The Impact of Climate Shocks on Social Networks: Understanding Sensitivity and Adaptation among Rural Indian Communities

Richard Ramsawak[1]

May 20, 2018

Abstract

This paper examines the relationship between climate shocks and investments in social network relationships. I leverage fluctuating long run precipitation patterns across India, to estimate the impact of lagged and long run average negative precipitation anomalies on social network relationships. In so doing I attempt to disentangle "direct" and "indirect" informational impacts of climate shocks on investments in social networks. I find that households which experience higher average negative precipitation shocks tend to invest more in family-caste (formal and informal) and vertical network relationships. These network relationships were also found to be associated with greater access to financial credit, credit accessed specifically from family members, higher reported collaboration, more diversified businesses, and use of private irrigation technologies, all of which are key to mitigating the negative impacts of climate shocks. Investments in linked networks were found to be lower among households living in villages dominated by Scheduled Castes and Tribes (SCSTs). Interestingly, villages dominated by High Caste (HC) grouping also recorded marginally lower investments in vertical linkage networks, in response to climate impacts. Interestingly, villages with higher levels average income, and households which were reported to be landowners, were found to have higher investments in linked networks relative to other members of the sample. This suggests that wealth rather than caste status would be key for a household's ability to access linked networks. Non-family-based or bridging networks were also found to be negatively impacted by repeated negative precipitation shocks. Interestingly, investments in linked networks were also found to be much lower among households living in villages with lower average village income.

JEL I15, Q10, Q51, Q54

Keywords: social capital, climate shocks, India

---

1 Department of Economics, Clark University and Faculty member Arthur Lok Jack Global School of Business, UWI. I would like to thank Magda Tsaneva, David Cuberes and Wayne Gray for their tremendous support and comments on earlier drafts of this study.

1.0 Introduction

The Inter-Governmental Panel on Climate Change (IPCC) estimates that, on average, global temperature levels will increase by 1.5 to 4.5 degree Celsius (with high confidence) relative to pre-industrial levels by the end of the 21st century (Rajendra K Pachauri et al., 2014). The IPCC also suggests that such profound changes in the climatic system during the 21st century will likely be felt hardest by households in developing countries which strongly depend on agricultural production (IPCC, 2013, 2014). Significant empirical research has been undertaken examining the impact of negative climate shocks on key economic and social outcomes, such as economic growth, productivity, health, crime, and conflict, to name a few (see Melissa Dell et al. (2014), Tamma A Carleton and Solomon M Hsiang (2016) for detailed review). Very few studies have analyzed the impact of climate shocks on social network relationships. This paper, therefore seeks to assess the impact of climate shocks on social networks in rural India. Investments in social networks have been found to be important in mitigating the negative impacts climate shocks (W Neil Adger, 2001, 2010, Johanna Wolf et al., 2010). Investments in social networks have also been found to be particularly useful for people living in rural and marginalized communities, where formal market-based and institutional solutions remain limited. Cornelia Butler Flora (1992), Marcel Fafchamps and Bart Minten (2002) and Francis Bloch et al. (2008) and Francis Bloch and Bhaskar Dutta (2011) have found a positive association between investments in social networks and information transfers, enforcement of social and contractual obligations and the provision of social assistance and emergency credit, all of which become crucial in times of crisis. It is hoped that this study can deepen our understanding of ways that negative climate events influence human social network relationships, which in some regions, become a key source of support in the face of negative climate events.

One of the challenges in assessing the impact of climate shocks is distinguishing between "direct" and "indirect" or information-based impacts of changing climate patterns (Tamma A Carleton and Solomon M Hsiang, 2016, Solomon Hsiang, 2016). "Direct" impacts include instances where harmful climate events such as droughts and high temperature levels, result in the loss of assets, livestock, business failure, illness or even death among households. Such events not only undermine a household's social standing in a community, but also negatively impact social network relationships. On the other hand, information impacts are driven by expectations, households develop either in response to past climate patterns or based on information of future climate events (Solomon Hsiang, 2016). This distinction is key to uncoupling climate shock impacts on social network relationships. Indeed, in the case of the former, negative climate shocks can have a "corrosive" impact on social networks relationships, while in the case of the latter, the experience of negative climate shocks during prior years can be "consensus building," as persons come together either to address future climate threats or repair damage of past adverse climate events. In the latter case, individuals have an incentive to increase investments in social network relationships, as a means of mitigating risks associated with future negative climate events (Marcel Fafchamps and Flore Gubert, 2007, Marcel Fafchamps and Bart Minten, 2002).

To distinguish between possible impacts, I leverage widely documented, fluctuating long-term rainfall patterns throughout India. Specifically, B Parthasarathy et al. (1987) and RH Kripalani and Ashwini Kulkarni (1997) have documented constantly shifting long-term rainfall patterns (movements between periods of heavy rainfall, followed by very dry rainfall patterns) over the course of the last 100 years across the continent of India. In this case, I argue that past realized rainfall trends contain information of future rainfall patterns and as such, can shape household's expectation of future weather patterns, which ultimately influence a household's decision to invest in social network relationships. In this way, this paper is most closely related to Vis Taraz (2017), who links fluctuating weather patterns in India to farmers decisions to adopt new irrigation technologies and select more climate resistant crops. In this case, I examine the extent that households adapt their portfolio of social network relationships in the face of changing climate patterns. Specifically, I utilize changes in long term average rainfall patterns, which vary across districts in rural India to examine the impact of household's investment in social network relationships. I assume households make a rational choice in terms of which types of social network relationships can better protect and support long-term consumption or production in the face of possible future negative climate events. I also follow Michael Woolcock (1998), Krishna Prasad Adhikari (2008) Robert L Hawkins and Katherine Maurer (2010) and Wouter Poortinga (2012) by differentiating among three types of social network relationships: (1) family/caste (bonding), (2) non-family (bridging) and (3) vertical (linking) social network relationships. Finally, I examine the extent social networks are impacted by repeated climate events. This analysis is used to assess the extent to which that social network relationships can also be eroded by negative climate events. Both approaches differ from other climate impact studies, which utilize year-to-year changes in climate variables to determine the impact on social and economic outcomes. While year-to-year variations in climate patterns can uncover shorter-term impacts on social and economic outcomes such as crime and productivity, it overlooks a households adaptation and sensitivity to past climate shocks or longer-term climate trends (Melissa Dell, Benjamin F Jones and Benjamin A Olken, 2014, Solomon Hsiang, 2016).

In terms of results, after controlling for positive temperature anomalies and negative rainfall shocks in the year prior to the survey period, I find households residing in regions with a higher levels of average negative rainfall shocks over a three-and five-year period, tend to be associated with greater investments in family and caste-based social networks, as well as greater investments in linking or vertical network relationships. I find investments in linked networks to be marginally lower among households located in villages dominated by minorities and lower caste groups (Scheduled Castes and Tribes (SCSTs)) and High Caste (HC), while investments in vertical networks are found to be higher among villages with higher average incomes and land owners. This suggests that wealth, rather than caste status, appears to be a significant factor which determines access to key vertical network relationships. I also find formal non-family/caste "bridging" network relationships such as membership cooperatives, self-help organizations to be negatively affected by repeated climate shocks. In terms of possible motives for investments in social network relationships, I find investments in family/caste-based relationships to be positively associated with number of new businesses and adoption of private tubular well technologies. In the case of vertical network relationships, I find a positive association with access to credit and reported collaboration among households. Collectively, these factors are key to insulating against shortfalls in rainfall.

This paper contributes to three key branches of literature. Firstly, the paper is one of the first attempting to assess the impact of climate shocks on social networks. Indeed, most research papers relating social capital to climate shocks have focused on ways households or communities utilize social network relationships to mitigate the negative impacts of climate shocks or aid in the recovery process, when such shocks occur (W Neil Adger et al., 2005, W Neil Adger et al., 2011, Johanna Wolf, W Neil Adger, Irene Lorenzoni, Vanessa Abrahamson and Rosalind Raine, 2010). However, as Alejandro De la Fuente (2007) also notes, climate shocks can ultimately undermine not only the physical assets of a network, but eventually human and social assets of a community, which include levels of trust and ultimately social network capital. Lakshmi Iyer and Petia B Topalova (2014) and David Blakeslee and Ram Fishman (2014) have also found a positive association between negative climate shocks and crime, particularly in the case of India. By focusing on longer-term trends in climate variations, I attempt to differentiate between adaptive impacts based on long-term averages of past climate events and the impact of successive or repeated climate events on social network relationships. In this way, I hope to differentiate between instances that climate shocks can be "consensus" building, or alternatively "corrosive" to social network relationships.

Secondly, by differentiating between key forms of social network relationships, I can identify which social network relationships become more important and useful in the face of rising climate events. I also exploit heterogeneity across communities in terms of caste composition, sources of income and average village income levels, to evaluate the extent "altruism" or loyalty to a potential ethnic network, and "pooled" income may affect investments in social networks in the face of negative climate events.

A third contribution of this paper is the adaptation of Stephen Coate and Martin Ravallion (1993), Marcel Fafchamps and Flore Gubert (2007), Joachim De Weerdt and Marcel Fafchamps (2011) theoretical framework on risk sharing and network formation to model the impact of short-term and persistent climate shocks on investments in social networks. The model predicts continued voluntary network participation in the face of negative climate shocks, once expected net future benefits from network participation exceeds the cost of deviating from the network. In the face of repeated negative climate shocks, the model makes three possible predictions. Scenario 1: if repeated climate shocks undermine expected net future benefits from network participation to the point that expected net future social benefits become negative, individuals will have a greater incentive to deviate from network obligations. Scenario 2: members continue to participate in network arrangements, in the face of diminished future network benefits. This can occur once expected net social benefits remain positive and above some minimum acceptable value determined by network members. This scenario explains instances where continued network participation provides utility benefits to network members beyond monetary transfers, as is the case of altruistic or kinship /family-based networks. Scenario 3: climate shocks affect members equally (covariate shocks). In this case, repeated climate shocks undermine the capacity of all members to reciprocate in future periods. As expected as net future benefits decline, members have a greater incentive to deviate from network obligations.

Understanding the impact of climate shocks on social networks can be particularly relevant to poor and vulnerable communities, since these communities tend to rely heavily on social network relationships for information, informal support, and collective action. Poorer communities also tend to have less diversified sources of income, own fewer productive assets, and are frequently located in areas which can be particularly vulnerable to sudden climate shocks, such as floods or droughts. This implies that negative climate events can have far-reaching consequences beyond loss of assets, illness, or death. By impacting both physical and social assets, negative climate shocks have the potential to undermine the long-term resilience of already vulnerable communities, thereby pushing them into a vicious cycle of poverty and underdevelopment.

This paper is divided into seven sections. Section 2 provides a brief theoretical framework outlining ways through which climate shocks affect investment community network relationships. In Section 3, I provide details of the data. The empirical strategy is discussed in Section 4, and main results are presented in Section 5. Robustness tests and extensions are provided in Section 6. Finally, concluding remarks and policy recommendations are outlined in Section 7.

2.0 Contextual Framework: Exploring Links between Climate Shocks, Risk Sharing and Social Network Relationships

Following Stephen Coate and Martin Ravallion (1993) and Joachim De Weerdt and Marcel Fafchamps (2011) model of risk sharing based on repeated game theory, I assume an economy consisting of two individuals i and j, who are infinitely lived and receive income y_t^i and y_t^j, respectively. For any given period, income is assumed to be uncertain and varies over time. Both individuals derive utility from earnings (primarily through consumption) and are assumed to be non-satiated and risk averse, such that for all $y > 0$, $u'(y) > 0$, and $u''(y) < 0$, with any form of savings assumed to be zero. Individuals are also assumed to mitigate risks primarily through investments in social network relationships. Social network relationships bring with them tangible and intangible social benefits and costs. Tangible social benefits include reciprocal income transfers among network members[2], shared labor, machinery, and stores. Intangible benefits can include prestige gained from becoming a network member, shared information, monitoring and

2 Reciprocal income transfers are assumed to be particularly important to households during times of crisis. Such transfers are used to supplement income shortfalls and sustain consumption along a permanent consumption level. However, households are expected to reciprocate transfers when other households are negatively impacted by idiosyncratic shocks.

enforcement of contracts, and access to key leaders or decisions makers. Social costs include reciprocal transfers made to affected network members, membership fees, and time spent attending network gatherings, which can otherwise be used to earn income[3]. Based on this, individual *i* is assumed to derive utility from income y_t^i earned in period *t*, plus net benefits from participation in social networks nsb_t^{ij} such that:

$$U_i = u_i(y_t^i + nsb_t^{ij}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

where

$$nsb_t^{ij} = sb_t^{ij} - sc_t^{ij}$$

Net benefits stem from the value of social benefits sb_t^{ij}, less costs incurred from network participation sc_t^{ij}. It is important to note that nsb_t^{ij} can be negative or positive for individual *i*. For instance, when individual *i* makes transfers to individual *j* in excess of the benefits received from the network participation, *nsb* can be negative. Alternatively, when individual *i* receives tangible and intangible benefits from network participation greater than the costs incurred to stay in the network, *nsb* will be positive. Finally, by participating in the network arrangement, individuals *i* and *j* not only benefit from increasing prestige, and, technological and information gains, but also can smooth consumption in the face of unforeseen shocks. I can formalize this aspect of the relationship by stating that through network participation, individual *i* can achieve a guaranteed level of consumption given by:

$$c_t^{ij} = y_t^i + nsb_t^{ij}$$

I also assume that the guaranteed level of pooled consumption c_t^{ij} will be based on some pooled level income y_t^{ij} such that

3 Other authors have researched the "dark-side" of social network relationships which can include discrimination, or negative sanctions against network members.

c_t^{ij}=y_t^{ij}

For any network arrangement to be implementable and self-reinforcing, the benefits from continued participation should be greater than the cost of defecting from the network in any period *s*. Therefore, for individual *i* an *implementarity* constraint takes the form of:

$$U_i((y_s^{ij}) - U_i(c_s^{ij})\ ) \leq E_t[\![F_i(t, nsb)]\!]\ldots\ldots\ldots\ldots\ldots\ldots\ldots.2$$

Where,

$$F_i(t, nsb) \equiv \sum_{s=1}^{\infty} \beta^s \big(U_i\big(c_{t+s}^{ij}\big) - U_i(y_{t+s}^{iA})\big)$$

The left-hand side of the inequality represents the cost of defecting from the network arrangement in time *s*. I assume that after defection, individual *i* will be penalized by the network and will be unable to participate in future network sharing arrangements. Therefore, individual *i* must balance the short-term net utility gain from leaving the network in period *s* against all possible net future benefits which can be gained from continued network participation. The benefit derived from deviating from the network arrangement becomes positive when individual *i* makes transfers or incurs network costs during time *s* to a value greater than the benefits derived from participating in the network sharing arrangement, such that $sb_s^i < sc_s^i$, or $nsb_s^{ij} < 0$. In this case, pooled consumption will be less than pooled income such that $c_s^{ij} < y_s^{ij}$ in period *s*.

The right-hand side represents the present value of net future benefits gained from continued network participation. This is the present value of all future guaranteed consumption generated through continued network participation, minus the future value of autarky level of earnings (y_t^{iA}). Autarky earnings represent income which can be earned if individual *i* chose not to be part of the network for all future periods. This expectation is based on information available at time *s* for all possible states of the world. When *i* is risk averse, the expected gain from the risk sharing is typically positive (Stephen Coate and Martin Ravallion, 1993) such that:

$$E_t[\![F_i(t, nsb)]\!] \geq 0$$

I assume non-satiation and risk aversion such that $U'(\cdot) > 0$, and $U''(\cdot) \leq 0 \; \forall \; i$ and $U''(\cdot) < 0$ for some *i*. Additionally, all future gains from continued network participation are assumed to share a common discount factor β which is less than one and reflects each member's time preference and ultimately value of future benefits gained from network participation. Since individuals *i* and *j* are assumed to be risk averse, the more impatient they are to receive benefits of network arrangements, the smaller the discount factor. However, for simplicity I assume that all households face similar time preferences such that $\beta_i^t = \beta_j^t$.

To guarantee continued network participation and for income sharing arrangements to be self-reinforcing, inequality 2 needs to be satisfied in all cases for all individuals and states of the world over time.

Including the Impact of Negative Climate Shocks

Joachim De Weerdt and Stefan Dercon (2006) and Joachim De Weerdt and Marcel Fafchamps (2011) modify the voluntary participation constraint (2) to include short-term and persistent health shocks. I again adapt this model by assuming all unexpected shocks to be derived from negative climate events. In this case, climate shocks can vary in intensity and be persistent in some regions, thereby having varied impacts on social network arrangements among individuals and across locations. The impact of negative climate shocks can also vary among individuals depending on the nature of income earning activities households are involved in (farm or non-farm income) and the degree of preparedness each household may be. I adapt Model 2 to suggest that individuals i and j are now both assumed to be vulnerable to negative climate shocks, such that the utility of individual i, is now given by $U_i = u_i\left(y_t^i + nsb_t^{ij} - w_t^i\right)$, where $w_t^i \geq 0$ denotes the value of losses due to negative climate events. Therefore, if there are no climate shocks in period *t*, $w_t^i = 0$.

Climate shocks can be considered transitory if the experience of climate shocks today, contains no information or indication regarding the experience of shocks in the future[4]. On the other hand, if past climate shocks are persistent, they can provide information and influence expectations for future occurrence of negative climate events such that $\partial E_{t|w_t^i}[w_{t+s}^i] / \partial w_t^i > 0$ for some period $s > 0$. In the face of negative climate shocks, the implementability constraint, which determines voluntary participation in a network, now takes the form:

$$u_i(y_s^{ij} - w_s^i) - u_i(c_s^{ij} - w_s^i) \leq E_{t|w_t^i, w_t^j}[\![F_i(t, nsb)]\!] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

where,

$$F_i(t, nsb) \equiv \sum_{s=1}^{\infty} \beta^s \big(u_i\big(c_{t+s}^{ij} - w_{t+s}^i\big) - u_i(y_{t+s}^{iA} - w_{t+s}^i)\big)$$

And c_s^{ij} continues to be defined by:

$$c_s^{ij} = y_s^i + nsb_s^{ij}$$

Any cooperation scheme must now satisfy:

$$E_{t|w_t^i, w_t^j}[\![F_i(t, nsb)]\!] \geq 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$

Equation 3 states that future payoffs are influenced by the expectation of future losses due to climate shocks. Indeed, if climate shocks are persistent, the expectation of future losses due to negative climate events will be higher. A basic assumption can be that, for any cooperation scheme to be implementable, the present value of expected net future benefits from continued network participation must be positive, even after discounting for expected losses due to future climate shocks (Equation 4).

4 An example of more transitory climate shocks include sporadic climate events such as spikes in temperature levels or sudden heavy rainfall patterns, which may not fit past climate patterns for a given location.

Conditions for Voluntary Participation

Conditions for voluntary network participation or the "implementability constraint" also directly sets an upper limit on the amount individual i is willing to invest in social networks, either through reciprocal income transfers, memberships fees, or the total value of any other network obligations (sc_t^{Max}). Specifically, for a given level of expected future benefit from participating in a social network ($\overline{sb}_{\ t}$), there exists a maximum net social benefit value (nsb_t^{Max}) which can be derived from participating in the network risk sharing arrangement. By extension, this implies that there is a potential maximum social cost individual i is willing to incur to stay within the network given by sc_t^{Max} such that:

$$nsb_t^{Max} = \overline{sb}_t^i - sc_t^{iMax} \geq 0 \text{ ....5}$$

In this case, continued voluntary participation can be re-written as

$$u_i(y_s^{ij} - w_s^i) - u_i(c_s^{ij} - w_s^i) \leq E_{t|w_t^i,w_t^j}[\![F_i(t, nsb^{Max})]\!] \text{............6}$$

Where,

$$E_{t|w_t^i,w_t^j}[\![F_i(t, nsb^{Max})]\!] \equiv \sum_{s=1}^{\infty} \beta^s \left(u_i\big((y_{t+s}^i + nsb_{t+s}^{Max}) - w_{t+s}^i\big) - u_i\big(y_{t+s}^{iA} - w_{t+s}^i\big)\right) \geq 0$$

This relationship can now be used to examine the impact of short term and repeated negative climate shocks on participation in social network relationships.

Scenario 1 – Short-term and Repeated Negative Weather Shocks Affecting Either Individuals *i* or *j*

In the face of short term climate shocks, individual *i* is willing to pay an income transfer to network member *j*, to the value $sc_t^i \leq sc_t^{Max}$ once the implementability constraint 6 is satisfied[5]. However, if negative climate shocks are expected to be persist, impacting individual *j*, individual *i* will now be expected to make continuous transfers to *j*. Additionally, since individual *j* is consistently impacted by negative weather shocks, this can undermine *j*'s future income and as such, their ability to reciprocate income transfers. This will have the effect of lowering future expected social benefits to individual *i* (i.e. $E'_{t|w_t^i,w_t^j}[\![F_i(t, nsb')]\!] < E_{t|w_t^i,w_t^j}[\![F_i(t, nsb^{Max})]\!]$, such that $sb_t'^i \leq \overline{sb}_t^i$ and $nsb_t' < nsb_t^{Max}$).

As social benefits decline, the maximum value individual *i* be willing to pay to stay in a network sharing arrangement will also decline such that $sc_t' \leq sc_t^{Max}$. The latter inequality implies that individual *i* will be contributing smaller and smaller amounts to the network sharing arrangement. Furthermore, the more persistent and deleterious climate shocks are expected to be, individual *i* will have a greater incentive to deviate and discontinue participating in the network relationship. Specifically, individual *i* will depart from the network sharing arrangement if the gains from deviating in period *s* are greater than the discounted expected net future benefits from participating in the network.

$$u_i\left(y_s^{ij} - w_s^i\right) - u_i\left(c_s^{ij} - w_s^i\right) \geq E'_{t|w_t^i,w_t^j}[\![F_i(t, nsb)]\!]$$

Scenario 2 – Negative Weather Shocks (Repeated) Affecting Individual *j (only)* and Individual *i* Continues Income Transfers

A second scenario predicts instances where individual *i* is willing to continue paying transfer costs to individual *j* in the face of repeated climate shocks. This can occur if net social benefits, however small, remain positive and tends to some minimum value ($\overline{sb}_t^{ij}$), which individual *i* is willing to accept to stay in the network arrangement such that $sb_t'^{ij} \rightarrow \overline{sb}_t^{ij}$. I assume that the implementability constraint 6 continues to be satisfied, since $nsb_t' > 0$ and $sc_t^{Max} \leq \overline{sb}_t^{ij}$. The key policy implication from this scenario will be

5 In this case climate shocks are assumed not be affecting individuals i or j equally, such that individual i can still support transfers to individual j even in the face of negative climate events.

to find ways to extend social benefits from network participation in the face of repeated shocks. Benefits can take many forms, both tangible and intangible. Examples include government transfers or technological assistance, which are delivered only through associations or formalized network arrangements rather than on an individual basis, adaptive technologies developed by network members who have experienced repeated climate shocks in the past, or utility and prestige gained from supporting other kin or family members (altruistic motives).

Scenario 3 – Negative Weather Shocks (Repeated) Affecting Both Individuals *i* and *j*

A third scenario examines the possibility of covariate shocks which are expected to negatively impact both individual i and j equally[6]. In this case the negative climate shocks will lower net future benefits for both parties, assuming constant relative utility of risk aversion, the more risk averse an individual becomes (Gershon Feder, 1980). Therefore, in the face of declining income the marginal utility of income will increase. Individuals i and j will then have a greater incentive to deviate from the network sharing arrangement. Indeed, this scenario is supported by the work of Robert M Townsend (1994),who argues that climate shocks become increasingly difficult to insure against through informal networks arrangements when risks become more wide-spread and systematic.

In general, the model predicts that network members will continue to invest in network relationships, once expected future benefits from network participation, exceed the short-term benefits or opportunity costs of deviating from the network arrangement. The model also predicts continued network participation in the face of short term (idiosyncratic) climate shocks, once the implementability constraint continues to be met, i.e. once network members are assured that net future benefits can be gained from network participation, either through contributions from other network members or as a result of other tangible and intangible benefits derived from being a network member. Once climate shocks become persistent or are expected to be more widespread (systematic), the model predicts network members have a greater incentive to deviate from a network sharing arrangement.

6 This is an example of systematic risks where both individuals i and j are expected to be simultaneously affected by negative climate events.

It should be noted that continued network participation in the face of repeated climate shocks depends on the ability to extend net future benefits among network members. These include instances where social networks continue to provide high social benefits in the form of adaptive information, income transfers, or prestige to the network members, or where "pooled" income levels are sufficiently high to insulate against repeated negative climate events. I therefore utilize the data to test the extent that "pooled" and "altruistic" motives can influence network participation in the face of negative climate shocks.

3.0 Data Sources and Summary Statistics

3.1 Climate Data

Following Shawn Cole et al. (2012), Melissa Dell et al. (2012) and Lakshmi Iyer and Petia Topalova (2014), historical weather data is taken from Terrestrial Temperature and Precipitation: 1901 to 2014, Gridded Monthly Time Serie Version 4.01 (Kenji Matsuura and Cort Willmott, 2007). This dataset provides global (terrestrial) monthly gridded temperature and precipitation estimates. Global grids are spaced at 0.5° latitude and 0.5° longitude width (approximately 56km x 56 km at the equator). Values are interpolated for each grid node from an average of 20 nearby weather stations, with corrections for elevation based on the spherical version of Shepherds distance-weighting method. I extract monthly district level climate estimates by overlaying climate gridded datasets to 2001 gridded India's Census district boundaries[7], and estimating monthly averages of nearest grid points located within each district.

7 2006. "Indiamap 2001," [New Delhi] :: ML Infomap,

For each month, longer term climate averages (precipitation and temperature levels) are generated by district over the period 1981 to 2010. Figure 1 represents the spatial distribution of long-term weather patterns by districts throughout India. It is important to mention that given the size of India, there exists significant spatial variation across the 30 different meteorological subdivisions (I Subbaramayya and CV Naidu, 1992, Vis Taraz, 2017). For instance, I find the driest regions to be in the North-West regions of India, including such states as Rajasthan, Haryana, Delhi, and Punjab. This is contrasted against wetter North-Eastern states of Assam, Nagaland, Manipur, and West Bengal.

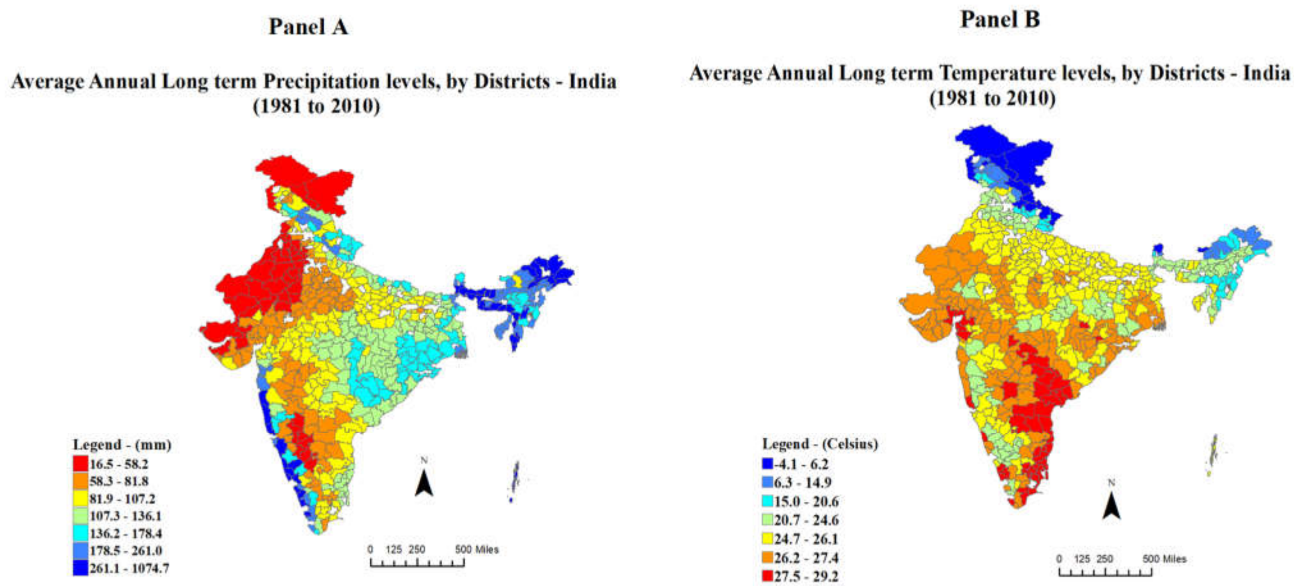
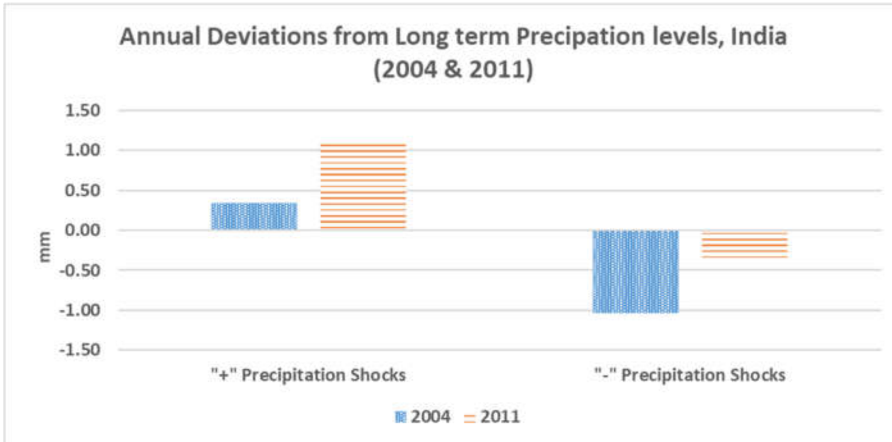


Figure 1– AVERAGE ANNUAL LONG-TERM CLIMATE PATTERNS, BY DISTRICTS IN INDIA (1981 TO 2010)

Notes: Figure 1 outlines annual average long-term climate patterns, by districts in India (1981 to 2010). Panel A provides average annual long-term precipitation levels, by districts all India (1981 to 2010). Panel B average annual long-term temperature levels, by districts, all India (1981 to 2010).

Monthly long-term climate averages are then used to generate annual precipitation and temperature anomalies. Climate shocks or anomalies are measured as the total number of months each year temperature and precipitation levels are more than one standard deviation above or below the long-term average estimated for a given month. Figure 2 summarize annual positive and negative deviations from the long-term precipitation and temperature averages among districts, for the years 2004 and 2011.

Panel A



Panel B

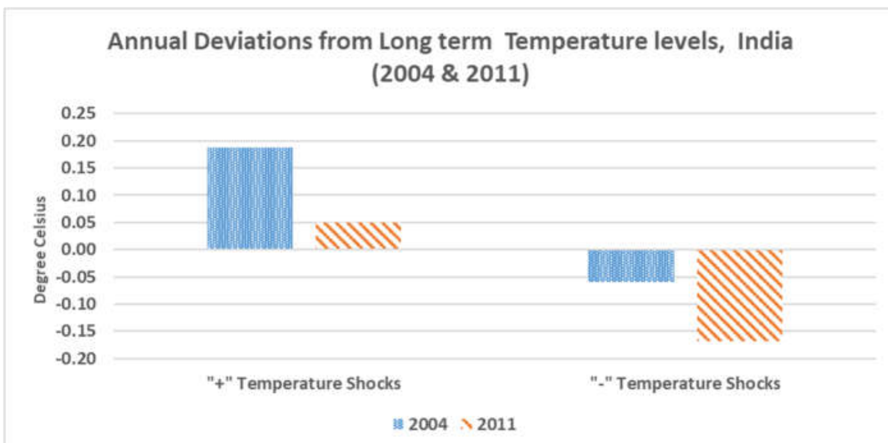


Figure 2 – ANNUAL DEVIATIONS FROM LONG-TERM CLIMATE PATTERNS, ALL INDIA (2004 & 2012)

Notes: Figure 2A and 2B outlines annual deviations from long-term climate patterns. Panel A displays annual deviations (positive and negative) from long term precipitation patterns, all India (2004 and 2011). Panel A displays annual deviations (positive and negative) from long term precipitation patterns, all India in 2004 and 2011. Panel B displays annual deviations (positive and negative) from long term temperature patterns, all India (2004 and 2011).

Annual climate anomalies are used to generate three and five-year average anomalies and lagged values for each district, which are used to represent information impacts of climate events. I also estimate the impact of lagged climate events up to the year of the last survey. I find that lags six and seven years prior to the survey year become small or insignificant in terms of impacts of social network relationships (Tables A.1A and A.1B).

In terms of repeated climate events, I identify districts which have been impacted by successive climate shocks at least two years prior to the start of the survey period. Specifically, I differentiate between districts which have experienced consecutive shocks over a three and five-year period. To measure the intensity of climate shocks, I calculate the total number of climate shocks occurring over a three and five-year period and use this as an intensive measure of repeated climate events (Figures A1 and A2).

3.2 Understating India's Fluctuating Interdecadal Rainfall Patterns

Apart from year to year fluctuations, researchers have widely documented longer term regional fluctuations, based on interdecadal rainfall patterns (P. Guhathakurta and M. Rajeevan, 2008, Nityanand Singh and Ashwini Ranade, 2010). Figure 3 highlights all India's interdecadal rainfall patterns over the period 1900 to 2012, which provide evidence of deviations from the long-term historical average in rainfall patterns based on a 31-year moving average. Clear patterns emerge of "dry" spells in rainfall over the periods 1900 to 1920 and 1989 to 2010, where rainfall averages are more than four standard deviations below the long-term average. There are also clear periods of "wet" spells over the periods 1930 to 1950 and 1965 to 1985.

From an economic perspective, one approach can be to treat fluctuating rainfall patterns as a hidden Markov Model (Vis Taraz, 2017). In this case the unobserved state variable is the regime type ("dry" – state 1 or "wet" – state 2), and the observed output variable is annual rainfall. I empirically test for differences in averages, and variance as well as the persistence of two states based on a Markov switching process (Table A2). Results confirm the presence of at least two regimes, with the average "dry" state estimated to be 4.28 standard deviations below the long-term average, and the "wet" state is 1.56 standard deviations above the long-term average. Both estimates are significant at the one percent level.

India's strong reliance on agriculture production, supports economic activity and ordinary family life among rural communities. Fluctuating rainfall patterns can be worrisome and have far-reaching consequences on both social and economic outcomes of people living in these communities. Indeed, more than 700 million people are estimated to be engaged in agriculture related activity with over 70% of fields utilizing rain feed irrigation techniques. However, given these patterns, long-term rainfall averages are no longer considered random (i.i.d.), but switches between periods of wet and dry cycles or regimes, due to changes in atmospheric-oceanic feedback mechanisms (Xin Wang et al., 2006). In this way, I assume that past rainfall patterns can give information about the current and possibly future rainfall regimes households face. Therefore, households can develop expectations of which regime they may be facing based on current and past realized rainfall patterns and this information can be used to make a rational choice in terms of which types of network investments to make in order to mitigate possible future rainfall risks.

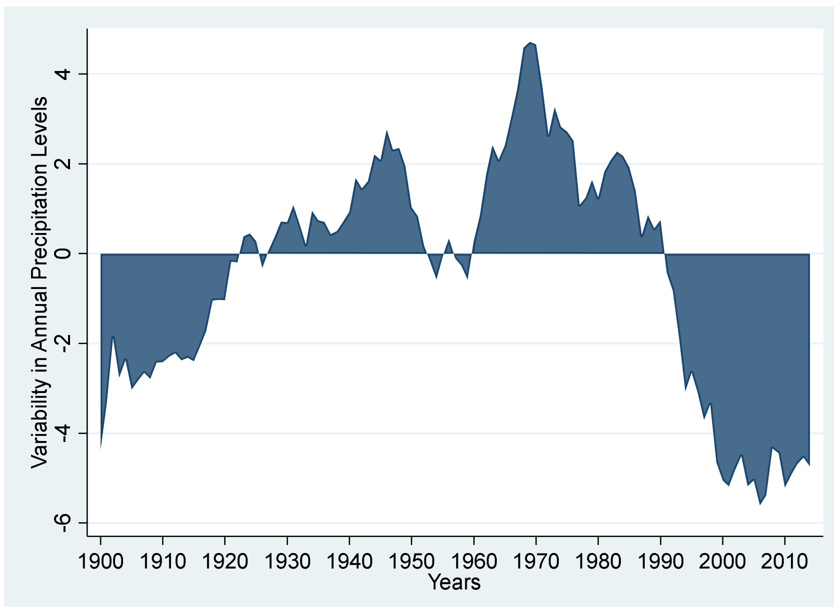


Figure 3– 31 YEAR MOVING AVERAGE OF ANNUAL DEVIATIONS FROM LONG-TERM PRECIPITATION LEVELS, ALL INDIA 1900 TO 2015

Notes: Figure 3 displays 31 year moving average of annual deviations from long-term precipitation levels, all India over the period 1900 to 2015.

It is also important to note, again, that rainfall patterns in India vary widely, both spatially and temporally (I Subbaramayya and CV Naidu, 1992). There is also considerable spatial variation in rainfall patterns across India's different meteorological sub-divisions in terms intensity and timing of "wet" and "dry' periods. Regions previously considered as "wet" can be considered as "dry" over the sample period 1998 to 2010, and the converse is also true for other areas (Figures A3 and A4). I exploit this heterogeneity across regions to determine the extent that longer-term variations in weather patterns may influence a household's decision to invest in social networks.

I also examine long tern trends in temperature patterns, however, unlike the regime switching observed in longer term rainfall patterns, the general trend has been an increase in longer-term temperature patterns across India (Figure 4). Based on the sample data, long-term temperature levels have increased by more than 0.1℃ in every decade since the 1980s. I also find less spatially diversity in rising surface temperature levels across India, relative to changing rainfall patterns. For this reason, it is unclear whether similar network adaptation effects can be captured in response to rising temperature levels. Despite this, I also control and empirically test the impact of lagged and longer-term average positive temperature shocks in our model specification.

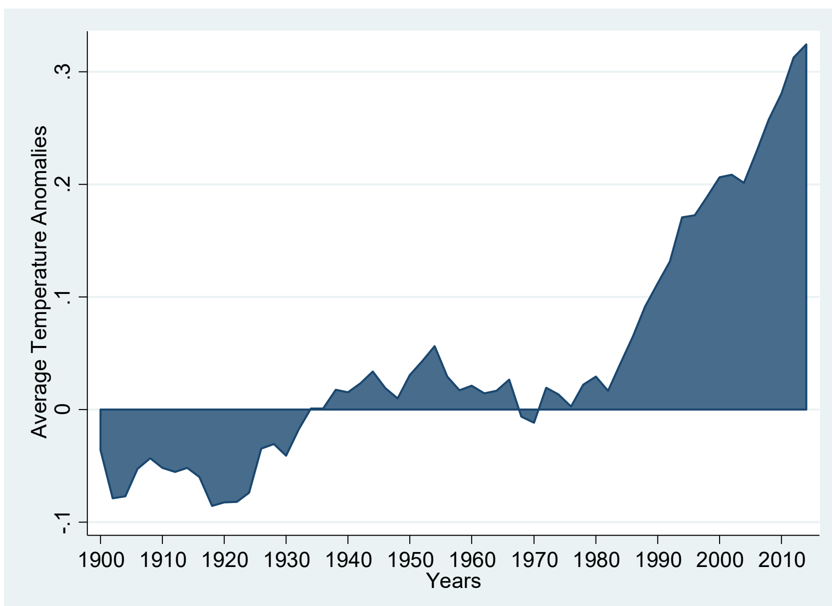


Figure 4 – 31 YEAR MOVING AVERAGE OF ANNUAL DEVIATIONS FROM LONG-TERM TEMPERATURE LEVELS, ALL INDIA (1900 TO 2015)

Notes: Figure 4 displays 31 year moving average of annual deviations from long-term temperature levels, all India over the period 1900 to 2015.

3.4 Social Capital and Key Control Variables

Following Deepa Narayan and Lant Pritchett (1999), Deepa Narayan (2002), and Robert D Putnam (2002), I measure social capital and by extension, investment in social networks primarily in terms of membership in local and regional community-based organizations. I also follow Michael Woolcock and Deepa Narayan (2000), Simon Szreter and Michael Woolcock (2004) and Peter Urwin et al. (2008), and differentiate among three key forms of social networking capital, bonding (family-based), bridging (non-family-based) and linking (hierarchical-or-power-based) capital. Specifically, I utilize information from the Indian Human Development Survey (IHDS) to measure "bonding" capital (BOND), as the number of family-caste-religious based organizations a household has reported to have joined or is currently a member. Similarly, "bridging" capital (BRIDGE) measures the number of non-family-based organizations household are members of. This includes Non-Governmental Organizations (NGOs), sporting clubs, cooperatives, and self-help groups (Exhibit A1 – Sample Household Questionnaire). To boost the strength of network measures beyond formal membership-based network relationships, I develop two alternative measures of informal social network relationships. "Linking" capital (LINK) measures the proportion of a household's network contacts, with persons in authority, such as doctors, senior government officials, and school principals or teachers. NETFAM, measures the average percentage of a household's network (medical, government, and educational), which is related by family, or is of the same caste status. I also utilize survey responses to generate district level measures of reported collaboration (COLLAB) and conflict (CONFLICT) among households (see Table 1).

Overall, between both waves, I observe increases in non-family/caste relationships (Bridging networks), linking networks (Link), and informal family-based relationships (NetFam), as well as reported collaboration between the 2005 and 2012 waves. As a final step, I find the standardized values of all measures to ensure a common interpretation based on results of the overall sample[8].

8 I also estimate correlation matrix of social capital variables to check for possible multicollinearity among key measures of social capital (Table A4 and A5). I find higher correlation between measures of bonding and bridging capital (approximately 20 percent), but other measures such as linked and Netfam are not found to be highly correlated.

Table 1– SUMMARY STATISTICS OF KEY OUTCOME VARIABLES

Key Outcome Variables	2005 mean/sd	2012 mean/sd	% Change
Bond	0.14	0.11	-23.1%
	(0.30)	(0.27)	
Bridge	0.06	0.08	38.8%
	(0.13)	(0.14)	
Link	0.23	0.36	52.8%
	(0.31)	(0.34)	
NetFam	0.15	0.24	53.1%
	(0.26)	(0.31)	
N	**20941**	**20941**	

Notes*:* Table 1 reports summary statistics of key outcomes variables used in the estimation models.
Source: Estimates derived from IHDS Survey Waves I & II

4.0 Empirical Strategy

In this section, I provide an empirical strategy for estimating the experience of past climate shocks on social network relationships.

4.1 Testing for Network Adaptation to Climate Shocks

Let SC_{ijkt} be some measure of household's i social network relationship in time t. I estimate standard household fixed effects model, where investment in social network relationships for household *i,* in village j located in district *k,* during year *t* is impacted by rainfall and temperature shocks in the year prior to the survey, and average deviations in both temperature and rainfall levels, at least two years prior to the survey period (2004/2005 and 2011/2012). I also control for household and village characteristics, with time fixed effects, with errors are clustered at the district level.

$$SC_{ijkt} = \beta_1 Rainshock_{kt-1} + \beta_2 AverageRainShock_{kt-2} + \varphi_1 TempShock_{kt-1} + \varphi_2 AverageTempShock_{kt-2} + \gamma_1 HH_{ijkt} + \gamma_2 Vill_{jkt} + \delta_i + t + e_{ijkt} \quad (1)$$

In this case, β_2 and φ_2 capture adaptation or "information" impact of climate shocks on household's decisions to invest in social network relationships. If current social network decisions are in no way influenced by prior experiences of climate shocks, I expect $\beta_2 = \varphi_2 = 0$. It is also important to mention that coefficient values can be positive or negative, depending on the extent climate shock has a "consensus building" or "corrosive" impact on social network relationships. One key advantage of this study is that I can also distinguish among the diverse types of social network relationships households participate in, and as such I can determine which network relationships will likely be more important in the face of negative climate shocks.

To test the impact of repeated climate events on social networks, I estimate Model 2. Specifically, after controlling for climate shocks occurring in the year prior to the survey periods. I then identify districts which have been impacted by successive negative climate anomalies over three-and five-year periods beginning in 2003 and 2010, respectively. For these districts, I assign a value of one (and zero otherwise) to classify these areas as repeated climate impact districts. I also calculate the total number of negative precipitation anomalies affecting these repeated impact districts. This measure is meant to capture the intensity of repeated climate shocks impacting these districts.

$$SC_{ijkt} = \beta_1 Rainshock_{kt-1} + \varphi_1 TempShock_{kt-1} + \beta_2 RepeatedRainShock_{kt-2} + \gamma_1 HH_{ijkt} + \gamma_2 Vill_{jkt} + \delta_i + \theta_k + t + e_{ijkt} \quad (2)$$

4.2 Tracing Heterogeneous Effects

To test the extent that ethnic or altruistic motives influence network relationships, I leverage caste composition at the village level. Specifically, I differentiate between villages which have greater homogeneity in caste status among village members, focusing on villages which have a concentration in higher and lower caste groups. The assumption is that group, rather than individual, caste status is more important to generate dynamics in certain social network relationships. Specifically, in villages where there is greater homogeneity in caste status, norms and values will likely be more uniform and altruistic motives will be greater. Additionally, monitoring and enforcement of network obligations (particularly through negative sanctions) will be more likely effective (George Akerlof, 1976). I consider this classification important for testing "peer" effects and possible altruistic motives that influence continued investments in social network relationships. I adapt Model 1 by adding a dummy variable taking a value of one for households living villages where more than 50 percent of the village population are reported to be of the same caste status during the base period in 2005. I also differentiate between villages comprising primarily of lower Scheduled Castes and Scheduled Tribes (SCSTs) and villages where Higher Caste (HC) groups predominate[9]. I also test empirically, the extent individual relative to community caste characteristics shape investments in social network decisions and find dominance of community relative to individual caste status (Tables A8 and A9).

I also test the importance of "pooled" income on investments in social networks[10]. I measure "pooled" income as average earned income at the village level, and also differentiate between high and low income-earning villages. High income villages are villages where average income levels are 75 percent, or more than the sample average. Conversely. low income villages are villages where average income levels are 50 percent or less than the sample average. Finally, since households may be respond to climate shocks based on where their main source of income stems from, I also test for differences based on key earning sources of households.

5.0 Results

5.1 Estimating "Informational" Impacts of Climate Shocks

Table 2 outlines results of household Fixed Effects (FE) models. I find a positive association between the three-year average of negative precipitation anomalies on measures of linking social capital (vertical network relationships), the percentage of the informal (Netfam), and formalized (Bonding) family/caste-

9 Higher caste groups include Brahims, and High Caste grouping.

10 In the context of this study, pooled income is measured in terms of average village income. I also test for the importance of individual as opposed to village income in investments in social networks (See Appendix)

based networks. Specifically, a one month increase in the three-year averages of negative precipitation anomalies is associated with greater investments in vertical (power-based) networks, which is approximately 0.04 standard deviations higher than the sample average. I also find a one month increase in average (three-year) negative precipitation anomalies to be associated with higher investments in informal and formal family/caste-based networks, approximately 0.03 standardized points more than the sample average. Collectively, these results point to greater investments in vertical and family/caste-based networks among household located in regions, where negative precipitation shocks tend to be more frequent. For both models, I find very limited impacts of positive temperature shocks on social network relationships. This may reflect the overall difficulty rural communities have adapting to temperature shocks (Vis Taraz, 2017). I repeat our estimation using five-year averages (Table 3) and find continued importance of vertical and informal family-based networks to negative precipitation events.

Table 2– RESULTS ASSESSING IMPACTS OF CLIMATE SHOCKS (3-YEAR AVERAGES) ON KEY MEASURES OF SOCIAL CAPITAL

	1	2	3	4	5	6	7	8
	BondStd	**BondStd**	**BridgeStd**	**BridgeStd**	**LinkStd**	**LinkStd**	**NetFamStd**	**NetFamStd**
Positive Temperature Anomalies Lag1	-0.0508**	-0.0509**	0.0317*	0.0317*	-0.0265	-0.0265	-0.0107	-0.0107
	(0.0256)	(0.0257)	(0.0170)	(0.0170)	(0.0266)	(0.0266)	(0.0178)	(0.0177)
Negative Precipitation Anomalies Lag1	0.0540	0.0552	0.0243	0.0256	-0.0633	-0.0606	0.0276	0.0257
	(0.0447)	(0.0447)	(0.0338)	(0.0346)	(0.0450)	(0.0462)	(0.0315)	(0.0316)
Positive Temperature Anomalies (3 Yr Average)	0.00242		0.00242		0.00504		-0.00364	
	(0.00705)		(0.00589)		(0.0104)		(0.00584)	
Negative Precipitation Anomalies (3 Yr Average)	0.0304	0.0331*	-0.00999	-0.00726	0.0413**	0.0470**	0.0398***	0.0358***
	(0.0207)	(0.0197)	(0.0135)	(0.0138)	(0.0193)	(0.0194)	(0.0135)	(0.0126)
Year	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**
R-sq	**0.065**	**0.064**	**0.023**	**0.023**	**0.059**	**0.059**	**0.033**	**0.033**
adj. R-sq	**0.063**	**0.063**	**0.022**	**0.022**	**0.058**	**0.058**	**0.032**	**0.032**

Notes: Table 2 reports results of impacts of climate shocks on key measures of social network relationships. Lagged climate shocks represent temperature and precipitation anomalies occurring in the year prior to the survey period. Average climate anomalies represent average positive temperature anomalies, and negative precipitation anomalies occurring over the period 2000 and 2003 and 2007 and 2010. Errors are clustered at the district level and standard errors are in parenthesis.

** p<0.10 ** p<0.05 *** p<0.01*

Table 3– RESULTS ASSESSING IMPACTS OF CLIMATE SHOCKS (5-YEAR AVERAGES) ON KEY MEASURES OF SOCIAL CAPITAL

	1	2	3	4	5	6	7	8
	BondStd	**BondStd**	**BridgeStd**	**BridgeStd**	**LinkStd**	**LinkStd**	**NetFamStd**	**NetFamStd**
Positive Temperature Anomalies	-0.0504**		0.0297*		-0.0163		-0.00235	
Lag1	(0.0249)		(0.0170)		(0.0273)		(0.0175)	
Negative Precipitation Anomalies	0.0569	0.0632	0.0241	0.0171	-0.0580	-0.0371	0.0304	0.0381
Lag1	(0.0467)	(0.0488)	(0.0354)	(0.0373)	(0.0458)	(0.0487)	(0.0330)	(0.0368)
Positive Temperature Anomalies	0.0175		0.00424		0.0490		0.0145	
(5 Yr Average)	(0.0371)		(0.0293)		(0.0466)		(0.0264)	
Negative Precipitation Anomalies	0.0579	0.0709	-0.0313	-0.0212	0.112	0.178*	0.144*	0.157**
(5 Yr Average)	(0.116)	(0.120)	(0.0788)	(0.0752)	(0.107)	(0.0980)	(0.0797)	(0.0724)
Year	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
District FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**
R-sq	**0.061**	**0.062**	**0.022**	**0.023**	**0.053**	**0.060**	**0.031**	**0.031**
adj. R-sq	**0.060**	**0.061**	**0.021**	**0.022**	**0.052**	**0.058**	**0.030**	**0.030**

Notes: Table 3 reports results of impacts of climate shocks on key measures of social network relationships. Lagged climate shocks represent temperature and precipitation anomalies occurring in the year prior to the survey period. Average climate anomalies represent average positive temperature anomalies, and negative precipitation anomalies occurring over the period 1998 and 2003 and 2005 and 2010. Errors are clustered at the district level and standard errors are in parenthesis.

** p<0.10 ** p<0.05 *** p<0.01*

5.2 Assessing the Impact of Repeated Climate Shocks

I also test the impact of repeated negative climate shocks on household social network relationships. Specifically, after controlling for climate shocks in prior periods, I identify districts which have been impacted by consecutive climate shocks (negative precipitation anomalies) over a three-and five-year period (Table 4). I find investments in (non-family/caste) bridging networks to be marginally lower in regions which have experienced repeated climate events (three years). However, I continue to find higher investments in linked and family-based networks (formal and informal) in regions repeatedly impacted by consecutive negative precipitation anomalies. This indicates the continuing resilience of vertical and family-based networks, and less investments in non-family networks in these regions. To test the robustness of these results and the extent that baseline results are not driven by shocks occurring in one specific year, I estimate impacts of lagged climate shocks on social network relationships (Table A3). I find negative precipitation lags (one-to three-year) to be positively associated with investments in Bonding, Linking and NetFam. I also find negative precipitation lags occurring in period 5 to be negatively associated with investments in bonding, bridging, and linking capital and investments in informal family/caste-based networks.

Table 4 – RESULTS ASSESSING THE IMPACTS OF LAGGED AND REPEATED CLIMATE SHOCKS ON KEY MEASURES OF SOCIAL CAPITAL

	1 BondStd	2 BondStd	3 BridgeStd	4 BridgeStd	5 LinkStd	6 LinkStd	7 NetFamStd	8 NetFamStd
Repeated Negative Precipitation Anomalies 3 Yr (Total)	0.0132		-0.0137*		0.0341**		0.0187**	
	(0.0158)		(0.00768)		(0.0147)		(0.00932)	
Repeated Negative Precipitation Anomalies 5 Yr (Total)		0.0230		-0.00272		0.0150		0.0151**
		(0.0144)		(0.00729)		(0.0107)		(0.00711)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lag 1 Climate Shocks	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Caste Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of Survey	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	41878	41878	41878	41878	41878	41878	41878	41878
R-sq	0.043	0.043	0.009	0.009	0.026	0.027	0.022	0.022
adj. R-sq	0.043	0.043	0.009	0.009	0.026	0.026	0.021	0.021

Notes: Table 4 reports results assessing the impacts of lagged and repeated climate shocks on key measures of social network relationships. Lagged climate shocks represent temperature and precipitation anomalies occurring in the year prior to the survey period. Repeated climate shocks are districts in India which have experienced consecutive years of negative precipitation anomalies over a 3 (and 5) year period. For these districts I estimate the total number of anomalies over the period 2000 (1998) and 2003 and 2007 (2005) and 2010. Errors are clustered at the district level and standard errors are in parenthesis.
** p<0.10 ** p<0.05 *** p<0.01*

Collectively, I find households to be more reliant on family-based (formal and informal) and linked (vertical) networks when faced with higher-than-average and repeated negative precipitation anomalies. I also find non-family (bridging) networks to be eroded in the face of repeated negative climate events. This result supports the general idea that households tend to be more reliant on family/caste-based networks relative to non-family networks in the face of repeated negative precipitation events. Perhaps an interesting result is the importance of linked or vertical networks to support repeated climate shocks.

5.3 Extensions and Robustness Tests

5.3.1 Exploring Heterogeneity Across Communities

In this section, I examine possible heterogenous responses to climate shocks based on differences in caste concentration within villages, average village income, and household characteristics. Firstly, I examine the impact of climate shocks on households residing in villages where SCSTs make up more than 50 percent of the village population in 2005. SCSTs are considered the lowest of the caste groupings, and in spite of significant changes in national legislation and reservation spots in state, local and educational institutions, these lower-caste groups continue to experience lower earning capability (Ira N. Gang et al., 2008, Viktoria Hnatkovska et al., 2013, Yoko Kijima, 2006). Firstly, I find households located in villages where SCSTs make up more than 50 percent of the village population in 2005 tend to have marginally lower investments in vertical and in informal family-based networks case (Table 5). Interestingly, I find similar results among villages dominated by HC groupings (Table 6).

I also note that households residing in rural communities with higher average village level income[11] will invest between 0.25 and 0.33 standardized points more in Linked capital relative to households living in lower income villages (Table 7). As a robustness check, I find a similar result among households which can be classified as landowners (Table A6), suggesting that wealth rather caste status, is significant determinant of access vertical-based networks.

11 We define high income villages as villages where average income levels are 70 percent or more than the sample average.

Table 5 – RESULTS ASSESSING THE IMPACTS OF AVERAGE CLIMATE SHOCKS ON SOCIAL NETWORKS AMONG VILLAGES DOMINATED BY SCHEDULED CASTES AND SCHEDULED TRIBES (SC & ST) GROUPS

	1	2	3	4	5	6	7	8
	BondStd	**BondStd**	**BridgeStd**	**BridgeStd**	**LinkStd**	**LinkStd**	**NetFamStd**	**NetFamStd**
Positive Temperature Anomalies		-0.00754		0.0138		0.0201		-0.0385
(3 Yr Average)		(0.0347)		(0.0282)		(0.0452)		(0.0319)
Negative Precipitation Anomalies	0.0602	0.0542	-0.0563	-0.0413	0.269***	0.292***	0.233***	0.192***
(3 Yr Average)	(0.109)	(0.100)	(0.0744)	(0.0803)	(0.100)	(0.107)	(0.0707)	(0.0671)
SCST_05*Positive Temperature Anomalies		0.0411		-0.00854		0.00497		0.0657*
(3 Yr Average)		(0.0395)		(0.0321)		(0.0504)		(0.0350)
SCST_05*Negative Precipitation Anomalies	0.100	0.0571	0.0377	0.0467	-0.202*	-0.207*	-0.0870	-0.156*
(3 Yr Average)	(0.117)	(0.123)	(0.0873)	(0.0854)	(0.110)	(0.113)	(0.0765)	(0.0807)
Year	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Lag Climate Shocks	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Caste Controls	**No**	**No**	**No**	**No**	**No**	**No**	**No**	**No**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40386**	**40386**	**40386**	**40386**	**40386**	**40386**	**40386**	**40386**
R-sq	**0.065**	**0.065**	**0.023**	**0.023**	**0.061**	**0.061**	**0.033**	**0.034**
adj. R-sq	**0.064**	**0.064**	**0.022**	**0.022**	**0.060**	**0.060**	**0.032**	**0.033**

Notes: Table 5 reports results assessing the impacts of average climate shocks on social networks among villages dominated by SCSTs in 2005. In this case villages where SCST groups represent 50 percent or more of the total village population take a value of one and zero otherwise. Errors are clustered at the district level and standard errors are in parenthesis. * $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table 6 – Results Assessing the Impacts of Average Climate Shocks on Social Networks Among Villages Dominated by High Caste (HC) Groups

	1	2	3	4	5	6	7	8
	BondStd	**BondStd**	**BridgeStd**	**BridgeStd**	**LinkStd**	**LinkStd**	**NetFamStd**	**NetFamStd**
Positive Temperature Anomalies		0.0176		0.0164		0.0273		0.0154
(3 Yr Average)		(0.0321)		(0.0268)		(0.0441)		(0.0244)
Negative Precipitation Anomalies	0.112	0.128	-0.0304	-0.0628	0.310***	0.240***	0.176***	0.169***
(3 Yr Average)	(0.0878)	(0.0819)	(0.0726)	(0.0645)	(0.0872)	(0.0840)	(0.0527)	(0.0539)
HC_05*Positive Temperature Anomalies		-0.0210		-0.0212		-0.00723		-0.0775**
(3 Yr Average)		(0.0431)		(0.0327)		(0.0439)		(0.0330)
HC_05*Negative Precipitation Anomalies	0.0113	-0.00653	0.0277	0.0604	-0.214**	-0.169**	-0.0701	0.00644
(3 Yr Average)	(0.0878)	(0.0991)	(0.0750)	(0.0700)	(0.0868)	(0.0852)	(0.0794)	(0.0735)
Year	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Lag Climate Shocks	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Caste Controls	**No**	**No**	**No**	**No**	**No**	**No**	**No**	**No**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40386**	**40386**	**40386**	**40386**	**40386**	**40386**	**40386**	**40386**
R-sq	**0.063**	**0.064**	**0.023**	**0.023**	**0.068**	**0.061**	**0.033**	**0.035**
adj. R-sq	**0.062**	**0.063**	**0.022**	**0.022**	**0.067**	**0.060**	**0.032**	**0.034**

Notes: Table 6 reports results assessing the impacts of average climate shocks on social networks among villages dominated by SCSTs in 2005. In this case villages where HC groups represent 50 percent or more of the total village population take a value of one and zero otherwise. Errors are clustered at the district level and standard errors are in parenthesis.

** p<0.10 ** p<0.05 *** p<0.01*

Table 7– RESULTS ASSESSING THE IMPACTS OF AVERAGE CLIMATE SHOCKS ON SOCIAL NETWORKS AMONG VILLAGES DOMINATED BY HIGH CASTE (HC) GROUPS

	1	2	3	4	5	6	7	8
	BondStd	**BondStd**	**BridgeStd**	**BridgeStd**	**LinkStd**	**LinkStd**	**NetFamStd**	**NetFamStd**
Positive Temperature Anomalies	0.0164		-0.00559		0.0575		-0.0113	
(3 Yr Average)	(0.0341)		(0.0259)		(0.0434)		(0.0274)	
Negative Precipitation Anomalies	0.108	0.127	-0.0377	-0.0373	0.0707	0.154**	0.158**	0.141**
(3 Yr Average)	(0.103)	(0.0924)	(0.0594)	(0.0578)	(0.0744)	(0.0777)	(0.0636)	(0.0556)
HIVILLINC_05*Positive Temperature Anomalies	-0.0242		0.0900*		-0.114*		-0.0175	
(3 Yr Average)	(0.0463)		(0.0526)		(0.0624)		(0.0367)	
HIVILLINC_05*Negative Precipitation Anomalies	0.0437	-0.0622	0.0515	0.128	0.339**	0.344**	-0.00481	0.00427
(3 Yr Average)	(0.117)	(0.114)	(0.0979)	(0.117)	(0.132)	(0.150)	(0.0962)	(0.0907)
Year	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Lag Climate Shocks	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Caste Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**
R-sq	**0.065**	**0.064**	**0.025**	**0.023**	**0.064**	**0.061**	**0.033**	**0.033**
adj. R-sq	**0.064**	**0.063**	**0.024**	**0.022**	**0.063**	**0.060**	**0.032**	**0.032**

Notes: Table 7 reports results assessing the impacts of average climate shocks on social networks among high average income in 2005. In this case villages where average income is 90 percent or more than the sample, takes a value of one and zero otherwise. Errors are clustered at the district level and standard errors are in parenthesis.

** p<0.10 ** p<0.05 *** p<0.01*

Finally, I examine the impact of repeated climate shocks on social networks based on differences in "pooled" or collective income. For villages classified as low income in 2005[12], I find linked networks to be marginally lower among villages which are repeatedly impacted by negative precipitation shocks (Table 8). This result underlies the volatility of linked networks to repeated climate events, particularly among lower income groupings. As a robustness test of these results I also test the impact of repeated climate shocks on villages classified as high income in 2005. However, I find no significant impact of repeated climate shocks on households located in these villages (Table A7).

These results highlight the importance of family-based networks and vertical networks to building resilience against climate shocks. However, wealth rather than caste status, is found to be a key determinant of a households' ability to access vertical networks. Households which are located in higher income villages and which are land owners tend to register higher investments in linked networks particularly in the face of higher than average negative precipitation shocks. Conversely, households residing in lower income villages, tend to be more susceptible to repeated negative precipitation events. I also find that households with more stable income sources (such as salary and wages earners) to have lower incentive to invest in social networks in the face of higher than average negative precipitation shocks.

12 Low income villages are villages where average village income is less than 50 percent of the overall average sample village income.

Table 8 – RESULTS ASSESSING THE IMPACTS OF REPEATED NEGATIVE PRECIPITATION SHOCKS ON KEY MEASURES OF SOCIAL CAPITAL (LOW INCOME VILLAGES)

	1	2	3	4	5	6	7	8
	BondStd	**BondStd**	**BridgeStd**	**BridgeStd**	**LinkStd**	**LinkStd**	**NetFamStd**	**NetFamStd**
Repeated Negative Precipitation Anomalies 3 Yr (Total)	0.0173		-0.0112		0.0437**		0.0198*	
	(0.0125)		(0.0110)		(0.0186)		(0.0110)	
Repeated Negative Precipitation Anomalies 5 Yr (Total)		0.0302***		-0.00286		0.00673		0.0110
		(0.00958)		(0.00936)		(0.0158)		(0.0115)
LowInc*Repeated Negative Precipitation Anomalies 3 Yr (Total)	-0.00294		-0.00503		-0.0390*		-0.0102	
	(0.0215)		(0.0128)		(0.0199)		(0.0120)	
LowInc*Repeated Negative Precipitation Anomalies 5 Yr (Total)		-0.0186		-0.00230		-0.00303		0.000191
		(0.0148)		(0.0124)		(0.0159)		(0.0107)
Year	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Lag Climate Shocks	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Caste Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**
R-sq	**0.062**	**0.064**	**0.024**	**0.023**	**0.055**	**0.050**	**0.029**	**0.029**
adj. R-sq	**0.061**	**0.063**	**0.023**	**0.021**	**0.054**	**0.048**	**0.028**	**0.028**

Table 8 reports results assessing the impacts of repeated precipitation shocks on key measures of social network relationships. Repeated climate shocks are districts in India which have experienced consecutive years of negative precipitation anomalies over a three-(and five) year period. Low income villages are villages where average income levels are 50 percent or lower than average income of all villages included in the sample. Errors are clustered at the district level and standard errors are in parenthesis. ** p<0.10 ** p<0.05 *** p<0.01*

5.4 Understanding Possible Motives for Investments in Social Networks

An additional step is to determine possible motives for investing in social networks. Based on past literature, social networks can be particularly useful for securing emergency credit, social insurance, facilitating technology adoption, social cooperation, and resolving conflicts, all of which become critical in the face of negative climate events. Using survey-based responses, I estimate the impact of investments in key social network relationships, on such variables as access and sources of credit, new business creation (measured by number of non-farm business households), and technology adoption (measured by use of tubular wells), reported conflict, and social cooperation among households (Table 9). Specifically, I find a positive association between investments in linking and bridging capitals, and the number of loans received by households. Not surprisingly, there is also a positive and significant relationship between investments in linked and family/caste-based networks, and loans obtained from family members and close friends (LoanFam). Investments in bonding and linked capital are also positively related to the number of non-farm businesses households are involved in, indicating family/caste-based relationships and vertical relationships are important contributors to having a more diversified portfolio of non-farm businesses. Higher investment in bonding capitals, is also negatively associated with reported conflict among village members, while higher levels of bridging capital are positively associated with levels of reported conflict. This provides supportive evidence of the importance of family/caste-based networks (relative to non-family-based networks) in resolving conflicts among members. Investments in linking capital are also positively associated with reported collaboration among households. Finally, investments in informal network capital is positively associated with adoption and use of private tubular wells relative to government/public wells among village households.

Table 9– EXPLORING MOTIVES FOR INVESTMENTS IN SOCIAL NETWORKS

	1 lnNloans	2 LoanFam	3 NBUS	4 Pritube	5 Conflict	6 Collab
BondStd	0.0125	0.0206**	0.0621**	0.00529	0.0168	-0.0533**
	(0.0260)	(0.0103)	(0.0271)	(0.00753)	(0.0179)	(0.0239)
BridgeStd	0.0513***	-0.0157***	-0.0222	-0.000440	0.00507	0.0196
	(0.0178)	(0.00578)	(0.0165)	(0.00630)	(0.0104)	(0.0162)
LinkStd	0.0763***	0.0248***	0.0347***	0.00432	0.0309***	0.00666
	(0.0153)	(0.00643)	(0.0126)	(0.00440)	(0.0116)	(0.0144)
NetFamStd	0.0123	-0.00524	-0.00368	0.0119**	0.000831	-0.000322
	(0.0161)	(0.00674)	(0.0210)	(0.00510)	(0.0116)	(0.0136)
SC measures(^2)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40354**	**40384**	**6553**	**40136**	**40384**	**40384**
R-sq	**0.089**	**0.033**	**0.045**	**0.023**	**0.102**	**0.041**
adj. R-sq	**0.088**	**0.032**	**0.037**	**0.022**	**0.101**	**0.040**

Notes: Table 9 reports results exploring motives for investing in social networks, based on survey responses. Errors are clustered at the district level and standard errors are in parenthesis. ** p<0.10 ** p<0.05 *** p<0.01*

As a test for the robustness of these channels, I estimate the impacts of investments in social networks, as well as past climate shocks (both separately and combined) (Tables A8 and A9) on the key socio-economic outcomes. I find investments in key social capital measures continue to dominate impacts on surveyed outcomes relative to past climate shocks. This result provides strong support of the directional channel of past climate shocks, triggering investments in social network relationships, which bring with them positive socio-economic benefits support recovery efforts or insulate against future negative climate events. I also test reliability of social capital measures.

Finally, I test the robustness of social capital measures to predict key social outcomes such as attendance to public meetings and measures of trust. I find a positive association between investments in Bonding, Bridging, Linking, and Netfam, and the probability that households will attend a public meeting and also a positive association between bonding and linking capital and reported confidence/trust in key institutions.

Table 10 – ASSESSING THE QUALITY OF SOCIAL CAPITAL MEASURES

	1 PubMeet	2 ConfGov	3 ConfSchs
BondStd	0.0453***	0.0251**	0.0410***
	(0.0158)	(0.0112)	(0.0155)
BridgeStd	0.0262***	-0.00907	0.00890
	(0.00997)	(0.00809)	(0.00961)
LinkStd	0.0457***	0.0225***	-0.00717
	(0.0110)	(0.00784)	(0.00947)
NetFamStd	0.0210*	0.00225	0.00343
	(0.0115)	(0.00858)	(0.00916)
SC measures(^2)	**Yes**	**Yes**	**Yes**
Year	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**
N	**40379**	**40379**	**40379**
R-sq	**0.041**	**0.021**	**0.039**
adj. R-sq	**0.040**	**0.020**	**0.038**

Notes: Table 10 reports results exploring quality of social capital measures, based on surveyed responses of households to measures of trust and confidence in key institutions. Errors are clustered at the district level, and standard errors are in parenthesis. * *p<0.10* ** *p<0.05* *** *p<0.01*

7. Conclusions

Using long-term averages in negative precipitation anomalies, as well as lagged climate shocks, I find households which experience higher average negative precipitation shocks tend to have greater investments in vertical and family-cast- based networks (formal and informal). I find investments in linked networks to be marginally lower among villages dominated by SCSTs and also HC groups, while households which reside in villages with high village income and are land owners tend to have greater investments in linked networks. This result suggests wealth, rather than caste status increases households' ability to access linked networks when faced with higher-than-average negative precipitation anomalies. Interestingly, I find little or no impact of negative precipitation shocks on investments in social network relationships among households which generate most of their income from salary and wages sources. Finally, I find investments in bridging (non-family networks) to be particularly sensitive to repeated negative precipitation anomalies. Collectively, these results highlight the importance of family/caste (formal and informal) and linked networks in supporting households impacted by higher than average and repeated negative precipitation shocks. Not surprisingly, I find investments in vertical and family-based networks to be associated with greater access to credit (and sourced from family members), greater diversification into non-farm businesses, higher levels of reported collaboration, and increasing use of private irrigation technology, all of which are key to mitigating the impact of negative climate shocks.

From a policy perspective, these result highlights the importance of supporting family and vertical network arrangements, either through direct financial support, dissemination of drought support programs, or improvements in governance structures and accountability frameworks within these communities. Such social support can extend the marginal social benefit of participating in these network relationships, extending spillover benefits to members, also making these network relationships more resilient to repeated negative climate events. Further research is required to understand possible channels though which social networks are affected by climate shocks. This can be due to such factors as increasing migration, loss of income, and illness or death of household members. It will also be useful to trace possible outcomes of eroded social networks, in terms of increasing crime, higher poverty levels, or more instances of implementation of poor climate mitigation strategies such as child marriages.

Appendix

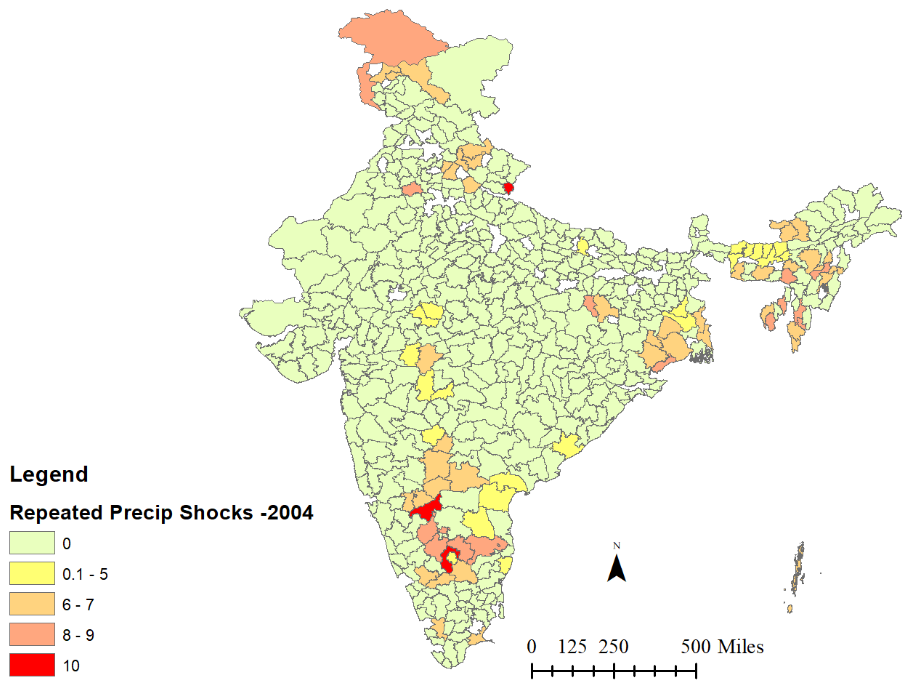


Figure A1– SPATIAL VARIATION IN REPEATED NEGATIVE PRECIPITATION SHOCKS – 2000 TO 2003

Notes: Figure A1 displays spatial variation in repeated negative precipitation shocks starting in 2000 ending in 2003.

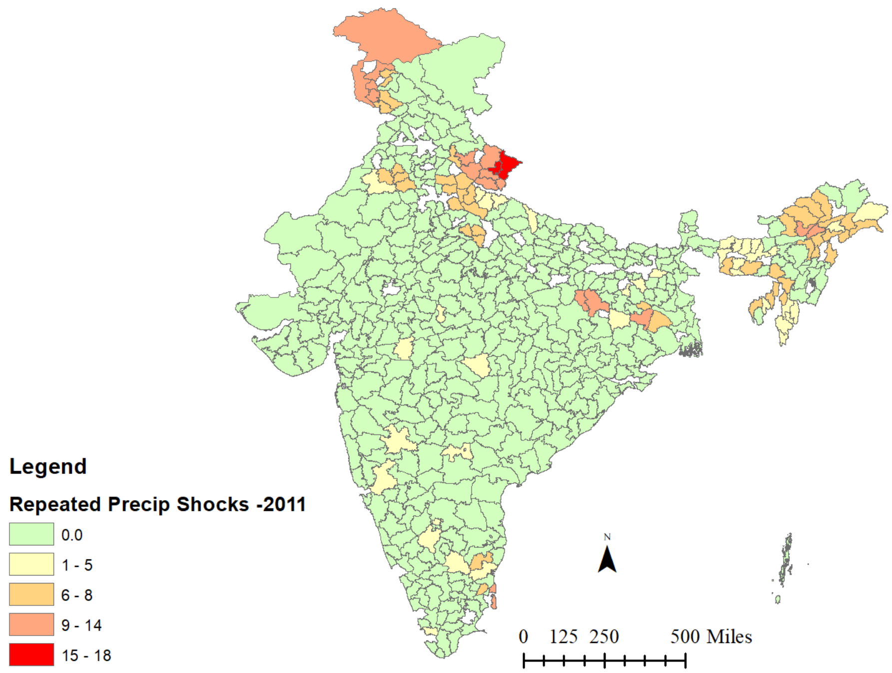


Figure A2 – SPATIAL VARIATION IN REPEATED NEGATIVE PRECIPITATION SHOCKS (2007 TO 2010)

Notes: Figure A2 displays spatial variation in repeated negative precipitation shocks in 20114, starting in 2007 ending in 2010

Table A.1A – Assessing the Impact of Lagged Climate Shocks (Seven-Year) on Key Measures of Social Capital

	(1) BondStd	(2) BridgeStd	(3) LinkStd	(4) NetFamStd
Total Positive Temperature Anomalies Lag1	-0.0315	-0.0228	-0.0741***	-0.0495***
	(0.0217)	(0.0172)	(0.0258)	(0.0182)
Total Positive Temperature Anomalies Lag2	-0.0291	0.00320	0.0530**	0.0369**
	(0.0215)	(0.0182)	(0.0260)	(0.0160)
Total Positive Temperature Anomalies Lag3	0.0246	-0.0224	0.00378	-0.0497**
	(0.0239)	(0.0216)	(0.0350)	(0.0203)
Total Positive Temperature Anomalies Lag4	0.0401	0.0558***	-0.0457*	-0.00902
	(0.0245)	(0.0195)	(0.0251)	(0.0184)
Total Positive Temperature Anomalies Lag5	-0.0125	0.00818	0.0467	0.00235
	(0.0297)	(0.0183)	(0.0357)	(0.0226)
Total Positive Temperature Anomalies Lag6	0.0234	0.0421**	-0.00880	0.00170
	(0.0237)	(0.0171)	(0.0223)	(0.0139)
Total Positive Temperature Anomalies Lag7	0.0248	-0.0434**	0.0459	0.0705***
	(0.0327)	(0.0169)	(0.0292)	(0.0162)

Table A.1B– ASSESSING THE IMPACT OF LAGGED CLIMATE SHOCKS (SEVEN-YEAR) ON KEY MEASURES OF SOCIAL CAPITAL

	1	2	3	4
	BondStd	**BridgeStd**	**LinkStd**	**NetFamStd**
Total Negative Precipitation Anomalies Lag1	0.0610	0.0218	0.0932**	0.0477*
	(0.0436)	(0.0312)	(0.0449)	(0.0278)
Total Negative Precipitation Anomalies Lag2	0.0968**	0.0202	-0.0178	0.0589**
	(0.0426)	(0.0236)	(0.0414)	(0.0287)
Total Negative Precipitation Anomalies Lag3	-0.0285	-0.0732	0.130**	0.0539
	(0.0485)	(0.0498)	(0.0640)	(0.0342)
Total Negative Precipitation Anomalies Lag4	-0.0143	-0.00247	0.0445	-0.0523*
	(0.0405)	(0.0357)	(0.0504)	(0.0284)
Total Negative Precipitation Anomalies Lag5	-0.0721**	-0.0504**	-0.0669	-0.0370
	(0.0335)	(0.0196)	(0.0434)	(0.0245)
Total Negative Precipitation Anomalies Lag6	0.00138	0.0152	0.0507	-0.00871
	(0.0523)	(0.0320)	(0.0543)	(0.0327)
Total Negative Precipitation Anomalies Lag7	-0.102*	-0.0000128	0.0410	0.0175
	(0.0576)	(0.0362)	(0.0479)	(0.0343)
Year	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**
District FE	**Yes**	**Yes**	**Yes**	**Yes**
N	**40384**	**40384**	**40384**	**40384**
R-sq	**0.080**	**0.042**	**0.076**	**0.047**
adj. R-sq	**0.078**	**0.041**	**0.074**	**0.046**

Notes: Tables A.1A and A.1B provides results of impacts of seven-year lagged negative precipitation shocks on social networks. Errors are clustered at the district level standard errors are in parenthesis. ** p<0.10 ** p<0.05 *** p<0.01*

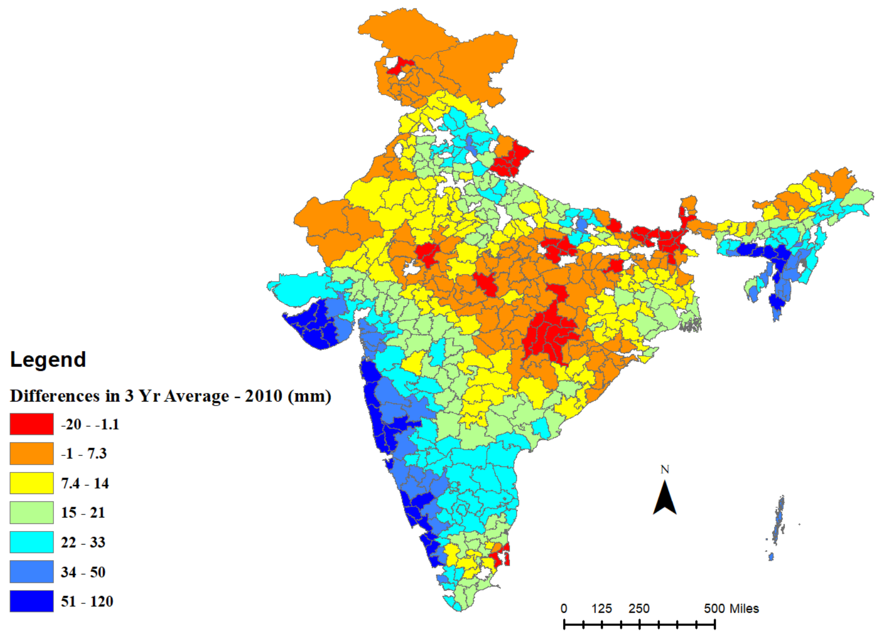


Figure A3 – SPATIAL VARIATION IN DIFFERENCES IN THREE-YEAR AVERAGE DEVIATION FROM LONG-TERM AVERAGES 2000 TO 2003, AND 2007 TO 2010

Notes: Figure A3 displays spatial variation in differences in three-year average negative precipitation anomalies 2007 to 2010, and 2000 to 2003.

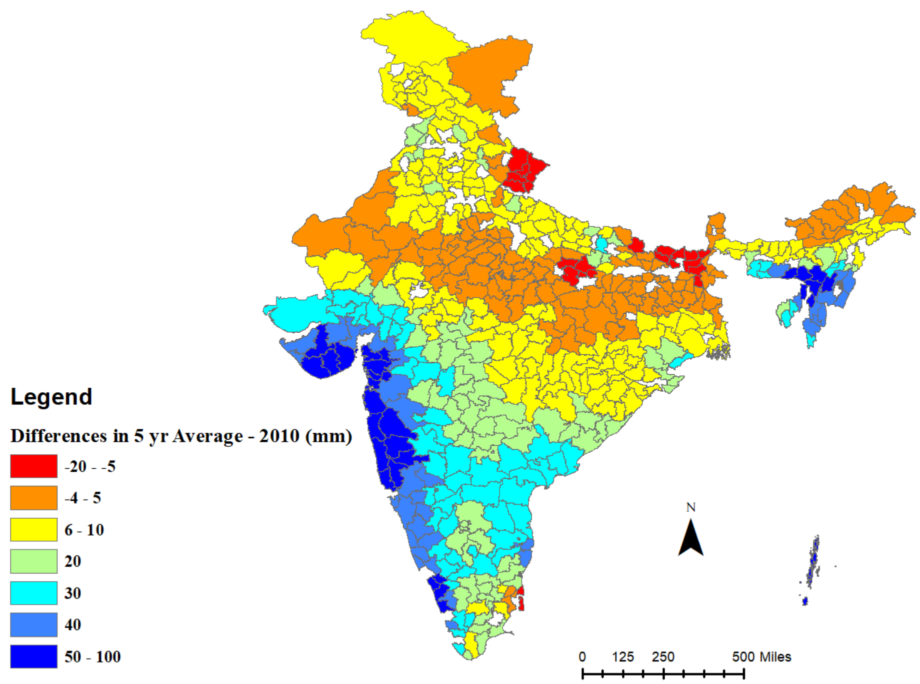


Figure A4 – SPATIAL VARIATION IN DIFFERENCES IN THREE-YEAR AVERAGE DEVIATION FROM LONG-TERM AVERAGES 2000 TO 2003, AND 2007 TO 2010

Notes: Figure A4 displays spatial variation in differences in three-year average negative precipitation anomalies 2007 to 2010, and 2000 to 2003.

Table A2 – RESULTS OF SWITCHING MODELS, AVERAGE AND STANDARD DEVIATION IN “WET” AND “DRY” PRECIPITATION REGIMES, 1900 TO 2014

Item	Coef.	Std Err.	P>z	(95% Conf. Interval)	
State1 **Average Precipitation Deviation_cons**	-3.48	0.23	0.0000	-3.921	-3.030
State 2 **Average Precipitation Deviation_cons**	1.25	0.16	0.0000	0.930	1.577
Standard deviation					
sigma1	1.28	0.16		1.00	1.63
sigma2	1.32	0.12		1.11	1.57
Probability of staying in state 1 & 2					
p11	**0.98**	**0.02**		**0.813**	**0.998**
p21	**0.02**	**0.02**		**0.004**	**0.086**

Notes: Table A2 provides results of switching models which estimates average and standard deviation in “wet” and “dry” precipitation regimes over the period 1900 and 2014.

Table A.3A– ASSESSING THE IMPACTS OF LAGGED CLIMATE SHOCKS ON SOCIAL NETWORKS

	1	2	3	4	5	6	7	8
	BondStd	**BondStd**	**BridgeStd**	**BridgeStd**	**LinkStd**	**LinkStd**	**NetFamStd**	**NetFamStd**
Total Positive Temperature Anomalies Lag1	-0.0193**	-0.0120	-0.0426***	-0.0300***	-0.0292***	-0.0462***	-0.00259	-0.00450
	(0.00914)	(0.0104)	(0.00840)	(0.00908)	(0.0109)	(0.0118)	(0.00746)	(0.00892)
Total Positive Temperature Anomalies Lag2	-0.0189*	-0.0305**	0.0267***	0.0141	0.0311**	0.0303**	0.0162*	0.0122
	(0.0112)	(0.0122)	(0.00850)	(0.00952)	(0.0132)	(0.0133)	(0.00934)	(0.00979)
Total Positive Temperature Anomalies Lag3	0.0422***	0.0285**	0.000625	-0.0172	0.0157	0.0156	-0.0366***	-0.0369***
	(0.0139)	(0.0142)	(0.0129)	(0.0127)	(0.0160)	(0.0177)	(0.0125)	(0.0134)
Total Positive Temperature Anomalies Lag4		0.0426***		0.0545***		-0.0396***		-0.00629
		(0.0131)		(0.0119)		(0.0141)		(0.0119)
Total Positive Temperature Anomalies Lag5		-0.00999		-0.00707		0.0612***		0.0189
		(0.0184)		(0.0111)		(0.0173)		(0.0136)

Table A3B– ASSESSING THE IMPACTS OF LAGGED CLIMATE SHOCKS ON SOCIAL NETWORKS

	1	2	3	4	5	6	7	8
	BondStd	**BondStd**	**BridgeStd**	**BridgeStd**	**LinkStd**	**LinkStd**	**NetFamStd**	**NetFamStd**
Total Negative Precipitation Anomalies Lag1	0.0419	0.0482*	0.0140	0.0197	0.0855***	0.109***	0.0565***	0.0600***
	(0.0263)	(0.0267)	(0.0198)	(0.0196)	(0.0256)	(0.0248)	(0.0187)	(0.0183)
Total Negative Precipitation Anomalies Lag2	0.107***	0.102***	0.0329**	0.0312**	-0.0191	-0.0264	0.0480***	0.0486***
	(0.0216)	(0.0221)	(0.0144)	(0.0148)	(0.0225)	(0.0227)	(0.0172)	(0.0177)
Total Negative Precipitation Anomalies Lag3	-0.0224	-0.0346	-0.0587**	-0.0670**	0.106***	0.117***	0.0371	0.0354
	(0.0302)	(0.0304)	(0.0297)	(0.0288)	(0.0362)	(0.0359)	(0.0242)	(0.0248)
Total Negative Precipitation Anomalies Lag4		-0.0200		-0.0149		0.0915***		-0.0153
		(0.0248)		(0.0210)		(0.0249)		(0.0190)
Total Negative Precipitation Anomalies Lag5		-0.0557***		-0.0286**		-0.0692***		-0.0316*
		(0.0182)		(0.0145)		(0.0231)		(0.0164)
Year	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**	**40384**
R-sq	**0.067**	**0.073**	**0.031**	**0.037**	**0.059**	**0.069**	**0.036**	**0.037**
adj. R-sq	**0.066**	**0.072**	**0.03**	**0.036**	**0.058**	**0.068**	**0.035**	**0.036**

Notes: Table A.3A and A.3B provides results of lagged climate shocks (temperature and precipitation shocks) on social networks. Errors are clustered at the district levels, standard errors in parenthesis.
** p<0.10 ** p<0.05 *** p<0.01*

Table A4 – CORRELATION BETWEEN KEY MEASURES OF SOCIAL CAPITAL – 2005

	BondStd	BridgeStd	LinkStd	NetFamStd
BondStd	1.0000			
BridgeStd	0.2307	1.0000		
	0.000			
LinkStd	0.0661	0.0751	1.0000	
	0.000	0.000		
NetFamStd	0.102	0.0993	0.5085	1.0000
	0.000	0.000	0.000	

Notes: Table A4 outlines correlation between key measures of social capital in 2005.

Table A5– CORRELATION BETWEEN MEASURES OF SOCIAL CAPITAL – 2012

	BondStd	BridgeStd	LinkStd	NetFamStd
BondStd	1.0000			
BridgeStd	0.2411	1.0000		
	0.0000			
LinkStd	0.1411	0.094	1.0000	
	0.0000	0.0000		
NetFamStd	0.1759	0.086	0.5915	1.0000
	0.0000	0.0000	0.0000	

Notes: Table A5 outlines correlation between key measures of social capital in 2012.

15. Social Networks

Among your acquaintances and relatives, are there any who …	a Any?	b IF, YES What does he/she do? [code the highest]	c Is this person male or female? Male= 1 Female= 2	d Is he / she related to you? Not family= 0 Family, not hh= 1 In household= 2	e Is his / her community / jati the same as yours? Different jati =0 Same jati =1	f Does the person live in the same village or neighbourhood as you? Other place=0 Same=1
15.1 **… are doctors or nurses or who work in hospitals and clinics?**	No=0 Yes= 1 [ ] SN1a	Doctors=1 Nurses=2 Technician=3 Other=4 [ ] SN1b	[ ] SN1c	[ ] SN1d	[ ] SN1e	[ ] SN1f
15.2 **… are teachers, school officials, or anybody who works in a school?**	No=0 Yes= 1 [ ] SN2a	Teachers/Principal=1 Clerk=2 Other lower=3 [ ] SN2b	[ ] SN2c	[ ] SN2d	[ ] SN2e	[ ] SN2f
15.3 **… are in government service?** [other than doctors, teachers, above]	No=0 Yes= 1 [ ] SN3a	Officer and above=1 Clerk=2 Other lower=3 [ ] SN3b	[ ] SN3c	[ ] SN3d	[ ] SN3e	[ ] SN3f

16. Memberships and political activity

16. **Now, I would like to know about the groups or organizations that you and others in the household belong to.
Does anybody in the household belong to a …**

16.1 **Mahila mandal?**	No=0 Yes=1	[ ] ME1
16.2 **Youth club, sports group, or reading room?**	No=0 Yes=1	[ ] ME2
16.3 **Trade union, business or professional group?**	No=0 Yes=1	[ ] ME3
16.4 **Self Help Groups**	No=0 Yes=1	[ ] ME4
16.5 **Credit or savings group**	No=0 Yes=1	[ ] ME5
16.6 **Religious or social group or festival society?**	No=0 Yes=1	[ ] ME6
16.7 **Caste association?**	No=0 Yes=1	[ ] ME7
16.8 **Development group or NGO?**	No=0 Yes=1	[ ] ME8
16.9 **Agricultural, milk, or other co-operative?**	No=0 Yes=1	[ ] ME9
16.10 **Many people find it difficult to get to vote when there is an election. In the most recent national election, did you vote yourself?**	No=0 Yes=1	[ ] ME10
16.11 **Have you or anyone in the household attended a public meeting called by the village panchayat / nagarpalika / ward committee in the last year?**	No=0 Yes=1	[ ] ME11
16.12 **Is anyone in the household an official of the village panchayat / nagarpalika / ward committee ?** IF NO: **Is there someone close to the household, who is a member?**	Nobody close to household is a member = 0 Somebody close to household is a member = 1 Someone in household is a member = 2	[ ] ME12

Exhibit 1 – Sample Household Questionnaire – Questions related to Social Capital

Table A6 – RESULTS ASSESSING THE IMPACTS OF AVERAGE CLIMATE SHOCKS ON SOCIAL NETWORKS AMONG LAND OWNERS

	1 BondStd	2 BridgeStd	3 LinkStd	4 NetFamStd
Positive Temperature Anomalies	0.0296	0.0356	0.0876**	0.00732
(3 Yr Average)	(0.0347)	(0.0287)	(0.0403)	(0.0233)
Negative Precipitation Anomalies	0.0629	-0.0489	0.0706	0.130**
(3 Yr Average)	(0.0705)	(0.0691)	(0.0833)	(0.0523)
OwnLand_05*Positive Temperature Anomalies	-0.0310	-0.0408**	-0.106***	-0.0343*
(3 Yr Average)	(0.0275)	(0.0193)	(0.0240)	(0.0190)
OwnLand_05*Negative Precipitation Anomalies	0.0913	0.0145	0.148**	0.0455
(3 Yr Average)	(0.0646)	(0.0563)	(0.0694)	(0.0406)
Year	**Yes**	**Yes**	**Yes**	**Yes**
Lag Climate Shocks	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**
Caste Controls	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**
N	**40384**	**40384**	**40384**	**40384**
R-sq	**0.065**	**0.024**	**0.063**	**0.034**
adj. R-sq	**0.064**	**0.023**	**0.062**	**0.033**

Notes: Table A6 reports results assessing the impacts of average climate shocks on social networks among high average income in 2005. In this case households which respond positively in survey questions related to land ownership, takes a value of one and zero otherwise. Errors are clustered at the district level and standard errors are in parenthesis.
** p<0.10 ** p<0.05 *** p<0.01*

Table A7– RESULTS ASSESSING THE IMPACTS OF REPEATED NEGATIVE PRECIPITATION SHOCKS ON KEY MEASURES OF SOCIAL CAPITAL (HI-INCOME VILLAGES)

	1 BondStd	2 BridgeStd	3 LinkStd	4 NetFamStd
Repeated Negative Precipitation Anomalies	0.0151	-0.0164*	0.0288*	0.0191*
3 Yr (Total)	(0.0178)	(0.00868)	(0.0159)	(0.0112)
HiInc*Repeated Negative Precipitation Anomalies	0.00799	0.0115	0.0161	-0.00369
3 Yr (Total)	(0.0204)	(0.0132)	(0.0221)	(0.0130)
Year	**Yes**	**Yes**	**Yes**	**Yes**
Lag Climate Shocks	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**
Caste Controls	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**
N	**41878**	**41878**	**41878**	**41878**
R-sq	**0.035**	**0.011**	**0.031**	**0.023**
adj. R-sq	**0.035**	**0.010**	**0.031**	**0.022**

Table A7 reports results assessing the impacts of repeated precipitation shocks on key measures of social network relationships. Repeated climate shocks are districts in India which have experienced consecutive years of negative precipitation anomalies over a three (and five) year period. High income villages are villages where average income levels are 75 percent, or more than average income of all villages included in the sample. Errors are clustered at the district level and standard errors are in parenthesis.

** p<0.10 ** p<0.05 *** p<0.01*

Table A8– RESULTS ASSESSING THE IMPACT OF CLIMATE SHOCKS (THREE-YEAR AVERAGES) ON KEY MEASURES OF SOCIAL OUTCOMES

	1	2	3	4	5	6	7	8	9
	lnNloans	**LoanFam**	**NBUS**	**Collab**	**Conflict**	**Pritube**	**PubMeet**	**ConfGov**	**ConSchs**
Positive Temperature Anomalies (3 Yr Average)	-0.114***	-0.0301***	-0.00638	-0.0319*	0.0000732	0.00384	0.00121	-0.0121	0.00797
	(0.0261)	(0.00856)	(0.0105)	(0.0162)	(0.0230)	(0.00629)	(0.0116)	(0.0126)	(0.0130)
Negative Precipitation Anomalies (3 Yr Average)	0.0258	0.0313*	0.0323	0.0121	0.0642	0.0132	-0.0352	0.0530**	-0.0447
	(0.0475)	(0.0185)	(0.0210)	(0.0349)	(0.0565)	(0.0120)	(0.0266)	(0.0251)	(0.0319)
Lag Climate Shocks	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
SC measures(^2)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40354**	**40384**	**6553**	**40384**	**40384**	**40136**	**40384**	**40384**	**40384**
R-sq	**0.102**	**0.035**	**0.035**	**0.103**	**0.041**	**0.023**	**0.024**	**0.021**	**0.039**
adj. R-sq	**0.101**	**0.034**	**0.028**	**0.102**	**0.040**	**0.022**	**0.023**	**0.020**	**0.038**

Notes: Table A8 provides results of impacts of negative precipitation anomalies (three-year averages) on key social outcomes. Errors are clustered at the district level, and standard errors in parenthesis.
** p<0.10 ** p<0.05 *** p<0.01*

Table A.9A– RESULTS ASSESSING THE IMPACT OF KEY MEASURES OF SOCIAL CAPITAL AND CLIMATE SHOCKS (THREE-YEAR AVERAGES) ON KEY MEASURES OF SOCIAL OUTCOMES

	1 lnNloans	2 LoanFam	3 NBUS	4 Collab	5 Conflict	6 Pritube	7 PubMeet	8 ConfGov	9 ConSchs
BondStd	0.00975	0.0187*	0.0628**	0.0193	-0.0531**	0.00454	0.0472***	0.0225**	0.0419***
	(0.0250)	(0.00997)	(0.0273)	(0.0180)	(0.0236)	(0.00756)	(0.0158)	(0.0110)	(0.0152)
BridgeStd	0.0544***	-0.0147**	-0.0220	0.00318	0.0151	-0.000953	0.0266***	-0.0103	0.00983
	(0.0162)	(0.00578)	(0.0166)	(0.0105)	(0.0154)	(0.00620)	(0.00984)	(0.00798)	(0.00923)
LinkStd	0.0763***	0.0240***	0.0365***	0.0327***	0.00856	0.00451	0.0492***	0.0227***	-0.00816
	(0.0145)	(0.00631)	(0.0129)	(0.0113)	(0.0142)	(0.00450)	(0.0107)	(0.00765)	(0.00953)
NetFamStd	0.0193	-0.00419	-0.00434	0.00295	-0.00333	0.0109**	0.0227**	0.000429	0.00445
	(0.0161)	(0.00665)	(0.0210)	(0.0114)	(0.0133)	(0.00515)	(0.0115)	(0.00862)	(0.00895)

Table A.9B– RESULTS ASSESSING THE IMPACT OF KEY MEASURES OF SOCIAL CAPITAL AND CLIMATE SHOCKS (THREE-YEAR AVERAGES) ON KEY MEASURES OF SOCIAL OUTCOMES

	1 lnNloans	2 LoanFam	3 NBUS	4 Collab	5 Conflict	6 Pritube	7 PubMeet	8 ConfGov	9 ConSchs
Positive Temperature Anomalies (3 Yr Average)	-0.114***	-0.0300***	-0.00600	-0.0314*	-0.000234	0.00362	-0.000300	-0.0121	0.00870
	(0.0252)	(0.00838)	(0.0104)	(0.0161)	(0.0227)	(0.00630)	(0.0116)	(0.0126)	(0.0130)
Negative Precipitation Anomalies (3 Yr Average)	0.0115	0.0280	0.0245	0.00679	0.0703	0.0112	-0.0499*	0.0485*	-0.0471
	(0.0460)	(0.0180)	(0.0208)	(0.0349)	(0.0570)	(0.0122)	(0.0286)	(0.0254)	(0.0318)
SC measures(^2)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Household FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Village Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Month of Survey	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	**40354**	**40384**	**6553**	**40384**	**40384**	**40136**	**40384**	**40384**	**40384**
R-sq	**0.113**	**0.039**	**0.046**	**0.108**	**0.048**	**0.024**	**0.043**	**0.023**	**0.041**
adj. R-sq	**0.112**	**0.037**	**0.038**	**0.107**	**0.047**	**0.023**	**0.042**	**0.022**	**0.039**

Notes: Table A.10A and A.10B provides results of impacts of key measures of social capital and negative precipitation anomalies (three-year averages) on key social outcomes. Errors are clustered at the district level, and standard errors in parenthesis.

** p<0.10 ** p<0.05 *** p<0.01*

References

Adger, W Neil. 2001. "Social Capital and Climate Change." *Tyndall centre for Climate change research working paper*, 8.

____. 2010. "Social Capital, Collective Action, and Adaptation to Climate Change," *Der Klimawandel.* Springer, 327-45.

Adger, W Neil; Nigel W Arnell and Emma L Tompkins. 2005. "Successful Adaptation to Climate Change across Scales." *Global Environmental Change*, 15(2), 77-86.

Adger, W Neil; Katrina Brown; Donald R Nelson; Fikret Berkes; Hallie Eakin; Carl Folke; Kathleen Galvin; Lance Gunderson; Marisa Goulden and Karen O'Brien. 2011. "Resilience Implications of Policy Responses to Climate Change." *Wiley Interdisciplinary Reviews: Climate Change*, 2(5), 757-66.

Adhikari, Krishna Prasad. 2008. "Bridging, Linking, and Bonding Social Capital in Collective Action." *Collective Action and Property Rights CAPRi*, 1-23.

Akerlof, George. 1976. "The Economics of Caste and of the Rat Race and Other Woeful Tales." *The Quarterly Journal of Economics*, 90(4), 599-617.

Blakeslee, David and Ram Fishman. 2014. "Weather Shocks, Crime, and Agriculture: Evidence from India." *Social Science Research Network.*

Bloch, Francis and Bhaskar Dutta. 2011. "Formation of Networks and Coalitions." *Handbook of social economics. North Holland, Amsterdam*, 305-18.

Bloch, Francis; Garance Genicot and Debraj Ray. 2008. "Informal Insurance in Social Networks." *Journal of economic theory*, 143(1), 36-58.

Carleton, Tamma A and Solomon M Hsiang. 2016. "Social and Economic Impacts of Climate." *Science*, 353(6304), aad9837.

Coate, Stephen and Martin Ravallion. 1993. "Reciprocity without Commitment: Characterization and Performance of Informal Insurance Arrangements." *Journal of Development Economics*, 40(1), 1-24.

Cole, Shawn; Andrew Healy and Eric Werker. 2012. "Do Voters Demand Responsive Governments? Evidence from Indian Disaster Relief." *Journal of Development Economics*, 97(2), 167-81.

De la Fuente, Alejandro. 2007. "Climate Shocks and Their Impact on Assets." *Occasional paper for UNDP*.

De Weerdt, Joachim and Stefan Dercon. 2006. "Risk-Sharing Networks and Insurance against Illness." *Journal of Development Economics*, 81(2), 337-56.

De Weerdt, Joachim and Marcel Fafchamps. 2011. "Social Identity and the Formation of Health Insurance Networks." *Journal of Development Studies*, 47(8), 1152-77.

Dell, Melissa; Benjamin F Jones and Benjamin A Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics*, 66-95.

____. 2014. "What Do We Learn from the Weather? The New Climate–Economy Literature." *Journal of Economic Literature*, 52(3), 740-98.

Fafchamps, Marcel and Flore Gubert. 2007. "The Formation of Risk Sharing Networks." *Journal of Development Economics*, 83(2), 326-50.

Fafchamps, Marcel and Bart Minten. 2002. "Returns to Social Network Capital among Traders." *Oxford Economic Papers*, 54(2), 173-206.

Feder, Gershon. 1980. "Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty." *Oxford Economic Papers*, 32(2), 263-83.

Flora, Cornelia Butler. 1992. *Rural Communities: Legacy and Change*. With Mark B. Lapping and Mark L. Weinberg. Boulder and Oxford:Westview Press.

Gang, Ira N.; Kunal Sen and Myeong-Su Yun. 2008. "Poverty in Rural India: Caste and Tribe." *Review of Income and Wealth*, 54(1), 50-70.

Guhathakurta, P. and M. Rajeevan. 2008. "Trends in the Rainfall Pattern over India." *International Journal of Climatology*, 28(11), 1453-69.

Hawkins, Robert L and Katherine Maurer. 2010. "Bonding, Bridging and Linking: How Social Capital Operated in New Orleans Following Hurricane Katrina." *British Journal of Social Work*, 40(6), 1777-93.

Hnatkovska, Viktoria; Amartya Lahiri and Sourabh B. Paul. 2013. "Breaking the Caste Barrier: Intergenerational Mobility in India." *Journal of Human Resources*, 48(2), 435-73.

Hsiang, Solomon. 2016. "Climate Econometrics." *Annual Review of Resource Economics*, 8, 43-75.

Iyer, Lakshmi and Petia Topalova. 2014. "Poverty and Crime: Evidence from Rainfall and Trade Shocks in India," Harvard Business School, Harvard Business School Working Papers: 14-067, 43 pages.

Iyer, Lakshmi and Petia B Topalova. 2014. "Poverty and Crime: Evidence from Rainfall and Trade Shocks in India." *Harvard Business School BGIE Unit Working Paper*, (14-067).

Kijima, Yoko. 2006. "Caste and Tribe Inequality: Evidence from India, 1983-1999." *Economic Development and Cultural Change*, 54(2), 369-404.

Kripalani, RH and Ashwini Kulkarni. 1997. "Climatic Impact of El Nino/La Nina on the Indian Monsoon: A New Perspective." *Weather*, 52(2), 39-46.

Matsuura, Kenji and Cort Willmott. 2007. "Terrestrial Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series, Version 1.01." *University of Delaware. http://climate. geog. udel. edu/climate*.

Narayan, Deepa. 2002. "Bonds and Bridges: Social Capital and Poverty." *Social capital and economic development: well-being in developing countries. Northampton, MA: Edward Elgar*, 58-81.

Narayan, Deepa and Lant Pritchett. 1999. "Cents and Sociability: Household Income and Social Capital in Rural Tanzania." *Economic Development and Cultural Change*, 47(4), 871-97.

Pachauri, Rajendra K; Myles R Allen; Vicente R Barros; John Broome; Wolfgang Cramer; Renate Christ; John A Church; Leon Clarke; Qin Dahe and Purnamita Dasgupta. 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, Ii and Iii to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC.

Parthasarathy, B; NA Sontakke; AA Monot and DR Kothawale. 1987. "Droughts/Floods in the Summer Monsoon Season over Different Meteorological Subdivisions of India for the Period 1871–1984." *Journal of Climatology*, 7(1), 57-70.

Poortinga, Wouter. 2012. "Community Resilience and Health: The Role of Bonding, Bridging, and Linking Aspects of Social Capital." *Health & Place*, 18(2), 286-95.

Putnam, Robert D. 2002. *Democracies in Flux: The Evolution of Social Capital in Contemporary Society*. Oxford University Press.
Singh, Nityanand and Ashwini Ranade. 2010. "The Wet and Dry Spells across India During 1951–2007." *Journal of Hydrometeorology*, 11(1), 26-45.

Subbaramayya, I and CV Naidu. 1992. "Spatial Variations and Trends in the Indian Monsoon Rainfall." *International Journal of Climatology*, 12(6), 597-609.

Szreter, Simon and Michael Woolcock. 2004. "Health by Association? Social Capital, Social Theory, and the Political Economy of Public Health." *International Journal of Epidemiology*, 33(4), 650-67.

Taraz, Vis. 2017. "Adaptation to Climate Change: Historical Evidence from the Indian Monsoon." *Environment and Development Economics*, 1-29.

Townsend, Robert M. 1994. "Risk and Insurance in Village India." *Econometrica: Journal of the Econometric Society*, 539-91.

Urwin, Peter; Giorgio Di Pietro; Patrick Sturgis and Gregor Jack. 2008. "Measuring the Returns to Networking and the Accumulation of Social Capital: Any Evidence of Bonding, Bridging, or Linking?" *American Journal of Economics and Sociology*, 67(5), 941-68.

Wang, Xin; Chongyin Li and Wen Zhou. 2006. "Interdecadal Variation of the Relationship between Indian Rainfall and Ssta Modes in the Indian Ocean." *International Journal of Climatology*, 26(5), 595-606.

Wolf, Johanna; W Neil Adger; Irene Lorenzoni; Vanessa Abrahamson and Rosalind Raine. 2010. "Social Capital, Individual Responses to Heat Waves and Climate Change Adaptation: An Empirical Study of Two Uk Cities." *Global Environmental Change*, 20(1), 44-52.

Woolcock, Michael. 1998. "Social Capital and Economic Development: Toward a Theoretical Synthesis and Policy Framework." *Theory and Society*, 27(2), 151-208.

Woolcock, Michael and Deepa Narayan. 2000. "Social Capital: Implications for Development Theory, Research, and Policy." *The world bank research observer*, 15(2), 225-49.