding inequality of capabilities and opportunities, which examines the possibilities to generate income (Atkinson & Bourguignon, 2015). Monetary inequality comes in two forms, flows and stocks, with income or consumption referring to the former while the latter being wealth. Flows are calculated over a certain period of time while stocks are measured at a particular time. The two different types may provide different capabilities for livelihoods.

A normative approach argue that the flow variable, being income or consumption, is an indicator and proxy for wellbeing (Decancq, Fleurbaey & Schokkaert, 2015). Hence, inequality becomes an indicator for the distribution of resources and wellbeing in a society. Consumption expenditure is included as the flow variable. Deaton (1997) argue that consumption is preferred over incomes in developing countries due to accuracy reasons, another motivation for including consumption in this thesis is data availability. Although consumption function as a proxy for income, notable differences exists (Duclos & Araar, 2006). Azam & Bhatt (2016) show the significant difference of consumption and income inequality in India, with the Gini coefficient increasing by 0.15. Consumption, compared to income, may dampen the effect of a shock since consumption is smoothened across bad and good years (Duclos & Araar, 2006). Hence, if a climate shock implies a negative hit for the poor, actual income losses could be more substantial.

Moreover, in addition to general consumption expenditures is the inequality of food expenditures investigated. Due to climate change will food insecurity increase (IPCC, 2019) and India has still a large share of deprived with low food availability and weak food purchasing power (Saxena, 2009). The literature review suggested that food inequality may change differently compared to non-food inequality (Baez & Mason, 2008; Karim & Noy, 2016). Although food consumption and aggregated consumption are closely interlinked, the food consumption inequality may signal increased agricultural prices and sensitivity may differ between the two.

Turning to wealth indicators. According to Piketty (2014) does capital and wealth have two vital functions, it can both be rented (i.e. apartment) and works as a productive asset (i.e. machinery). Deininger & Squire (1998) argue that wealth in landholdings are crucial and different from income since land possession is a crucial determinant of individuals productive capacity and the ability to invest. Additionally, land holding may work as an insurance for unexpected events. Historically, the size of landholding has generally been how wealth distribution is measured in rural areas (Kilby & Liedholm, 1987). Land ownership is contributing to a majority of the wealth in India (Bharti, 2018) and almost 90 % (for 2001) of the Indian population owns any land (Jayadev, Motiram & Vakulabharanam, 2007). Erickson & Vollrath (2004) describe that land quality is unequal distributed, with increased soil quality is land holdings decrease, leading to an upward bias of land inequality. Furthermore, landholdings are not representative of total wealth. Rich tend to own less land and more financial resource (Milanovic, 2016), and Bharti (2018) concludes that land holdings are much more critical for low-income earners. In sum, wealth is proxied by land ownership due to data availability and since it is the most vital asset.

Additionally, the distribution of land cultivated is introduced for understanding changed possibilities of gaining income and more clearly measure the implications for agricultural incomes. The literature suggest that the share of the agricultural sector in the economy is to a large degree determining the economic impact of climate change (Acevedo et al., 2018). The land cultivated does more strongly capture the agricultural sector than land ownership. Further, it describes the possibilities to increase intensity that has previously been described as important due to productivity shocks (Jayachandran, 2006) and that land availability is a major fundament of existing inequality (Villareal & Moreira, 2016).

4.2.2 Inequality Computation

Inequality can be measured be several different indicators. Haughton & Khandker (2009) argues that a good measurer of income inequality should have the following characteristics: *mean independence* implying that a doubling of incomes would not change inequality; *population size independence* argues that inequality does not change with population size; *symmetry* argues that if two people swap incomes, nothing should happen with inequality; and the *Pigou-Dalton transfer sensitivity,* indicating that a transfer of income from rich to poor should decrease inequality. The Gini coefficient is the most widely used method for calculating inequality and satisfies all of the above-standing characteristics (Haughton & Khandker, 2009).

The Gini-coefficient is based on the Lorentz curve (figure 4.7), a cumulative frequency curve, that compares the observed distribution with a distribution that represents perfect equality (Haughton & Khandker, 2009).

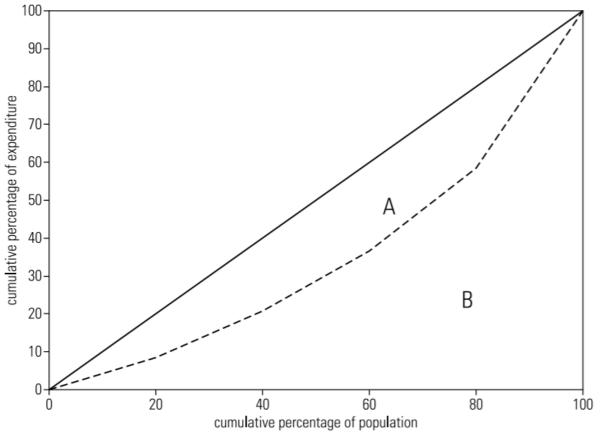

Figure 4-7 Lorentz curve. Source: Haughton & Khandker (2009, p.105)

The area of the Lorentz curve determines the Gini-coefficient, which can be calculated with equation 1. With the distribution following the 45-degree line, there is an equal distribution of the variable of interest, implying a Gini-coefficient of 0, the most unequal possibility is a Gini-coefficient of 1.

$$Gini = {}^{A}/_{(A+B)}$$

Equation 4-1 Gini calculation

The Employment and Unemployment Survey (EUS) conducted by the Indian National Sample Survey Office (NSSO) will be used for calculating the inequality rates. Several studies (Belser & Rani, 2011; Chancel & Piketty, 2019; Menon & Rodgers, 2017) have used the dataset for understanding socio-economic features of Indian. The rounds that will be used are 1999-2000, 2004-2005, 2007-2008, 2009-2010 and 2011-2012, and the data is collected from the first of July to the last of June the following year. The years above are included since they are the latest available and was used during my last thesis (Lindelöw, 2019). General consumption expenditure is included for all years, however food expenditures have missing data for the 1999-2000 survey while the 2007-2008 survey does not incorporate land ownership nor cultivation.

Further, some notes on Gini calculation. The Gini coefficients are calculated by the per capita for households, implying that the distributional variable of interest is divided by the number of people in the household. Dividing the consumption-based estimates by the household size is regarded as standard in the literature (Deaton, 1997), for consistency, it also done for the land ownership and land cultivated. Milanovic (2016) notes that consumption from survey data is skewed and biased and underreporting at both ends of distribution contributes to this. However, there are no possible ways of including this in the thesis. Lastly, as done by Deininger & Squire (1998), only those who own land are included, hence are landless excluded. Naturally, this method has limitations since inequality increases when including landless (Erickson & Vollrath (2004). However, including those with zero holdings are not possible due to data issues and the time limit of this thesis.

Districts are regularly rearranged and renamed between 1999 and 2012. The meteorological data is assembled by a district categorization from 2014 using ArcGIS (2014) while the NSSO data have their districts based on their specific year. Additionally, the indicators assembled for the VRIP framework uses different district boundaries based on their compilation year. Therefore, some regions disappear during the process.

Figure 4.8 describes the inequality on the district level in India based on the four different types of inequality measured applied. The inequality is measured as the average inequality for the respective indicator between the years 1999-2012. The mean consumption inequality on the district level is 0.287 in India (see Appendix B) The inequality rates are spread out at the country level; however, the northeastern districts do, in general, have lower inequality levels. Inequality by food consumption is the most egalitarian distribution with a mean Gini coefficient of 0.213. There is less variation in food inequality at the district level than for consumption inequality. Land ownership has the most considerable recorded inequality of the four indicators with 0.668. The pattern seems to be that the smaller, in acres, are less egalitarian. The most inegalitarian districts are found in the southeast and northwest. Lastly, land cultivated is more equally distributed than land ownership, the most unequal districts are found in the southwest while the remainder of the districts experiences inequality at rates less than 0.6.

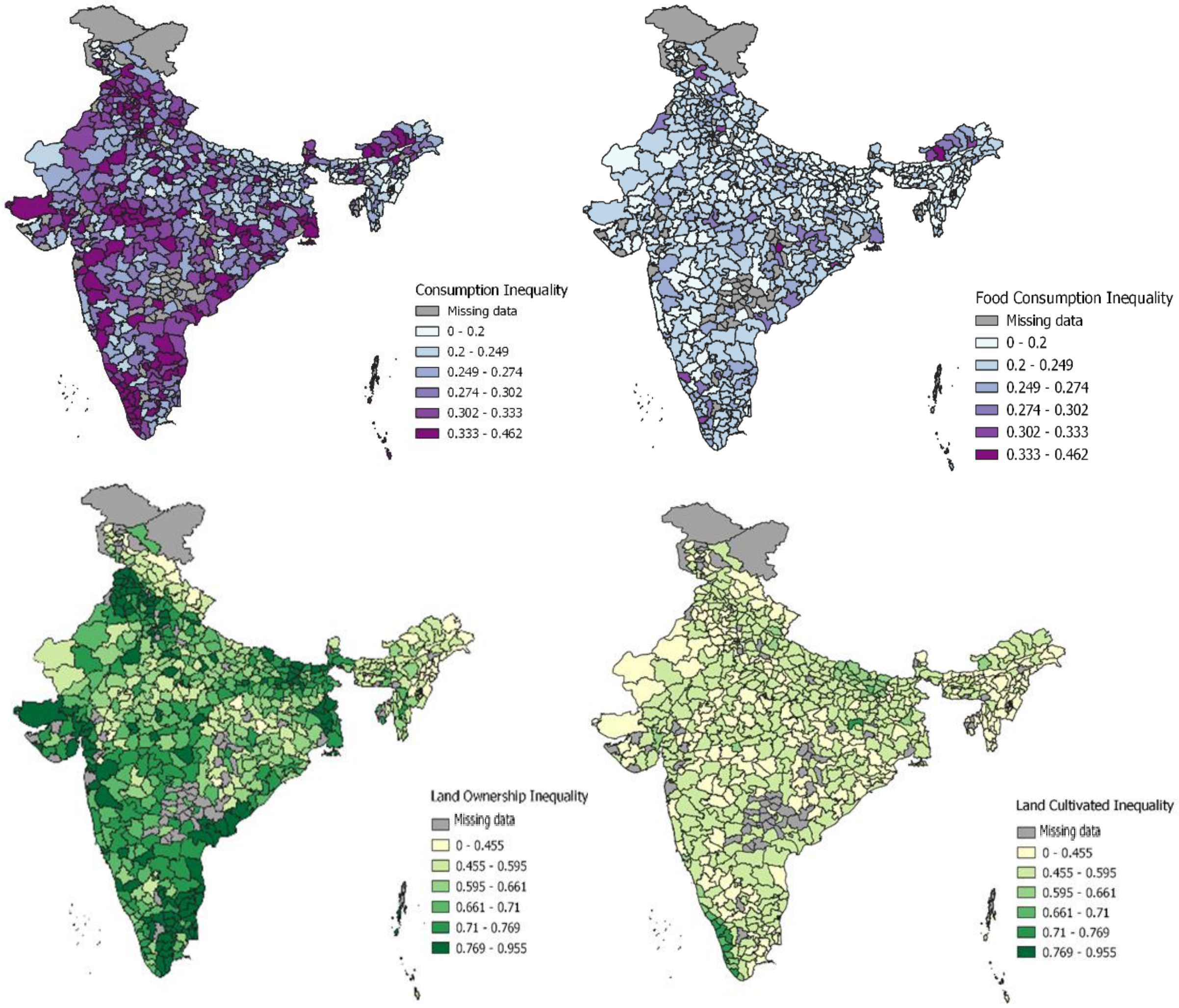

Figure 4-8 Mean Gini coefficients, between 1999-2012 at the district level in India. Own calculations.

4.3 Econometric Specification

The research questions are empirical, arguing for a quantitative research approach. Thus, for understanding how climate extremes impact inequality, an econometric estimation technique is necessary. The empirical analysis is performed in two steps. Firstly, understanding the link between climate related shocks on the different inequality indicator. Secondly, introduce the VRIP framework to understand the mechanisms driving the impact of climate extreme events on inequality.

4.3.1 Fixed-Effect Procedure

The first step, calculating the impact of a climate shock, is done by utilizing the fixed-effect model. The compiled dataset has a structure of a panel data, with multiple observation for each district. Districts have multiple district-specific characteristics that determines its distributions, which contributes to that econometric models will easily pick up omitted-variable bias. Angrist & Pischke (2008) describe that the fixed-effect model estimates the change within the observation over time. It calculates the change in variant variables holding invariant characteristics out of the model, making it suitable for understanding the impact of a sudden shock. The fixed-effects model estimates the district and time as coefficients, which then includes the unobserved characteristics that bias the model.

The fixed-effect model assumes strict exogeneity, implying that the mean-difference errors are uncorrelated with the shock for any period (Townsend et al., 2013). If the shocks are related to each other, implying a correlation between shock at t and t-1 and between t-1 and the error term, the model would be biased. Hence, according to Wooldridge (2002), time lags should resolve that the strict exogeneity assumption holds. The fixed-effects model is preferred over random effects due to three reasons. Firstly, the fixed-effects model has more relaxed assumptions than random effects; the fixed-effects model allows for the time-invariant unobservable variables to be correlated with the independent variable (Wooldridge, 2002). Thus, the fixed-effects model is more robust (Angrist & Pischke, 2008). Secondly, previous literature has extensively used the fixed-effects model while the random effects have not been applied (Jaumotte, Lall & Papageorgiou, 2013; Keerthiratne & Tol, 2018; Yamamura, 2015). Thirdly, a Hausman test, introduced to determine wheatear a fixed- or random-effects model is preferred, suggest that the fixed-effects model is superior to the random effects.

Fixed-effects models are notoriously affected by attenuation bias that drives estimation towards zero (Angrist & Pischke, 2008). Naturally, this could be a problem. As can be found from figure 4.3-4.6, there are the fewest amount of negative precipitation shocks, therefore are negative precipitation shocks least probable to be significant since the amount of variation is smallest. In comparison, negative temperature shocks and positive precipitation shocks have the most amount of shocks; hence, there is more variation to exploits in the fixed-effect regression. A performed Breusch-Pagan test for heteroscedasticity suggests robust standard errors. Lastly, the timing of the shock has received notable interest (Banerjee, 2007; McSweeney & Coomes, 2011; Yamamura, 2015), therefore is multiple time-lags introduced until 5 years after the impact.

The formalized regression model for the fixed-effect estimation can be stated as below:

$$I_{t,d} = \beta * Shock_{t-0/1/2/3/4/5,d} + Controll_{t,d} + District_d + Time_t + \varepsilon_{t,d}$$

Equation 4-2 Regression model

Where $I_{t,d}$ is the inequality for that district, Shock is a vector of shock dummies that includes positive and negative, precipitation and temperature, shocks as defined in 4.1 for the time lags zero to five years before the inequality calculation. District is a dummy for each district while time is a dummy for each year, providing the unique features of the fixed-effects model. $\varepsilon_{i,t}$ is assumed to be a random error term. Control variables included is the mean consumption on the district level and the share of urban households to describe the importance of agricultural incomes for livelihood. Having the mean consumption level and a proxy for agriculture is regarded as standard within the literature (Keerthiratne & Tol, 2018; Mendiratta, 2015; Yamamura, 2015).

4.3.2 Incorporating the VRIP Framework

For understanding the empirical relationship between climate extremes and inequality, the VRIP framework is applied in the second step. Similar to empirical studies including Masambaya, Oludhe, Lukorito & Onwonga (2018) this study investigate how climate extremes are impacting society based on resilience and vulnerability indicators. Additionally, Yenneti, Wei, Chen & Joshi (2016) investigate how vulnerability to climate change has changed by partly utilizing the VRIP and Dunford, Harrison, Jäger, Rounsevell & Tinch (2015) uses another, yet similar, vulnerability and resilience prototype to understand the consequences of climate change in Europe and its socio-economic risks.

By investigating the change in inequality for districts that have received a shock, and then plot that against each indicator, it is possible to graphically analyze whether a relationship exist between a shocks impact on inequality and the VRIP. Importantly, the VRIP does not state whether the effect has a positive or negative impact; it provides a framework for an understanding of the magnitude of the impact. However, whether the indicator is contributing to a negative or positive impact of the climate shock is naturally of interest.

The VRIP is included as a mediator of the impact of climate extremes, implying that it partly determines the impact of a climate extreme. If a society is vulnerable and not resilient, the impact of a climate extreme would lead to larger impacts than for a society with resilience and that is not vulnerable. Thus, ideally, the VRIP should be measured just before the impact of a climate shock for capture the reality. However, this is not possible. The data have different periods of observations, and shortest calculated is with a gap for two years. Thus, only shocks occurring at t-1 and t-0 can be included since a shock occurring in t-2 would impact the VRIP. As an example, for 2009 and 2011, if a shock occurs at t-2, then it affects the society in 2009 and the VRIP is impacted; thus, only shocks occurring in 2010 and 2011 can be understood. Although some survey years’ experience longer time between observations, the shocks occurring at t-1 and t-0 is used for consistency.

As per construction of the analysis of mediating factor, I am not able to say whether the factors increase or decrease the causal effect of climate extreme on inequality on the district level in India. Instead, by employing the VRIP framework with the approach taken, it is possible to argue whether district who have experienced a shock experience another trend on inequality, based on underlying district features before the shock happened.

4.3.3 Introducing the VRIP Variables and Summary Statistics

The following chapter describe how the VRIP is transformed into variables and their respective data sources. A list of the variables data sources is in Appendix A and summary statistics are in Appendix B.

Starting with coping and adaptive capacity indicators. The economic capacity’s first variable is calculated as the mean consumption at the district in logarithmic scale. The inequality distribution used for the VRIP is consumption. Above primary education is one of the human and civic resource variables. Brenkert and Malone (2005) use literacy; yet the share which is not literate in the dataset is minuscule, implying that the share of the higher education level is of interest. Dependency ratio, the other human and civic variable, is defined as the total number of aged 15-65 compared to those aged 0-15 and 65 and older. For environmental capacity, population density is measured by estimating the population divided by the area of the district, the area of districts are from ArcGIS (2014) while the population from NSSO. The SO_2 level for each district is calculated by using the EDGAR dataset (Crippa, Janssens-Maenhout, Dentener, Guizzardi, Sinderlarova, Muntean, Van Dingenen & Granier, 2016) and applied similarly to the weather data in QGIS. The SO_2 level is converted to the logarithmic scale. The percentage share of land unmanaged is the sum of forest land and barren and unculturable land divided by the district area, the data is from data.gov.in (2014).

Turning to the sensitivity indicators. Settlement and infrastructure are measured with the population with access to toilets; the data is gathered from the Department of Drinking Water and Sanitation (2011). The mean of access across the districts is 45 %; however, there are large differences. For food security is the rice productivity used. Since the dataset (data.gov.in, 2013) used to describe various agricultural goods is in the size of the production area, and the output in weight can only one product be incorporated. Rice is the most produced crop (Government of India, 2017) and is also the only cereal reported in the data; thus the weight of rice output divided by the agricultural area for rice is applied to understand agricultural productivity. Ecosystem sensitivity include both share of land managed and fertilize usage. The percentage of land managed refers to the agricultural land managed, which is the land sowed divided by the district area. Sowed is the total area sown with crops and orchards, the data is from data.gov.in (2014). Fertilizer consumption data are gathered by the EDGAR dataset (Crippa et al., 2016) and aligned to the district level like the weather data in QGIS.

For human health sensitivity, it proved to be very difficult to find data sources with data for the crude birth rate and life expectancy. Therefore, based on the NSSO data, the crude birth rate is introduced which is the annual number of births per 1.000 population (UNICEF, 2020). Districts with a crude birth less than one or more than 100 are treated as missing data. The summary statistics show that the data is not particularly representative, leading to many districts with missing data. The water resource is gathered from the Department of Water Resources (2020) water resource information system (WRIS). The indicator used is the districts average height of groundwater, it is considered a standard indicator for measuring water availability (WMO & GWP, 2016).

Lastly, the sector share describes the share living in the urban sector for each district. The mean is 0.216, implying that the mean share of urban citizens is 21 % for districts in India. This is not the same for the all Indian case since it is not weighted against the relative size for each district, naturally this is the case for all variables previously described.

5 Empirical Analysis

Chapter four outlined the necessary steps for empirically examine the relationship between climate extremes and inequality on the district level in India. The following chapter will make use of that possibility and gain knowledge of the association. Firstly, a baseline regression of the direct link between climate extremes and the different inequality indicators. Based on estimations for districts classified as temperate and arid can the results be better understood. Secondly, by introducing the VRIP framework, it is possible to realize mediating factors for the impact of climate extremes on inequality. The chapter will end with a discussion of the results.

5.1 Baseline Results

Table 5.1 provides estimates of how extreme climate shocks impacts inequality on the district level in India. Inequality is measured by investigating the distribution of consumption expenditures, food consumption expenditures, land ownership and the land cultivated. Remember, a Gini-coefficient of 0 means perfect equality, while 1 implies perfect inequality. Hence, a positive (negative) coefficient implies increasing (decreasing) inequality.

Starting with precipitation shocks. A positive precipitation shocks implies excessive rainfall. For land cultivated, the inequality increases significantly in the short-term with the largest magnitude in the entire table. Consumption inequality is decreased because of positive precipitation shocks in the medium-term; this could imply that low income earners experience relative more substantial gains of positive rainfall. There is no impact of positive precipitation shocks on either food expenditures or land ownership.

Negative precipitation shocks, or droughts, impacts the distributions of consumption expenditures, food expenditures and land ownership. Land ownership is increased significantly at the year of the shock while peter out. The impact on inequality in food consumption and general consumption is similar. The two-year lag shows a positive sign, describing increasing inequality. In contrast, the three-year lag suggests a more egalitarian distribution.

Turning to temperatures. Positive temperature shocks impact all the included distributions. It has an increasing impact on inequality for consumption and food, a decreasing impact of inequality on land cultivated while both negative and positive for land ownership. For food expenditures, the temperature shock has both a direct and longer-term effect, with both effects being increased inequality. Thus, abnormal hot weather for a district adversely impacts the lower end of the distribution for general and food consumption expenditures, while the land cultivated gets more spread out.

Table 5-1 Base regression of climate extremes impact on different distributions on the district level in India

	(1) Consumption	(2) Consumption	(3) Food Exp.	(4) Food Exp.	(5) Land Own.	(6) Land Own.	(7) Land Cult.	(8) Land Cult.
Precip. Pos. t-5	0.003	0.002	-0.001	-0.001	-0.004	-0.004	-0.000	0.001
Precip. Pos. t-4	-0.013***	-0.010**	-0.004	-0.004	-0.007	-0.007	-0.004	-0.006
Precip. Pos. t-3	-0.000	-0.002	0.001	0.002	0.001	-0.001	0.009	0.009
Precip. Pos. t-2	-0.007*	-0.006	-0.006	-0.006	-0.012	-0.014	0.003	0.002
Precip. Pos. t-1	-0.002	-0.004	0.002	0.002	0.002	0.002	0.001	0.003
Precip. Pos. t-0	-0.009	-0.003	-0.008	-0.007	0.009	0.012	0.032***	0.029***
Precip. Neg. t-5	-0.004	-0.012	-0.004	-0.007	-0.007	-0.009	-0.022	-0.018
Precip. Neg. t-4	0.005	0.008	0.003	0.004	0.013	0.012	0.003	-0.001
Precip. Neg. t-3	-0.010	-0.015**	-0.011*	-0.012**	-0.003	-0.008	0.010	0.010
Precip. Neg. t-2	0.010	0.013**	0.008	0.009*	0.006	0.006	-0.008	-0.011
Precip. Neg. t-1	-0.000	-0.000	0.002	0.003	-0.010	-0.015	0.012	0.009
Precip. Neg. t-0	-0.008	-0.007	-0.008	-0.008	0.022**	0.027**	0.003	0.005
Temp. Pos. t-5	0.011	0.009	0.012*	0.013*	0.014	0.011	0.020	0.021
Temp. Pos. t-4	0.003	0.004	0.006	0.008*	0.018**	0.015*	-0.007	-0.008
Temp. Pos. t-3	0.011**	0.009*	0.007	0.007	-0.003	-0.006	-0.003	-0.002
Temp. Pos. t-2	-0.001	0.003	-0.001	0.001	-0.010	-0.013*	-0.021**	-0.024***
Temp. Pos. t-1	-0.005	-0.006	-0.006	-0.008	-0.005	-0.005	0.005	0.005
Temp. Pos. t-0	0.006	0.007	0.010**	0.011***	-0.003	-0.003	0.004	0.004
Temp. Neg. t-5	0.005	0.006	0.003	0.003	0.005	0.005	0.002	0.001
Temp. Neg. t-4	-0.005	-0.009**	-0.002	-0.002	0.012	0.014*	0.012	0.019**
Temp. Neg. t-3	-0.002	-0.004	-0.005	-0.007*	-0.010	-0.009	0.005	0.008
Temp. Neg. t-2	-0.011*	-0.013**	0.005	0.005	-0.014	-0.011	-0.012	-0.011
Temp. Neg. t-1	-0.010***	-0.009***	-0.006**	-0.005*	0.000	-0.001	-0.003	-0.005
Temp. Neg. t-0	0.006	0.005	0.003	0.002	-0.002	-0.002	-0.001	-0.001
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES
Control variables	NO	YES	NO	YES	NO	YES	NO	YES
Obs.	2788	2788	2349	2349	2215	2215	2200	2200
R-squared	0.491	0.521	0.050	0.061	0.063	0.088	0.049	0.059

Fixed-effect model. Robust standard errors. Control variables include mean district consumption and the share of urban households. *** p<0.01, ** p<0.05, * p<0.1

Negative temperature shocks do also impact all distributions included. With control variables do the ownership and cultivation of land become significant, implying that four years after the shock is the distributions more unequal. The effect is stronger for the expenditure-based estimates where the distributions are impacted negatively, implying decreasing inequality in both short- and medium-run. The effect is most potent for general consumption, arguing for that impacts for non-food items is even stronger. Hence, with lower temperatures are expenditures more equal on the district level in India, the trend is more definite for the shock with one time-lag.

Between the types of distributions, the consumption-based distributions have more significant coefficients than the wealth-based. However, the wealth-based distributions experience larger absolute impacts on their distributions since the magnitude of their coefficients are larger.

5.1.1 Alternative Estimates

Table 5.2-5.4 provide estimations on different subsamples or with different classifications. By investigating types of districts can the previously found results be further understood. Table 5.2 shows the impact of climate shocks on inequality for districts with mean temperatures above 20°C. Tropical zones are, according to Köppen's classification, those who have a minimum of 20°C all year round (Oliver, 2005). Naturally, the annual mean of 20°C includes more district than a district with at least 20°C every month, yet it was not possible at this stage to disentangle these states.

Compared to the baseline results in table 5.1 does positive precipitation shocks show similarities. Consumption inequality is still decreasing in the medium-run while food expenditure inequality has not any significant coefficients. Land cultivation inequality does also experience increasing inequality. Since the timings are both in the short-term, at the year or the year before, is it expected that the impact is similar. Land ownership inequality is decreased in the medium-term, something that was not picked up by the baseline regression.

For negative precipitation shocks does food expenditure see missing information, arguing for a significant amount of the shocks are occurring before the 1999-2000 survey since the survey does not report food expenditures. Consumption inequality is now uniformly increasing because of draughts. The sign is reversed at t-3, arguing for significant differences between tropical and non-tropical districts, with the former suffering increasing inequality. Land ownership inequality experience a similar impact, although the impact is moved from t-0 to t-2. The most significant change is for land cultivation since the distribution experience decreasing inequality for all medium-run impacts, the all-Indian estimates suggested that the shock had no significant effect.

Positive temperature shocks have similar impacts for both consumption-based distributions, yet it is potentially weaker for the food expenditure inequality. Land ownership does also experience a similar impact; though, the inequality increasing effect occurring at t-4 dissolves. Also, the inequality increasing effect for land cultivation vanishes. Lastly, only general consumption experiences a significant impact for negative temperature shocks in the case of tropical districts. The other three distributions, for tropical districts, does not receive any significant coefficients.

Table 5-2 Shocks for tropical zones

	(1) Consumption	(2) Food Exp.	(3) Land Own.	(4) Land Cult.
Precip. Pos. t-5	0.003	-0.002	-0.016	-0.007
Precip. Pos. t-4	-0.014**	-0.004	-0.002	-0.018
Precip. Pos. t-3	-0.004	-0.004	-0.035**	-0.000
Precip. Pos. t-2	-0.007	-0.015	-0.018	-0.011
Precip. Pos. t-1	-0.002	0.004	-0.010	0.018*
Precip. Pos. t-0	0.003	-0.009	-0.006	-0.003
Precip. Neg. t-5	0.013	-0.019*	0.008	-0.065**
Precip. Neg. t-3	0.081***		0.005	-0.047*
Precip. Neg. t-2	0.001		0.062***	-0.042*
Precip. Neg. t-0	-0.002		-0.001	0.004
Temp. Pos. t-5	0.010	0.012	0.008	-0.005
Temp. Pos. t-4	0.001	0.005	0.010	-0.017
Temp. Pos. t-3	0.011*	0.010	-0.005	0.009
Temp. Pos. t-2	0.002	0.001	-0.015*	0.003
Temp. Pos. t-1	-0.007	-0.007	-0.012	0.014
Temp. Pos. t-0	0.008	0.009*	0.000	-0.005
Temp. Neg. t-5	-0.002	0.003	0.012	0.023
Temp. Neg. t-4	-0.007	0.003	0.024	-0.004
Temp. Neg. t-3	-0.011	-0.010	-0.013	0.021
Temp. Neg. t-2	-0.021**	-0.004	-0.018	0.020
Temp. Neg. t-1	-0.023**	-0.016	0.004	-0.013
Temp. Neg. t-0	0.001	0.005	-0.001	0.010
Year dummies	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Obs.	934	792	739	737
R-squared	0.499	0.074	0.144	0.094

Fixed-effect model. Robust standard errors. Control variables include mean consumption and the share of urban households. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5.3 describes the impact of climate extremes for districts classifies as arid. Aridity is dependent on water balance, being both the inflow (rainfall), and the outflow which is due to evaporation and transpiration (Goudie, 2009). By estimating the arid districts, this thesis utilize only the precipitation component of the definition, according to the FAO (1989) does arid regions receive less than 300 mm annually, leading to a limit of less than 2.5 cm monthly (see figure 4.2).

The results for the arid districts, compared to the all Indian case, are similar for most of the indicators and shocks. Interestingly are the impact of negative precipitation shock insignificant for the large share of coefficients and only land cultivation experience a significant impact. Positive precipitation and positive temperature shocks has similar impact as the baseline result for most distributions.

For positive precipitation shocks are general consumption and land cultivation similar to the baseline regression in table 5.1, also the insignificant impact for the distribution of land ownership remains. A notable difference exists for food expenditure, inequality is decreased in both the short- and medium-run for positive precipitation shocks. For negative precipitation shocks, there is noteworthy change, the previous significant coefficients from the baseline regression disappears, while land cultivation receive a negative impact.

Continuing with the temperature-based shocks. For positive temperature shocks for arid districts is the impact in line with the baseline results for the full sample in table 5.1. The timing alters for food expenditure inequality, but the regression still portraits both a short- and medium-term effect due to the shock. For the other distributions, consumption expenditure, land ownership and land cultivation, does the timing, nor the magnitude change.

Lastly, negative temperature shock strengthens the result for land cultivation and is the same for general consumption. The result for consumption expenditures is decreased inequality in both the short- and medium-run. Land cultivation inequality is increased in the medium-run, and for arid districts are two lags significant compared to the previous one. The effect on food expenditure and land ownership inequality disappears. In the baseline regression did negative temperature shocks decrease food expenditure inequality while increase land ownership inequality, for arid district, the coefficients are insignificant.

Table 5-3 Estimates for arid

	(1) Consumption	(2) Food Exp.	(3) Land Own.	(4) Land Cult.
Precip. Pos. t-5	0.004	0.002	-0.008	-0.004
Precip. Pos. t-4	-0.015***	-0.008*	-0.000	-0.009
Precip. Pos. t-3	-0.002	-0.000	0.000	0.004
Precip. Pos. t-2	-0.005	-0.006	-0.017	-0.001
Precip. Pos. t-1	-0.006	0.001	0.000	0.005
Precip. Pos. t-0	-0.007	-0.011*	0.005	0.033***
Precip. Neg. t-5	-0.018	-0.014	-0.011	-0.038*
Precip. Neg. t-4	0.003	0.011	0.018	-0.006
Precip. Neg. t-3	-0.006	-0.008	-0.018	-0.001
Precip. Neg. t-2	0.008	0.003	0.006	-0.019
Precip. Neg. t-1	0.006	0.010	-0.016	0.005
Precip. Neg. t-0	-0.004	-0.007	0.022	0.015
Temp. Pos. t-5	0.018	0.022	-0.013	0.029
Temp. Pos. t-4	0.002	0.010*	0.018*	-0.010
Temp. Pos. t-3	0.012**	0.010*	-0.010	-0.007
Temp. Pos. t-2	-0.002	-0.004	-0.014*	-0.027***
Temp. Pos. t-1	-0.002	-0.004	-0.006	0.011
Temp. Pos. t-0	0.003	0.011**	-0.013	0.012
Temp. Neg. t-5	0.003	0.004	0.009	0.005
Temp. Neg. t-4	-0.013***	-0.003	0.014	0.017*
Temp. Neg. t-3	-0.006	-0.007	-0.009	0.021*
Temp. Neg. t-2	-0.019***	0.000	-0.018	-0.001
Temp. Neg. t-1	-0.008*	-0.003	-0.000	-0.011
Temp. Neg. t-0	0.002	-0.001	-0.003	0.005
Year dummies	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Obs.	1921	1615	1525	1512
R-squared	0.548	0.074	0.101	0.074

Fixed-effect model. Robust standard errors. Control variables include mean consumption and the share of urban households. *** p<0.01, ** p<0.05, * p<0.1

Table 5.4 investigates the impact of extreme weather shocks on inequality with a different classification. Remember, the shock is the mean plus/minus one standard deviation, in 5.4 it is the mean plus/minus two standard deviations. A limitation exist with the methodology since the extreme values of precipitation is not uniformly distributed and the distribution is skewed to the right, the mean minus two standard deviations implies a limit of negative precipitation for some districts, naturally this is not possible and is a significant limitation of this study.

For positive precipitation shocks is inequality in food expenditure and land ownership not significantly impacted. Similarly, land cultivation does not change, and the impact is still considerable large. Consumption inequality does receive considerable changes with inequality increasing at the year of the shock and at t-5, while decrease at t-1. Compared to the earlier result with strictly decreasing inequality due to its effect, this suggest that precipitation shocks have a non-linear effect.

For positive temperature shocks does consumption change as well, from an inequality increasing effect in the medium run to an increasing short run impact. Food expenditures received numerous significant coefficients in the baseline regression, yet with the more severe shock have the significant coefficients vanished. Land ownership inequality experience now a more uniform impact with positive temperature shocks now only leading to a more egalitarian outcome. For land cultivation is the effect more ambiguous with both inequality increasing and decreasing effects.

Considerable differences for the negative temperature shocks is a consequence when using the stronger limit of a climate extreme. Land cultivation receive a nonuniform impact, yet mostly towards an inequality increasing effect. The medium run effect of increased land ownership inequality is starker in the case of the alternative classification. In addition, food inequality experiences a more considerable effect and the effect is stronger in the medium-run while insignificant in the short-run. For general consumption does the effect get ambiguous compared to the previous uniform impact.

Table 5-4 Regression results with alternative classification of climate extremes (+/- 2 std)

	(1) Consumption	(2) Food Exp.	(3) Land Own.	(4) Land Cult.
Precip. Pos. t-5	0.014**	-0.003	0.004	-0.005
Precip. Pos. t-4	-0.004	-0.001	0.003	-0.010
Precip. Pos. t-3	0.004	-0.005	-0.014	0.007
Precip. Pos. t-2	-0.003	-0.003	-0.021	-0.010
Precip. Pos. t-1	-0.012*	-0.001	-0.011	0.001
Precip. Pos. t-0	0.028**	0.005	0.050	0.038*
Temp. Pos. t-4	-0.010	-0.012	-0.028	-0.043
Temp. Pos. t-3	0.001	0.002	0.001	0.011
Temp. Pos. t-2	-0.016	-0.009	-0.042**	-0.042*
Temp. Pos. t-1	-0.010	-0.014	-0.009	0.038***
Temp. Pos. t-0	-0.030***	-0.010	0.000	0.013
Temp. Neg. t-4	-0.017***	-0.018***	-0.004	0.034**
Temp. Neg. t-3	-0.006	-0.044***	0.092***	0.108**
Temp. Neg. t-2	0.067***		-0.014	-0.081***
Temp. Neg. t-1	-0.004	-0.005	-0.001	-0.009
Temp. Neg. t-0	0.009	0.012	0.022	0.048*
Year dummies	YES	YES	YES	YES
Control variables	YES	YES	YES	YES
Obs.	2770	2334	2197	2182
R-squared	0.516	0.048	0.085	0.057

Fixed-effect model. Robust standard errors. Control variables include mean consumption and the share of urban households. *** p<0.01, ** p<0.05, * p<0.1

5.2 The VRIP as a Determinant of the Impact

The VRIP section examine the short-run effect of climate extremes on inequality through the mediating effects of vulnerability and resilience. Figure 5.1 show the incorporation of the VRIP for understanding how shocks impact societies. As noted from subchapter 4.3.2, the impact can only be incorporated for the short-term impact, and only the significant shock(s) from the baseline Indian result is incorporated. The discussion will focus on consumption inequality, for the distribution only negative temperature shock have a significant impact, and this negatively, implying decreased inequality.

As per construction of the analysis of mediating factors, I am not able to say whether the factors increase or decrease the causal effect of climate extremes on inequality on the district level in India. Instead, by employing the VRIP framework with the approach taken, it is possible to investigate whether district who have experienced a shock experience different impacts on inequality based on the VRIP.

The most striking result to emerge from the data is that the economic capacity indicators in the VRIP are most dominantly determining the impact of climate extremes on consumption expenditure inequality in India. In addition, the settlement and infrastructure sensitivity, here, measured in toilette access, and partly environmental capacity, for the indicator population density, are important for understanding the shock.

Starting with the indicators for coping and adaptive capacity, important for societies potential to react to a catastrophe. The *economic capacity* indicators: district mean consumption and initial consumption inequality are important features to mediate the effect of negative temperature shocks. The mean income is grouped into two clusters, with the lower cluster experiencing a decreasing impact of extreme weather on the distribution for most of the observations. For the second cluster, there is an evident mean of impact around zero and the impact is both towards increasing and decreasing inequality. For consumption inequality, there is a remarkable strong effect, more inequal district experience negative impacts of shocks. For more egalitarian districts, the effects opposite. Hence, the climate shock counteracts the existing inequality level, with more egalitarian districts experience increased inequality while more inequal district experience a more egalitarian short-term outcome.

The *human and civic resource* indicators; dependency rate and educational rate have a limited effect as mediators in determining the effect of climate extreme weather on the district inequality in India.

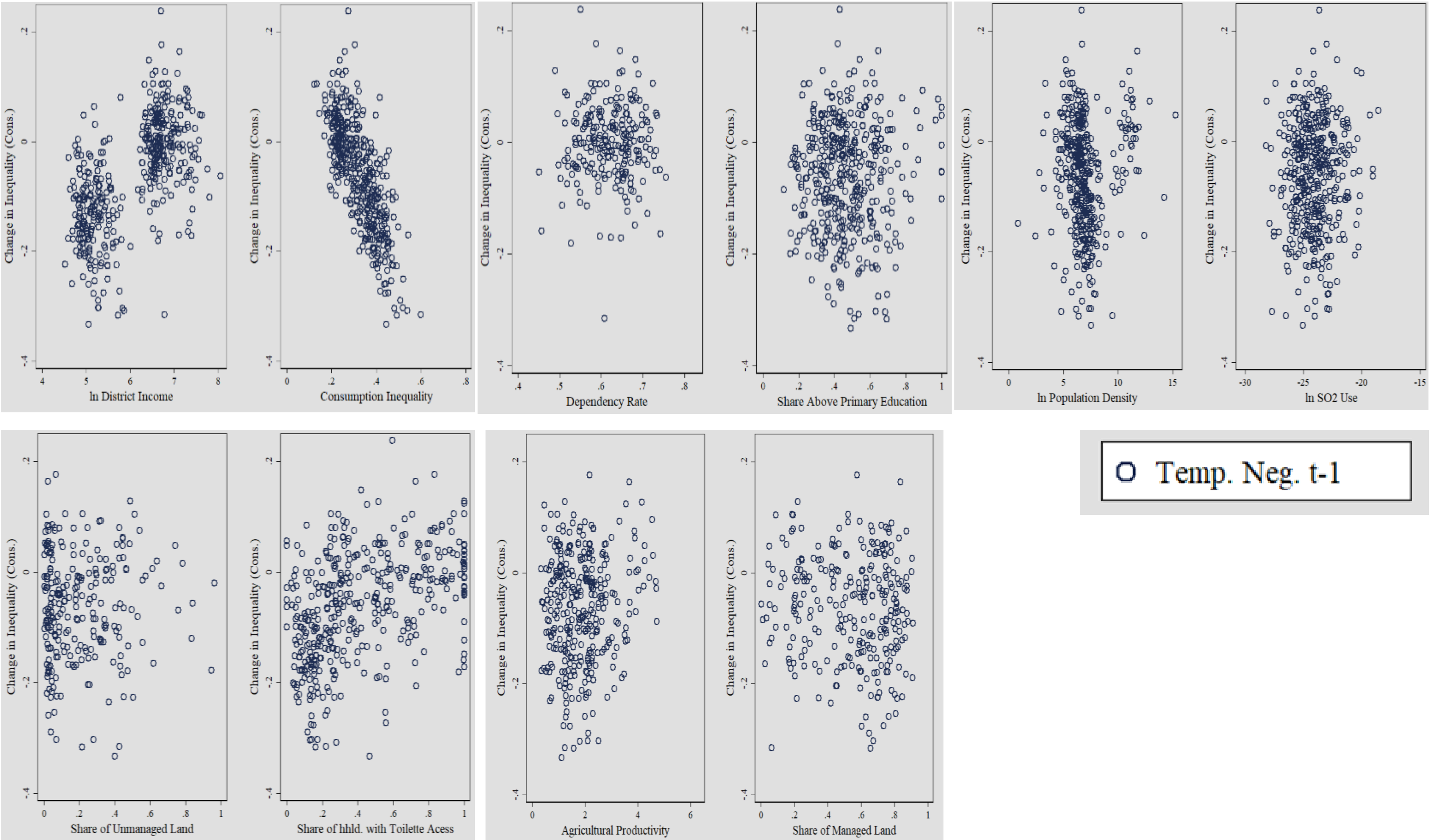

Figure 5-1 VRIP indicators for change in consumption expenditure inequality. Own calculations.

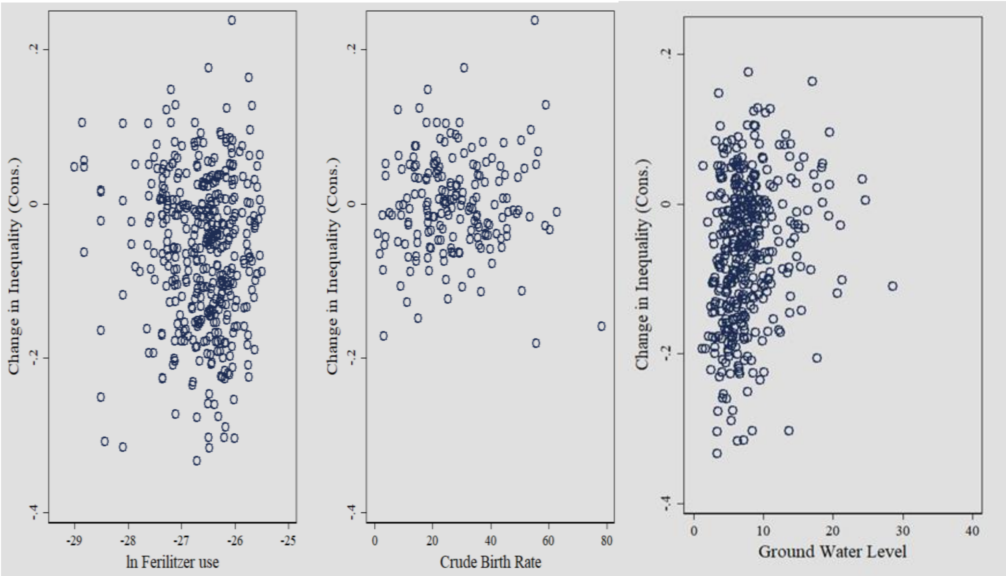

Figure 5.1 Cont.

Environmental capacity has a weak impact on the effect of negative temperature shocks on inequality. The indicators include population density, SO_2 and the share of land unmanaged, with especially the first being of significance. Population density is grouped into two clusters, with the second, more densely populated group experience significantly less changes in inequality. For the less densely populated group, increased density implies a distinct negative impact of extreme weather on inequality, here are also the largest magnitudes found. The share of unmanaged land has a weak effect as mediator of climate extremes. For the very low shares are the magnitudes the largest, and the effect drives towards zero as the share of unmanaged land decreases; however, the relation is weak. Lastly, the SO_2 level does not seem to have strong impact on the effect of climate extremes.

Moreover, the sensitivity indicators describe more directly the vulnerability of societies. The first sensitivity indicator, *settlement and infrastructure*, is showing a significant impact of determining the impact of climate extreme events. The indicator is applied by the share of households with toilette access. The indicator has a determining effect most strongly for the very low shares of access. For the districts where the share of households having access are less than 50 %, increasing the share implies a more moderate impact of extreme weather. The impact of climate extremes for district with less than 20 % of households with toilette access is strong and decrease inequality in the short-term.

Food security, here calculated by production of rice per hectare, is a moderate impacting factor for determining the impact of on consumption inequality. The data portraits a weak relationship that low agricultural productivity leads to a larger effect of an extreme weather impact, this with a decreasing effect of inequality.

Ecosystem sensitivity measured by share of land managed and fertilizer usage is not of major importance for determining the effect of a climate extreme shock on inequality. For share of land managed, the impact seems almost perfectly spread out, however, at the largest shares does the lowest values occur. Fertilize usage, does not provide a potent explanation whether inequality is impacted due to an extreme weather event. Similarly, *human health sensitivity*, measured by the crude birth rate, does also have a limited effect on inequality. A weak relationship describes that with increasing crude birth rate are inequality increased as a consequence.

Lastly, *water resource sensitivity*, measured by the ground water level, does provide some information regarding the impact. Districts experiencing the lowest levels of ground water does also experience the largest decreased inequality, however this is not the case for all districts. The data does weakly suggest that the less ground water, the more vulnerable are district for shocks.

Additional analysis of the VRIP indicators for the impact of extreme weather on the distribution of food expenditure, land ownership and land cultivation provide less strong results. For interest, the plots are found in Appendix D. The rest of this section will just shortly describe the results.

Compared to the consumption estimates, the impact on the distribution of food expenditure, land ownership and land cultivated, there are some notable differences. For consumption inequality is the economic capacity indicators more determinant of the impact. For food inequality, neither variable of the VRIP does have a clear-cut effect of how either negative or positive temperature shock impact inequality. Food expenditure is the most egalitarian distribution included and the changes are also smallest, the effect seem not to be dependent on the vulnerability and resilience characteristics of districts.

For land ownership inequality, the VRIP provides some answers in which districts experience the largest changes due to negative precipitation shocks. Larger district income decreases land ownership inequality, as well as higher agricultural productivity. Additionally, reversed to the findings for consumption inequality, less access to toilettes increase inequality while increased access decrease inequality.

Lastly is the impact of positive precipitation shock on land cultivation. The share of managed land does experience a significant amount of the largest impacts for the very low share of managed land. Also, for district which shares similarities in the share of unmanaged land seem to experience decreased inequality for the low amounts of agricultural land. The population density is negatively correlated with the impact, more densely populated districts receive a negative cultivation inequality impact.

5.3 Discussion

Table 5.1 to 5.4 provided understanding of how climate extremes impacts inequality in India, finding that the impact is not uniform. Karim & Noy (2016) state that there is no "…'one-size fits all' description of the ways disasters have an impact on poverty" (p.17). This study presents similar findings for inequality in India. The results have shown that the consumption-based estimates are more sensitive to shocks, since they have more significant signs; yet, the land-based estimates see larger magnitudes. This section will discuss each shock separately to gain understanding of how it impacts distributions.

5.3.1 Precipitation Shocks

Positive precipitation shocks have a significant impact on consumption inequality as well as land cultivation. For consumption inequality, positive rainfall shocks contribute to decreased inequality, but only in the mean-run and the impact is weak. The insignificant impact on food expenditure inequality shows that the decreased inequality is related to consumption of non-food items, that the food consumption is less impacted is found in the literature (Baez & Mason, 2008; Karim & Noy, 2016). Previous literature has argued that above normal rainfall increase agricultural productivity and wages in India (Jayachandran, 2006; Mahajan, 2017; Shah & Steinberg, 2017). However, above normal precipitation may also lead to the risk of floods, which the larger limit in Table 5.4 aims to embrace. When positive precipitation shock is calculated as two times the standard deviation, the impact for consumption is changed. The effect is similar to Banerjee's (2007) finding for Bangladesh of reversing impacts; however, the impact is in the medium-run inequality increasing.

The most robust finding is the short-run increasing effect of positive precipitation shock on land cultivation inequality. The finding suggests that rich can adjust the amount of land cultivated in times of favorable agricultural conditions. Erickson & Vollrath (2004) argue that there is a general upward bias of land inequality since the areal ownership and cultivation does not incorporate soil quality, implying that people with less land experience more qualitative soil. If households with larger areas have lower soil quality which potentially needs better conditions, then they will make us of that land during good years while that is not an available option for agricultural smallholders. Thus, the existing evidence put together suggests that for the agricultural population, positive precipitation shocks implies that poorer household increase intensity on the land available (Shah & Steinberg, 2017) and receive relatively larger income gains (Jayachandran, 2006), yet wealthier household are more able to adjust the area of land cultivated.

Regarding negative precipitation shocks, for consumption of food and in general, the effect is mixed in the medium-run, yet land ownership inequality is increased at the year of impact. Narayanan & Sahu's (2011) case-study is a potent explanation of the result, arguing for that low-income earners are selling assets as a coping mechanism to keep consumption stable. The result is opposed to Carter et al.'s (2007) findings for Ethiopia where they show that wealth was kept intact while consumption decreased.

The VRIP analysis for change in land ownership inequality due to negative precipitation shocks, suggest that richer districts are more prone to change their assets of landholdings. Potentially, they have more posibilities to do so if they have financial access which Lee & Villaruel (2016) argue is of key concern for limiting the fluctations of income due to climate change. However, the link could also be due to poorer districts does more strongly rely on agricultural incomes and land owners does not want to change ownership (this is also suggested by 5.3.3).

Earlier studies have estimated the impact of negative temperature shocks on wages in India, arguing that droughts increase inequality since wages are most responsive to shocks at the lower end of distribution (Jayachandran, 2006; Mahajan, 2017). Jayachandran (2006) find that wealthier are better off if they are employers since labor costs decreases. The result obtained in this thesis cannot contrast nor strengthen these results.

5.3.2 Temperature Shocks

Previous research has focused to a limited degree on the impact of temperature shocks on inequality, making it hard to compare to other cases. The results in this thesis suggest that it should receive a similar amount of interest.

For temperature shocks, the baseline regression shows uniformly that inequality increases for consumption expenditure and food expenditures during warmer-than-average years while inequality decreases for colder years. Since most of the Indian districts experience mean temperatures above 13°C (above 90 % of the districts according to the data) does a positive temperature shock imply decreased productivity while a negative increase, according to Burke, Hsiang & Miguel (2015). Thus, the result argue that low-income individuals are more sensitive to temperatures, making inequality in consumption and food expenditures increase during warmer years while decrease during colder.

For positive temperature shocks, the result is stronger for food than for non-food consumption, which could be a consequence of poor are being both agricultural and non-agricultural workers. Guleria & Gupta (2018) notes that heatwaves lead to impacts on agriculture with higher crop mortality and decreased productivity which increases prices. Bohle, Downing & Watts (1994) argue that urban poor and wage workers are more vulnerable to climate change since they are not able to capitalize on increased food prices which agricultural workers are. Thus, increased food prices could amplify the inequality of food expenditures while simultaneously keep incomes stable between low- and high-income earners.

The negative effect for consumption expenditure due to negative temperature shocks is robust through the tropical and arid districts. For arid areas does Skoufias & Vinha (2012) suggest that consumption inequality should increase; however, in India does consumption inequality decrease. Notable difference exists for food inequality. Negative temperatures have significant decreasing inequality effect on food expenditures in the base regression and with the alternative classification, for arid and tropical zones, it is having none. The result suggest that non-arid and non-tropical zones drives the result of decreasing food inequality due to negative temperature shocks.

The VRIP analysis discuss district characteristic which are important for the impact of the shock. For consumption, the economic capacity indicators are major determinants of the impact of negative temperature shocks. Anbarci, Escaleras & Register (2005) argues that inequality increase the impact of disasters since prevention efforts are undervalued. Evidently, this is also the case in India for climate extremes since initial unequal districts are significantly more impacted in terms of changed inequality levels.

Turning to the impacts of temperature shocks on land inequality in India. The impact of positive temperature shocks decreases land cultivated inequality, and that this is driven by non-tropical and arid districts. For land ownership, the effect of positive temperature shocks is nonuniform, inequality is both increased and decreased in the medium term. The inequality increasing effect disappears in tropical zones and with the alternative classification of a shock but persist for arid districts. The inequality decreasing effect stays robust throughout the samples. The effect of negative temperature shocks on land are uniform. Both land cultivated and land ownership is increased, the effect is driven by non-tropical and arid districts for the former while non-tropical and non-arid for the latter.

Dell, Jones & Olken (2012) show that positive temperature shocks decrease both agricultural and industrial output, as well as investments. Thus, the general findings for this study, regarding investments in land, suggest that the wealthier are the contributor of the investments since inequality in land increase during colder-than-average temperatures while the reverse is true.

The alternative classification of a climate shock (two standard deviations from the mean) alter the result for both land and consumption-based estimates in the case of temperature shocks. For the distributions of consumption and land cultivation does the effect gets partly reversed for both positive and negative temperature shocks. Both Burke, Hsiang & Miguel (2015) and Lee & Villaruel (2016) find that temperatures have a non-linear effect of productivity, this thesis results suggest that also temperature shocks may have non-linear effects. However, the effects for food expenditure and land ownership gets exaggerated which argues for increasing effects of climate shocks. Climate change is set to increase the intensity and frequency of climate extremes (IPCC, 2019), thus the findings of intensifying effects of the double impacts suggest accelerating consequences of climate change.

5.3.3 Differences between Sectors

As the discussion and literature suggest (i.e Acevedo et al., 2018; Diffenbaugh & Burke, 2019), the impact of climate extreme events goes through the link of employment and differences may exist between the agricultural and non-agricultural population. A study by Andersson & Palacio Chaverra (2016) suggest that the structural transformation process is important to understand distributional aspects. Earlier studies on India have investigated the agricultural population alone (Jayachandran, 2006; Mahajan, 2017). Thus, investigating how rural and urban districts are impacted aversely is an avenue of interest.

In the data, agricultural is the main occupation for 65 % of the rural population while services contribute to 55 % of urban employment. Lastly, manufacturing and construction employment contribute to 32 % in urban areas and 15 % in rural. Figure 5.2 show the impact of respective shock to each distributional indicator in relation to the share of the sectors population being rural and urban, with one indicating a complete urban population in the district.

For consumption inequality, there is a weak trend that districts that almost are completely rural experience more negative inequality impacts due to negative temperature shocks, yet the trend is not particularly strong since more urban districts also experience large shocks. For food expenditures, no strong impact of the share of population in urban or rural sector is given.

The most significant impact seems to be for land ownership inequality where the most rural districts experience increased inequality. The data suggests that an increasing share of urban population lead to that a negative precipitation shock decrease land ownership inequality. For land cultivated, there is no strong trend; however, the most rural districts receive the largest impacts. Although we are not able to scrutinize the hypothesis that the impact of extreme weather event runs through the agricultural sector, we can argue that rural districts that has experienced climate extremes do not receive larger changes in inequality than more urban districts.

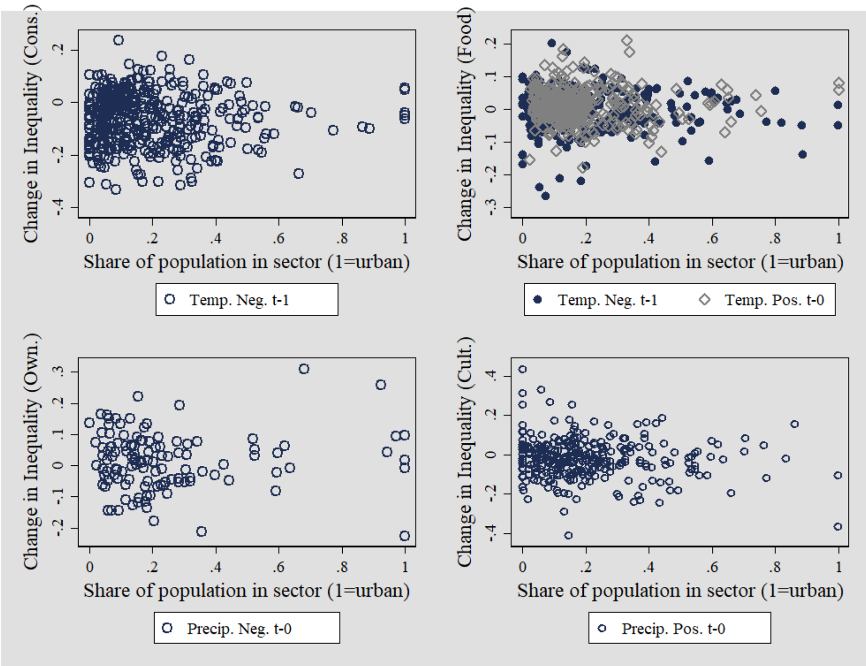

Figure 5-2 Rural and urban households as mediators. Own calculations.

6 Conclusion

The present study appears to be the first study to empirically investigate the impact of climate change on inequality in India. The chief objectives were; to understand how countries' distributions are affected by climate change, to understand how inequality in India is impacted by climate change, and if climate change has contributed or counteracted the increasing inequality trend in India. Subsequently, the research questions have been posed as: how does climate extremes impact inequality in India?

The most obvious finding to emerge is the varying impact of climate extremes on inequality in India. The effect is nonuniform on the type of inequality indicator used as well as the type of shock. For the full sample and with the baseline definition of a climate extreme event do no type of shock have a uniform impact for all the indicators. Simultaneously, no distribution experience impacts in the same direction for all shocks applied.

Nevertheless, uniform impacts exist. For all the four different regressions performed the short-term effect of a positive precipitation shock implies increased land cultivation inequality. By excluding the second definition of a climate extreme, positive precipitation shocks and negative temperature shocks have a decreasing impact on consumption inequality, while positive temperature shocks increase inequality. Positive temperature shocks do also increase food inequality at the in India, disregarding the type of district.

By taking an interdisciplinary approach and introduce the Vulnerability-Resilience Indicator Prototype developed by Brenkert & Malone (2005), this research has investigating important mediating factors of the impact of climate extremes on inequality in India. Finding that economic capacity being of central importance, initial inequality and mean income level at the district level are important determinants of how inequality is impacted. Further, settlement and infrastructure sensitivity have a determining impact, and partly environmental capacity. The findings suggest a role for inclusive economic growth for limiting the impact of climate extremes in India.

Taken together; this thesis highlights the importance of investigating different types of environmental shocks as well as including different types of distributional indicators for fully understand climate extremes. Due to data availability, this thesis has not covered the total wealth levels as well as income inequality, these indicators provide routes for further research.

These results add to the rapidly expanding field of how climate change, climate extremes and natural disasters impact socio-economic indicators in developing countries. The results are partly in line with the earlier findings for India finding that low income earners are responsive to positive precipitation shocks, however the results for negative precipitation shocks are not as uniform as previous studies suggests (Jayachandran, 2006; Mahajan, 2017; Mendiratta, 2015). The results are similar to several other studies who suggest that the impact is ambiguous and dependent on the type of economic inequality measured (Carter et al., 2007; McSweeney & Coomes, 2011; Silva, Matyas & Cunguara, 2015).

The insights gained from this study may be of assistance in understanding the impacts of climate change. However, the effect is limited to the scope of climate change used in this thesis. Thus, investigating gradual accumulated deviations or other indicators of climate change may provide other knowledge of its socio-economic consequences. Further, studies on the entire India are likely to not incorporate the heterogeneity within the country. I have investigated the subgroups of districts which are in the temperate and arid zones; however, the results can be driven by other characteristics. Additionally, how repeated climate shocks impacts long term inequality has not been investigated. As Keerthiratne & Tol (2018) show for Sri Lanka, districts that experience more disasters are more egalitarian, whether this is true for India is still to be found.

Lastly, the methodology used introduced a classification of extreme weather event that was not fully suitable for negative precipitation shocks, thus, how droughts impacts inequality needs further investigation. In addition to these limitations, this research has thrown up many questions in need of further research. Income inequality is significantly larger than consumption inequality and the result may diverge for the two different indicators. Further, a study with a longer-time perspective that captures a gradual changing climate should be undertaken.

Greater efforts are needed to ensure inclusive economic growth in India. This study has helped in understanding socio-economic consequences of climate change, as it is noted, it will impact societies widely, adversely and nonuniformly. Addressing the underlaying features of climate change is necessary, as well as understanding it consequences, with this thesis contributing to the latter.

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Appendix A

Variable	**Data source**
Gini Coeffficents	NSSO
Temperature and Precipitation data	University of Delaware see Matsuura & Willmott (2012a, 2012b)
Mean consumption per district	NSSO
Dependency ratio	NSSO
Education: Primary schooling or below	NSSO
Population density	Population gathered by NSSO, Area by ArcGIS (2014)
SO_2	Emissions Database for Global Atmospheric Research (EDGAR) see Crippa et al. (2016)
% Land unmanaged	Land data from data.gov.in (2014)
Population with no access clean water/sanitation	Households with access to toilets (Department of Drinking Water and Sanitation, 2011)
Cereals production/crop land area	Production of rice, gathered from data.gov.in (2013)
% Land managed	Land data from data.gov.in (2014)
Fertilizer per district	Emissions Database for Global Atmospheric Research (EDGAR) see Crippa et al. (2016)
Crude birth rate	NSSO
Renewable supply and inflow	Ground water from the Department of Water Resources (2020)

Appendix B

Variable	Obs.	Mean	Std. Dev.	Min	Max
Above primary education (1=yes)	2168	.52	.172	.047	1
Crude birth rate	589	26.368	13.87	.332	78.204
Dependency rate	1165	.639	.059	.45	.83
ln Fertilize usage	2150	-27.037	.718	-29.329	-25.499
Gini Consumption Expenditures	2788	.287	.084	.0513	.670
Gini Food Expenditures	2349	.213	.052	.032	.659
Gini Land Ownership	2215	.668	.134	.060	.986
Gini Land Cultivated	2200	.478	.106	0	.870
Ground water level	1988	8.833	5.452	.9	39.57
ln Mean district consumption	2788	6. 557	.72	4.52	8.389
ln Population density	2120	7.023	2.751	-.907	15.34
Agricultural Productivity	1854	1.865	.962	0	6.316
Sector share (1 = urban)	2788	.216	.192	0	1
ln SO2	2168	-24.537	1.706	-30.248	-18.554
Share of HHLD with Toilette access	2129	.45	.296	0	1
Share of Managed Land	1344	.485	.24	.001	.999
Share of Unmanaged land	1179	.233	.196	.002	.963

Own Calculations. See list of data sources in Appendix A.

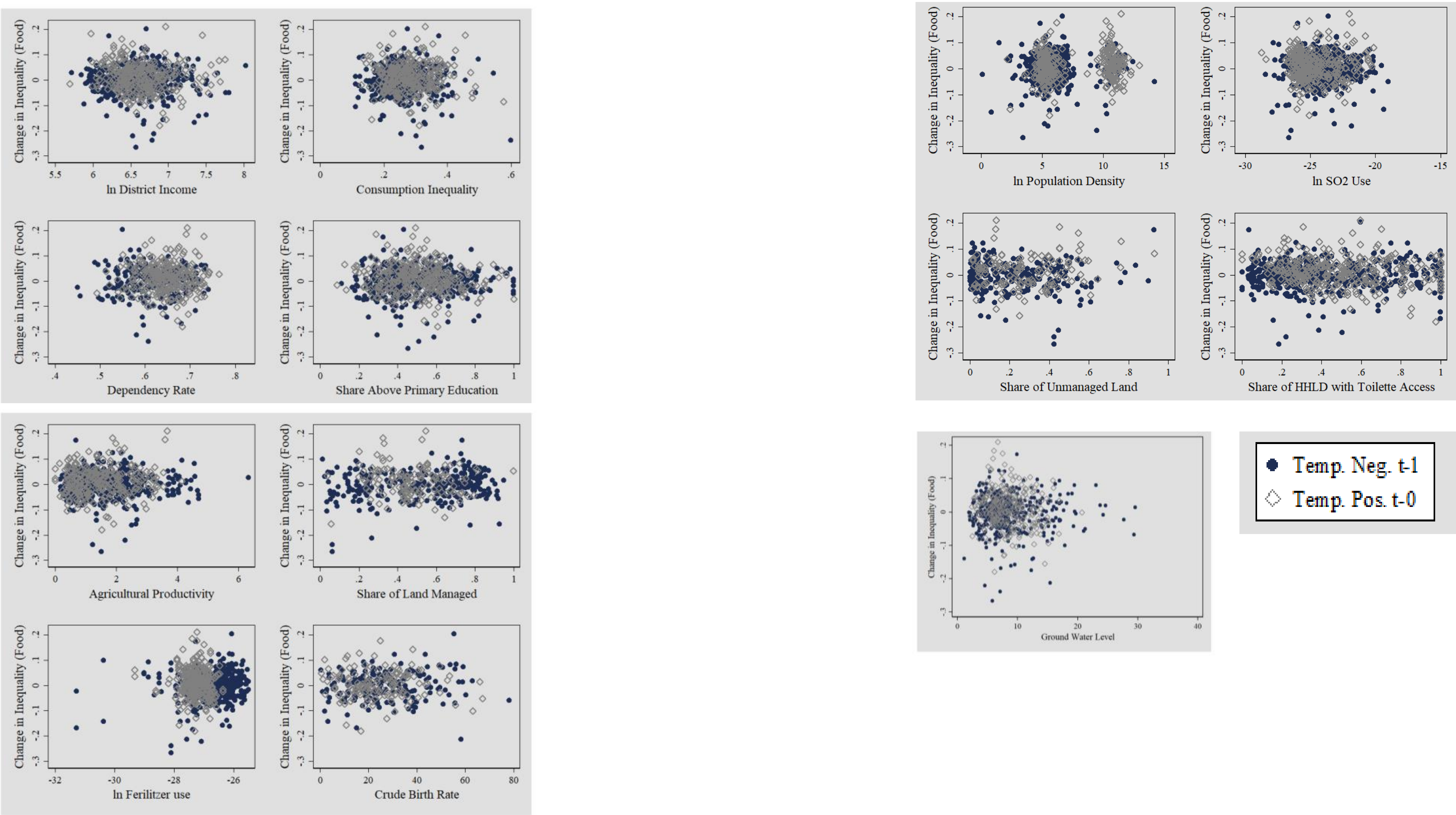
Appendix C

Summary statistics for the shock variables.

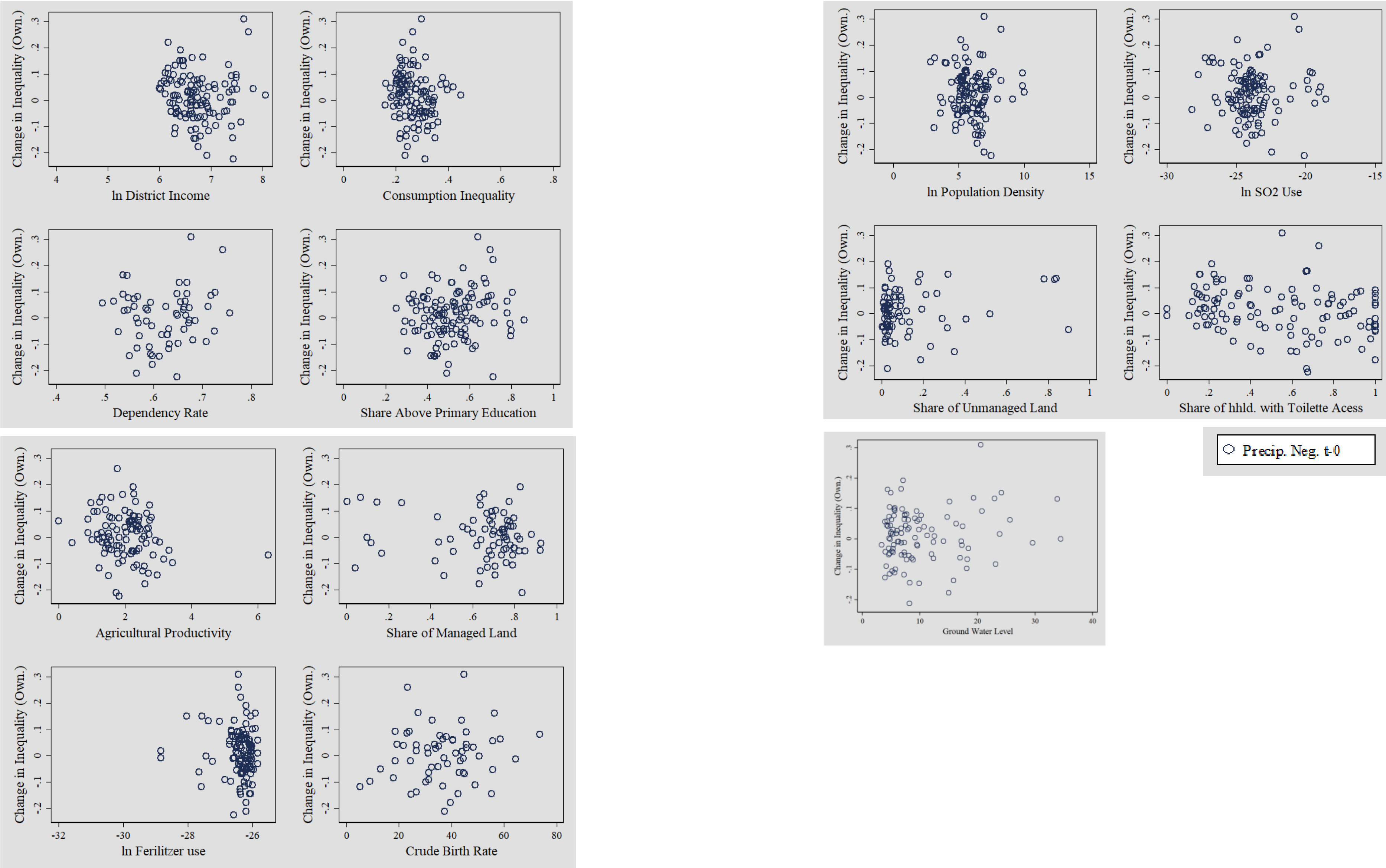
	Variable	Obs	Mean	Std.Dev.	Min	Max
Regular classification of climate extremes (the mean +/- 1 std)	Precip. Pos. t-5	2788	.151	.358	0	1
	Precip. Pos. t-4	2788	.223	.417	0	1
	Precip. Pos. t-3	2788	.142	.349	0	1
	Precip. Pos. t-2	2788	.184	.387	0	1
	Precip. Pos. t-1	2788	.126	.331	0	1
	Precip. Pos. t-0	2788	.164	.371	0	1
	Precip. Neg. t-5	2788	.037	.19	0	1
	Precip. Neg. t-4	2788	.047	.212	0	1
	Precip. Neg. t-3	2788	.067	.25	0	1
	Precip. Neg. t-2	2788	.062	.241	0	1
	Precip. Neg. t-1	2788	.066	.248	0	1
	Precip. Neg. t-0	2788	.088	.283	0	1
	Temp. Pos. t-5	2788	.029	.167	0	1
	Temp. Pos. t-4	2788	.084	.277	0	1
	Temp. Pos. t-3	2788	.157	.364	0	1
	Temp. Pos. t-2	2788	.103	.304	0	1
	Temp. Pos. t-1	2788	.074	.262	0	1
	Temp. Pos. t-0	2788	.082	.275	0	1
	Temp. Neg. t-5	2788	.079	.27	0	1
	Temp. Neg. t-4	2788	.201	.401	0	1
	Temp. Neg. t-3	2788	.08	.271	0	1
	Temp. Neg. t-2	2788	.072	.258	0	1
	Temp. Neg. t-1	2788	.2	.4	0	1
	Temp. Neg. t-0	2788	.182	.386	0	1
Alternative classification of climate extremes (the mean +/- 2 std)	Precip. Pos. t-5	2788	.069	.253	0	1
	Precip. Pos. t-4	2788	.188	.391	0	1
	Precip. Pos. t-3	2788	.046	.209	0	1
	Precip. Pos. t-2	2788	.161	.368	0	1
	Precip. Pos. t-1	2788	.038	.191	0	1
	Precip. Pos. t-0	2788	.019	.135	0	1
	Precip. Neg. t-5	2788	.006	.078	0	1
	Precip. Neg. t-4	2788	.006	.078	0	1
	Precip. Neg. t-3	2788	.006	.078	0	1
	Precip. Neg. t-2	2788	.006	.078	0	1
	Precip. Neg. t-1	2788	.006	.078	0	1
	Precip. Neg. t-0	2788	.006	.078	0	1
	Temp. Pos. t-5	2788	.006	.078	0	1
	Temp. Pos. t-4	2788	.011	.103	0	1
	Temp. Pos. t-3	2788	.122	.328	0	1
	Temp. Pos. t-2	2788	.016	.125	0	1
	Temp. Pos. t-1	2788	.022	.147	0	1
	Temp. Pos. t-0	2788	.014	.117	0	1
	Temp. Neg. t-5	2788	.008	.088	0	1
	Temp. Neg. t-4	2788	.049	.215	0	1
	Temp. Neg. t-3	2788	.009	.092	0	1
	Temp. Neg. t-2	2788	.008	.09	0	1
	Temp. Neg. t-1	2788	.054	.226	0	1
	Temp. Neg. t-0	2788	.013	.114	0	1

Appendix D

The VRIP with the change in food inequality due to positive temperature shock at t-0 and negative temperature shock at t-1. Own Calculations.



The VRIP with the change in land ownership inequality due to negative precipitation shock at t-0. Own calculations.



The VRIP with the change in land cultivation inequality due to positive precipitation shock at t-0. Own calculations. For clarification, the majority of the positive precipitation shocks occur for 2004. However, data is missing for 1999 for crude birth rate and dependency rate leading to too few observations. Own calculations.