Climate Change and Political Mobilization: Theory and Evidence from India*

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Abstract

What are the implications of climate change for political mobilization? Environmental pressures brought about by climate change can provide new opportunities for citizens to learn about: the loyalty of political leaders; the capacity of the state; and their ability to rely on members of their own community. Successful mobilization is more likely in the wake of climate change. We develop a model of collective action in the presence of climate shocks and show that uncertainty about causal attribution can lead citizens to rationally under-estimate environmental impacts, attributing observed outcomes instead to features of their political environment. We provide evidence for our claims using geocoded data on temperature extremes and a unique household-level panel survey from India. Unusually high temperatures reduce trust in leaders and security forces while increasing intra-community cooperation. High temperatures also increase anti-incumbent voting, voter turnout, and the frequency of agriculture-related anti-government protests.

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1 Introduction

Climate change is already having dramatic impacts on earth's ecosystems. The impacts of climate change on human systems will be no less profound. Climate change will reshape our agricultural systems and food production; the spread of disease and the burden of public health; and the demands placed on our social and physical infrastructure (Birkmann et al., 2022). A robust interdisciplinary literature has emerged over the last ten years studying the expected impacts of climate change on each of these features of human health, productivity, and demography (Somanathan et al., 2021; Heutel et al., 2021; Barreca et al., 2018). Yet we have only just begun to understand how climate pressures impact human political systems and behavior.

Most of what we know about the political impacts of climate comes from the study of natural disasters. For example, Sinclair et al. (2011) studies the impacts of Hurricane Katrina on voter turnout in New Orleans. Bechtel and Hainmueller (2011) estimate the effects of devastating floods which occurred in Germany in 2002 to understand how government responsiveness shapes long-term voter support for incumbents. Blankenship et al. (2021) studies electoral backlash to droughts and floods during monsoon season in India. What these studies share in common is an approach rooted in retrospective voting under conditions of uncertainty. Either due to psychological bias or rational updating, citizens punish leaders electorally in the wake of natural disasters while rewarding those who provide—often inefficient—*ex post* disaster relief (Healy and Malhotra, 2009; Ashworth et al., 2018).

We argue that the impacts of climate change are likely broader and more pervasive than this existing literature suggests. Climate change not only leads to the creation of new grievances against political leaders but also re-shapes citizen evaluations of state capacity and the ability of citizens to work together effectively at the local level. These effects are concurrent and mutually reinforcing, meaning that they cannot be disentangled or properly understood in isolation from one another. Moreover these changes to citizen beliefs have wide ranging implications for political behaviors, from electoral mobilization to protest activity and violent conflict. Our theoretical framework thus provides a broad view of how climate is likely to shape political behavior, one which also connects the studies of natural disaster noted above with a separate, but robust literature on the relationship between climate pressures and violent conflict (Burke et al., 2015; Mach et al., 2019).

To develop our arguments we bring together two distinct theoretical literatures. First, models of retrospective voting explore how citizens learn about and evaluate leaders in situations where they cannot directly observe candidate quality. In the absence of verifiable information, voters optimally condition their choice on an outcome which is directly observable but only imperfectly correlated with the quality of the incumbent. We build on this logic of updating under conditions of uncertainty to explore how correlated shocks induced by climate change leads to citizen learning across a number of politically-relevant dimensions. In particular, we show that climate shocks lead citizens to simultaneously revise their beliefs about the quality of the incumbent; the capacity of the state itself; and the ability of citizens to work together effectively at the local level.

The second part of our theoretical approach builds on models of protest behavior and collective action (Little et al., 2015; Shadmehr and Bernhardt, 2011). A standard set of tools for analyzing political mobilization, these models build on the logic of global games to study how citizen behavior is shaped simultaneously by pre-existing grievances, expectations of state capacity, and the behavior of other citizens. Where climate change not only leads to the creation of new grievances—such as those expressed via anti-incumbent voting—but also changes in these social and political expectations, citizens will be far more effective in overcoming collective action problems. By bringing these two approaches together we model how climate shocks 1) shape citizen perceptions of their political and social environment and 2) increase the likelihood of effective collective action and mobilization.

The channels of learning we highlight are particularly relevant in the context of climate change which will bring to bear extraordinary new pressures on states with limited fiscal resources and capacity. Worsening public health, higher rates of violent crime, and new demands for government redistribution are all natural—potentially inevitable—consequences of a warming climate. The implications of this for the quality of citizen encounters with the state and their resulting expectations of state capacity have received little attention so far. And much as in the case of natural disasters, environmental pressures broadly challenge citizens to both compete for resources and to work together to overcome challenging circumstances. During natural disasters citizens compete for food, but must also cooperate to rescue neighbors from rising floodwaters. Similarly during times of drought citizens compete for access to existing water resources, but may also find local cooperation beneficial in order to smooth incomes or to build new irrigation infrastructure. Thus climate pressures can be expected to re-shape how local communities view one another and their ability to work together towards political goals.

We test our predictions in the context of Indian politics. We select India as our case in part due to its unusual vulnerability to the impacts of climate change (Lüdeke et al., 2014). India's strong reliance on agriculture and scarcity of freshwater resources combined with weak or variable state capacity aligns it closely with the core assumptions of our theory (Kapur, 2020). Yet in other respects India is similar on a range of political and socio-demographic dimensions to many low and lower middle income states.[1] India is also a stable democracy with a federal system of government and clear constitutional delineation of policy making authority (Chatterjee et al., 2022), which allow us to empirically evaluate the scope of emerging grievances.

We begin our empirical analysis by confirming that—as in the case of natural disasters—the temperature shocks widely associated with climate change do indeed lead to higher rates of anti-incumbent voting. Analyzing thirty years worth of electoral returns from India's Vidhan Sabha—the State Legislative Assembly—we document a negative and statistically significant impact of temperature shocks on the probability of incumbent re-election. Next we test the prediction that in addition to increasing anti-incumbent sentiment, climate shocks also increase citizens' ability to mobilize. We do so by testing the impacts of climate shocks first on rates of voter turnout – again in state-level elections – and second on the frequency of anti-government protests. We estimate precise positive effects in both cases. Specifically, in the latter context, we estimate a positive effect of environmental pressures on citizen protests involving both traffic obstruction and hunger strikes, two tactics commonly associated with India's agricultural population, who are precisely

[1] See the Appendix for further discussion.

those most likely to be impacted by temperature shocks.

Next, we investigate the mechanisms of our theory using successive waves of the Indian Human Development Survey (IHDS). The IHDS collects data on individual well-being, experiences in the community, and political views, repeatedly interviewing the same set of households over time. This survey design enables us to estimate the within-household effects of quasi-exogenous temperature variation on a wide range of outcomes. Across all analyses we incorporate a set of pre-treatment covariates to account for potentially time-varying confounders, including urbanization, pollution, access to irrigation, soil moisture and rainwater run-off. The results provide robust support for the mechanisms. Statistical analysis shows that unusually high temperatures are associated with lower confidence in government *and* in the security capacity of the state. At the same time, temperature shocks lead to more frequent intra-community cooperation related to the use of water resources. Climate shocks are further associated with lower agricultural income and our results are driven primarily by those respondents residing in rural areas, households whose income depends on the agricultural sector, and areas with low state capacity.

Our contributions are three-fold. Conceptually, we expand on the literature's emphasis on retrospective voting in order to consider climate's holistic impacts on political mobilization and collective action (Bechtel and Hainmueller, 2011; Blankenship et al., 2021). In particular, we shed light on how climate pressures simultaneously impacts citizens' grievances against incumbent politicians as well as their expectations regarding state capacity and the behavior of other citizens. Theoretically we bring insights from models of political accountability and learning under uncertainty to bear on the process of citizen mobilization and protest (Ashworth et al., 2018; Little et al., 2015). We show that these channels operate in parallel and are mutually reinforcing, supporting the emergence of more frequent collective action in the wake of climate pressures.

Empirically we show that retrospective voting occurs not only following high-profile natural disasters, but also in the wake of slower-onset climate pressures such as unusually high temperatures. We also expand the set of political outcomes linked to climate pressures to include voter turnout, anti-government protest, and intra-community cooperation (Grossman and Slough, 2022;

Grossman et al., 2024). And finally we provide evidence to support our theorized mechanisms, showing that increases in anti-incumbent voting and political mobilization are under-pinned by shifts in perceptions of both leaders, state capacity, and rates of cooperation within local communities.

2 Model

In this section we first introduce a model of collective action and subsequently model the process by which environmental pressures lead citizens to re-evaluate their beliefs about features of the political environment. Let there be an incumbent political leader whose type, $\alpha_L \in (\overline{\alpha}, \underline{\alpha})$, is unobservable to citizens. The prior probability that the incumbent is the aligned type is $pr(\alpha_L = \overline{\alpha}) = p \in (0,1)$. There is a set of citizens arranged along the unit interval $i \in (0,1)$ who decide whether to mobilize or not. Denote i's mobilization decision by $v_i = 1$ if i mobilizes and $v_i = 0$ otherwise. If mobilization is successful the incumbent is replaced by a challenger whose type is drawn from the same distribution as the incumbent, $\alpha_C \in (\overline{\alpha}, \underline{\alpha})$ with $pr(\alpha_C = \overline{\alpha}) = p$.

Denote the share of citizens who mobilize by $\psi \in [0,1]$. The probability that an incumbent is removed via mobilization is given by $\phi(\psi, \omega)$ where ω is a measure of state capacity, $\omega \in \{\overline{\omega}, \underline{\omega}\}$.[2] Like incumbent type, state capacity is unobserved with prior probability of a weak state, $pr(\omega = \underline{\omega}) = q \in (0,1)$. We assume that ϕ is linear in its first argument with $\phi_1 > 0$ and $\phi(\cdot, \underline{\omega}) > \phi(\cdot, \overline{\omega})$ for any ψ. Assume that if the entire population turns out—$\psi = 1$—then the incumbent is removed with certainty even if state capacity is high and if no one turns out—$\psi = 0$—the incumbent retains office with similar certainty even when state capacity is low.

Payoffs are as follows. At the end of the game citizens receive payoff of one if the final office holder is type $\overline{\theta}$ and zero if the leader type is $\underline{\theta}$. Payoffs also reflects a "warm glow" utility which is derived from having replaced an incumbent of type $\underline{\alpha}$ with a challenger of type $\overline{\alpha}$ (if the reverse occurs and an incumbent of type $\overline{\alpha}$ is replaced by a challenger of type $\underline{\alpha}$ then citizens experience

[2]The marginal impacts of any individual citizen on ψ are negligible given the very large (infinite) size of the population thus these do not factor into citizen decision making.

an equivalent disutility). Citizen expected utility is,

$$\mathbb{E}[u_i|v_i] = \begin{cases} \mathbb{E}[\alpha_C] + v_i\mathbb{E}[\tau_i(\alpha_C - \alpha_L) - c] & \text{if mobilization succeeds} \\ \mathbb{E}[\alpha_L] - v_i c & \text{otherwise.} \end{cases} \tag{1}$$

where $c \in (0, \overline{c})$ is a symmetric cost of mobilization and $\tau_i \in \{\overline{\tau}, \underline{\tau}\}$ is the citizen's own type, describing their degree of pro-sociality. The share of pro-social types in the population is given by a hyper parameter, $\gamma \in \{\overline{\gamma}, \underline{\gamma}\}$ where it is known that $pr(\gamma = \overline{\gamma}) = r \in (0,1)$. To preview the analysis, equilibrium behavior will depend on the three parameters introduced above, (θ, ω, γ), about which citizens hold only imperfect information. In the next section we describe how environmental pressures shape citizen beliefs and subsequently optimal behavior.

2.1 The Impacts of Climate Change

Each citizen observes a signal given by $s_i = (s_i^\theta, s_i^\omega, s_i^\gamma)$. Signals depend on their respective unobserved parameters making them informative to citizens. But each component of the signal is also influenced by environmental pressures: Let $\Delta \in \{\overline{\Delta}, \underline{\Delta}\}$ denote the state of environmental pressures. Δ is not observable itself nor is it (directly) payoff relevant. The prior probability of an adverse state is $pr(\Delta = \overline{\Delta}) = \delta$.

We next describe the signal generating process and its relation to underlying parameters of the model. Let component s_k of citizen i's signal be distributed according to continuously differentiable marginal density, $f_k(\cdot|k, \Delta)$, where $k \in \{\theta, \omega, \gamma\}$ indicates the unobserved parameter correlated with that component of the signal. f_k has full support on $\mathbb{R}$ for any realization of $k \in \{\theta, \omega, \gamma\}$ and any realization of Δ. To ensure that signal s_k is informative about parameter k we assume that the density f_k has a monotone likelihood ratio (MLR): $\frac{\partial}{\partial s_k}\left(\frac{f_k(s_k|\overline{k}, \Delta)}{f_k(s_k|\underline{k}, \Delta)}\right) > 0$ for any s_k and any Δ (A1). This ensures that higher signals are associated with a higher posterior probability of a $\overline{k}$ and a lower posterior probability of $\underline{k}$. This is a standard assumption employed in signaling models.

Formalizing the impacts of environmental pressure on the signal generating process requires two additional assumptions. In particular let $\frac{\partial}{\partial s_k}\left(\frac{f_k(s_k|\overline{k},\underline{\Delta})}{f_k(s_k|\underline{k},\overline{\Delta})}\right) > 0$ (A2) and $\frac{\partial}{\partial s_k}\left(\frac{f_k(s_k|\overline{k},\overline{\Delta})}{f_k(s_k|\underline{k},\underline{\Delta})}\right) > 0$ (A3). These assumptions generalize MLR to a two-dimensional parameter space: they state that higher signals are associated with a higher posterior probability of $\overline{k}$ *regardless of the realization of* Δ. Informally the realization of parameter k has a greater impact on signals than the realization of Δ. This seems a particularly reasonable pair of assumptions given our emphasis on temperature-related climate impacts rather than large-scale natural disasters. Finally, we assume that $f_k(s_k|k,\underline{\Delta})$ first order stochastically dominates $f_k(s_k|k,\overline{\Delta})$ (A4). This is a weaker assumption than MLR and states only that higher signals are more likely under $\underline{\Delta}$ (low environmental pressure) than under $\overline{\Delta}$ (high environmental pressure).[3]

2.2 Analysis

While the channels of learning we theorize overlap in practice, our theoretical setting enables us to isolate the impacts of each by analyzing the impacts of the three signals sequentially, holding others constant as we do so. First, we consider the impacts of signal s_θ, assuming that both s_ω and s_τ are degenerate so that no learning takes place. To simplify our analysis we also assume for now that $\overline{\tau} = \underline{\tau} = 1$. Denote citizen i's posterior belief about parameter k by β_k. Proposition 1 establishes the core mechanism by which climate impacts shape political perceptions. The proof of this and all subsequent results are included in Appendix A.

Proposition 1. *Following times of high environmental pressure citizens will on average hold worse evaluations of the incumbent:*

$$\mathbb{E}[\beta_\theta|\underline{\Delta}] > \mathbb{E}[\beta_\theta|\overline{\Delta}] \tag{2}$$

Proposition 1 states that adverse environmental pressures will on average undermine citizen views of their incumbent. This result is consistent with studies of retrospective voting in other

[3]There are a number of common distributions which exhibit the properties described above. One intuitive example is to suppose that individual signals correspond to the incumbent's type ($\overline{k}$ or $\underline{k}$) plus a random error ι distributed normally with mean $\mu = \Delta$ and variance σ_ι^2. Let $(\overline{k} - \underline{k}) > (\underline{\Delta} - \overline{\Delta})$. Then our example meets each of conditions (2.1-4) stated above.

contexts (Blankenship et al., 2021; Sinclair et al., 2011). While the empirical literature has often interpreted this through the lens of "irrelevant events"—or simply voter irrationality—our analysis echoes that of Ashworth et al. (2018) in its account of learning under uncertainty (Healy et al., 2010). Citizen preferences are not affected by irrelevant events but rather by events which are systematically correlated with outcomes that matter to them. Poor weather conditions themselves may not be relevant to the choice of leader, but crop failures which are correlated with both climatic conditions and the quality of public irrigation certainly are. Our next result establishes that adverse environmental pressures are further associated with anti-incumbent mobilization. Let ψ^* denote equilibrium rates of citizen mobilization.

Proposition 2. *There exists an equilibrium in which mobilization rates increase following times of high environmental pressure:*

$$\mathbb{E}[\psi_\theta^*|\overline{\Delta}] > \mathbb{E}[\psi_\theta^*|\underline{\Delta}] \tag{3}$$

Proposition 2 builds on Proposition 1: where grievances against an incumbent increase, citizens will be more likely to mobilize against him. Yet there is an added subtlety to the result in the context of collective action since changes in one citizen's evaluation of the incumbent, also shift that citizen's expectations of *others'* grievances and subsequent mobilization decisions. These effects reinforce one another. A citizen who views a negative signal expects that others will also view a negative signal and be more willing to mobilize as a result. Thus the signal not only increases the value of replacing the incumbent but also increases the likelihood that mobilization efforts will succeed.

Next we consider how adverse climate pressures shape mobilization decisions via citizen assessments of state capacity. Weather extremes create new demand for government services, stretching existing resources at the same time that more citizens request assistance. In our empirical case below we emphasize environmental impacts on insecurity and the subsequent uptick in civilian interactions with security services. High temperatures exert powerful physiological effects on human behavior, increasing the likelihood of inter-personal violence and aggression.[4] Higher rates of interpersonal violence increase aggregate demand on (budget constrained) police forces, while simultaneously providing negative signals about the state's ability to regulate citizen behavior and punish infractions.

To analyze this channel of learning let the signal s_ω be informative while s_θ and s_γ are degenerate. Proposition 3 describes when climate impacts support mobilization in this context.

Proposition 3. *Expected mobilization rates will increase following times of high environmental pressure if and only if there is a pre-existing grievance against the incumbent:*

$$\mathbb{E}[\psi_\omega^*|\overline{\Delta}, p_C > p_L] > \mathbb{E}[\psi_\omega^*|\underline{\Delta}, p_C > p_L] \tag{4}$$

Proposition 3 provides an important scope condition for the impacts of learning about state capacity on political mobilization. Where citizens hold identical valuations for incumbent and challenger, there can be no benefit from costly mobilization even if it is successful. Therefore evaluations of state capacity and the likely behavior of others has no impact: not mobilizing is a dominant strategy for all citizens. In contrast, where pre-existing grievances make it desirable to replace an incumbent, climate pressures generate negative signals of state capacity which in turn promote the emergence of political mobilization. The effects of these signals are two-fold: First, a signal of negative state capacity improves a citizen's assessment of the likelihood of successful mobilization. Second, the same signal increases the citizen's expectations of others' willingness to mobilize. Thus is has a direct role via citizen beliefs and an indirect role via its ability to coordinate citizen actions.

Our final proposition establishes an analogous result for signals of pro-sociality in the population. Let $1 > \overline{\tau} > \underline{\tau} > 0$ and suppose that s_γ is informative while the remaining signals are

[4] It is a long-standing empirical regularity in studies of human behavior that the prevalence of aggressive behavior including violent crime surge during periods of above average temperatures (Anderson and Bushman, 2002). This finding has been corroborated across a wide range of geographic and substantive settings. Burke et al. (2015) provide a review and meta analysis of empirical studies of this relationship. For more recent empirical evaluations see *inter alia* Blakeslee et al. (2021); Mares and Moffett (2019) and Stevens et al. (2019).

degenerate.

Proposition 4. *Expected mobilization rates will increase following times of high environmental pressure if and only if there is a pre-existing grievance against the incumbent:*

$$\mathbb{E}[\psi^*_\tau|\overline{\Delta}, p_C > p_L] > \mathbb{E}[\psi^*_\tau|\underline{\Delta}, p_C > p_L] \quad (5)$$

While the logic of Proposition 4 is similar to that of Proposition 3, it is worth emphasizing our assumptions in this case about the signal generating process. In particular, we assume that adverse environmental conditions lead to overall higher signals of citizen prosociality. This runs counter to conventional wisdom about the impacts of scarcity on inter-personal conflict, but intentionally so. Where scarcity leads to greater competition for resources, adverse environmental conditions would make signals of poor pro-sociality more likely. However this is not the only possibility. Adverse environmental conditions may lead to conflict over water resources or to cooperation with neighbors to build new irrigation infrastructure. Natural disasters may lead to competition for scarce food supplies. But neighbors may still work together in parallel to rescue community members from danger or to re-build the community. Whether citizens emerge from difficult times with better or worse assessments of one another's willingness to help is likely to be context-specific. Nonetheless we provide evidence below that at least in some cases, meaningful cooperation can still emerge from hard times.

Appendix A establishes that results analogous to Proposition 2 also hold for citizen learning about state capacity and pro-sociality: in both cases adverse environmental pressures lead to higher rates of mobilization all else equal. Thus all three mechanisms work together in supporting the emergence of political mobilization in the wake of adverse environmental circumstances. In the next sections we describe our empirical strategy for testing these predictions, first establishing the impacts of climate on political behavior and second providing support for the mechanisms highlighted above.

3 Research Design

We test our theory using data from India. Like many countries in the developing world, India faces significant challenges in fostering resilience to climate change. Census data suggest that 60 to 70 percent of India's population lives in rural areas while over half of all Indian people depend on agricultural activities as a primary income source. The Government of India reports evidence of declining agricultural yields—associated with an estimated 3% to 14% reduction in rural incomes—as a direct result of climate change (Government of India, 2018). Indian households also report generally low levels of crop diversification; slow adoption of new agricultural practices; and hurdles to the expansion of irrigation networks—features which exacerbate the problems of adaptation to increasingly extreme heat (Taraz, 2018). This makes India a most likely case for our theory. Yet we note that India is not exceptional among low or lower middle income countries in terms of its economic profile or developmental constraints. For instance, Appendix C analyzes similarities between India and other low and lower-middle income states, supporting the external validity of the findings below.

Two additional features of the Indian political context are of note for our analysis. The first is the salience of religious and ethnic identity in contemporary Indian politics. India is a parliamentary democratic republic which boasts an astonishing number of social cleavages across religion, language, ethnicity, caste, and class. Since the rise to power of the Hindu nationalist Bharatiya Janata Party (BJP) in 2014, Indian elections have been marked by two persistent cleavages: first, the degree to which the state should involve itself in the regulation of social norms and redistribution of wealth; and second the degree to which the state should provide special protections for the rights of marginalized groups against the majoritarian tendencies of mainstream Hindu society (Gulati et al., 2020; Chhibber and Verma, 2018). Although our period of analysis below finishes in 2012, we pay attention to the role of religion and caste in our analysis—the primary predictors of subsequent BJP support—as likely moderators of citizen political views.

The second feature of Indian politics that is relevant for our analysis is its federalist system of authority. India's constitution delineates the powers and responsibilities of governing across its three parliamentary bodies: the Lok Sabha, Vidhan Sabha, and Rajya Sabha. Agriculture in particular is the purview of the state government (Vidhan Sabha), with states responsible for—among other policies—irrigation, water subsidies, loan waivers, and the provision of power. Despite this *de jure* division of labor, the federal government has over time established a role for itself in agricultural governance, promoting adoption of green technologies and new seed varieties as well as incentivizing the production of cereal crops through assured procurement policies (Chatterjee et al., 2022). Thus we expect that state level government will be most relevant for citizens updating on the basis of agricultural outcomes, but we also explore below the possibility that incumbents at the federal level will be similarly affected. While we expect more visible effects on the former, we are agnostic about effects on the latter.

3.1 Data and Variables

Voting and Protest Behavior

For our electoral outcomes we rely on the Indian National and State Elections dataset (Bhavnani, 2014), which covers the period 1977-2015. The data provide constituency-level measures of voter turnout and incumbent party voteshare, for both Vidhan Sabha (state) and Lokh Sabha (national) elections. Lok Sabha elections are held every five years starting in 1952. Vidhan Sabha elections do not take place in the same year for all Indian constituencies. Our data uses the first election in each state after 1976 as the first time period for that observation. We estimate the impacts of climate shocks on two voting-related outcomes: voter turnout and rates of anti-incumbent voting.

We employ geolocated protest data from the Integrated Crisis Early Warning System (ICEWS). The ICEWS relies on real-time data from more than 100 data sources and 250 international and regional newsfeeds. News stories are processed and corroborated by AI technology and humans, and coded for a variety of politically salient events. We aggregate protest event counts by tactic and type (CAMEO event code 14) at the regional district level and month-year of occurrence. Figure B1 in the appendix shows the distribution of events. Protests are rare overall but peaceful protests are more likely than violent ones. Further, although these counts are significantly skewed, the spatial distribution is not highly unequal, indicating that protests are more likely to occur in multiple districts about the same time. Since the resulting count variables are significantly skewed, we employ the logarithm for our analyses.[5]

Public Opinion

In addition to our behavioral tests we also explore the mechanisms of our theory employing successive rounds of the India Human Development Survey (IHDS). The survey design enables us to estimate the within-household impacts of climate variation on attitudes and experiences. The IHDS is a multi-topic panel survey of 41,554 Indian households. The survey is nationally representative with households drawn from 1,503 villages and 971 urban areas. The survey was conducted in two waves with the same households interviewed in both. The first survey period took place from 2004 to 2005; the second from 2011 to 2012. The survey data exhibit very low levels of non-response for all of our questions of interest (2.2%) as well as a low rate of attrition between rounds (1%), although a number of households split into new ones (11%) and (or) move from urban to rural areas and vice versa (30%).[6]

Our analysis relies on the household questionnaire, which inquires about characteristics of each respondent's household. This survey was administered to the head of the household or, if unavailable, the next most senior person. The questionnaire covers a wide range of topics, including social, demographic, and economic characteristics of the household, household members, and household head.[7] It also includes a number of questions related to political, economic, and social views and experiences. We use respondent confidence in state government and the police to measure beliefs about the state and its capacity, respectively.[8]

[5]Poisson and negative binomial models have attractive properties for count variables but they don't address a multitude of other problems that hamstring statistical inference, such as incidental parameters, heterogeneity robustness, necessary variance-covariance matrix adjustments, among other.

[6]In the Appendix we show that our results are robust to accounting for singletons, split households, and migrant households.

[7]All economic variables—income, transfers, and consumption—are converted into constant 2004 prices taking into account spatial variation in the subnational distribution of prices.

[8]We dichotomize all variables so that a one corresponds to "some" or "a great deal" of confidence while zero corresponds to "hardly any" confidence (Table B1). We do so for conceptual reasons as the first two categories are most similar and therefore most likely to be used inter-changeably by respondents. Discussions with survey administrators

To assess the frequency of pro-social behavior in the wake of adverse environmental pressures we employ a question which asks about the frequency of cooperation over water resources within the community. Many citizens in India rely on rainwater, rivers, canals and wells to obtain water. Water cooperation involves mobilizing community labor for constructing and maintaining field channels; for repairing, maintaining and controlling water allocation from community wells and other water sources; and for preventing over-exploitation by owners of private pumps in areas with fragile aquifers (Bardhan, 2000).[9] Table B1 in the Appendix contains the wording of each survey item employed in our analysis as well as the coding of all responses.

Additional tests rely on household responses related to agricultural income, government transfers, consumption, and perceptions of conflict within the community. These are described in more detail in the analysis below and Appendix B. Table A2, in the Appendix, displays the summary statistics for all of the aforementioned variables. The panel exhibits rich variation overall apart from minimal over-representation of rural respondents.

Climate Extremes

We focus on temperature as our key independent variable.[10] Recalling our theoretical analyis we predict that temperature extremes will be associated with greater political mobilization all else equal. Our measure of adverse environmental conditions is constructed from temperature data taken from the University of Delaware's Terrestrial Air Temperature and Precipitation: 1900-2017 Gridded Monthly Time Series (DANTE). This data is widely used in studies of climate impacts

confirm that interviewers do not specify the precise meaning of "state government" but that respondents typically associate "state government" with the Vidhan Sabha (state legislature). An alternative coding which collapses "some" or "hardly any" confidence into the same category does not increase variation captured by our measures and is less straightforward to justify conceptually; nevertheless we explore this alternative in the Appendix.

[9] We note that the effects estimated below are comparatively short-term and decay over time. Our research design therefore limits our ability to make strong assertions about the long-run implications of cooperative shocks on social capital accumulation.

[10] Though we discuss various mediating variables within the theory, our key independent variable in both the theory and empirical analysis is environmental conditions. Conditioning on income for example would not necessarily capture the diverse channels by which environmental pressures can impact economic well-being (for example food scarcity or predicted future earnings). Additionally, in empirical terms conditioning on these mediator variables would induce post-treatment bias. Nonetheless, we perform a demediation analysis (Acharya et al., 2016) in Appendix B , and obtain additional suggestive evidence for our main mechanisms.

(Hsiang et al., 2013). The dataset is made up of temperature measurements in degrees celcius drawn from weather stations around the country and describes grid-cell level daily weather conditions for the past one hundred years.[11]

To construct a measure of temperature extremes we first aggregate local grid point estimates at a 0.5-degree resolution to the month-district level using weighted averages to reflect the (imperfect) overlap of grid cells with district boundaries. (The lowest available geographic identifier in the IHDS data is the district.) Next we calculate the mean deviation in temperature by month and district. Deviations are defined relative to the long-run (50-year) mean where the last year of the long-run average is defined as the year prior to administration of the first IHDS wave. This long-run grid-cell level mean is a standard measurement which is included in the DANTE dataset. For our analysis of electoral outcomes, we construct a similar measure, this time aggregating grid cells to the electoral constituency, as constituencies do not map directly to districts.

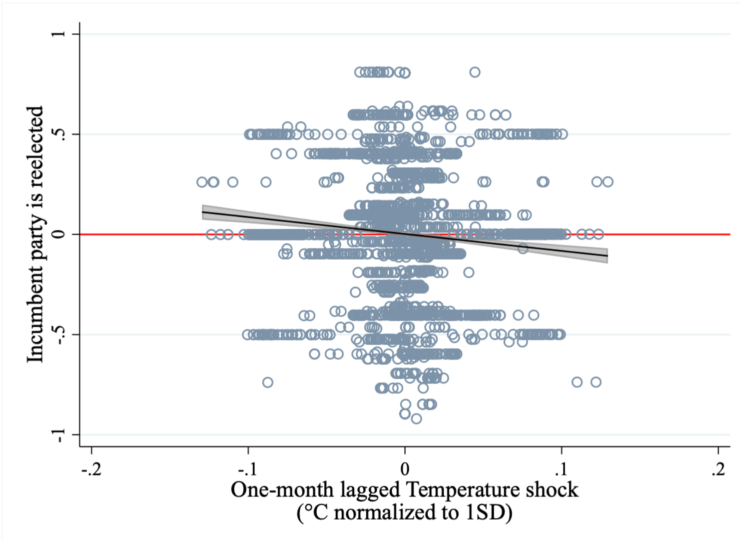
For ease of interpretation we standardize both resulting variables (district and constituency level) so that a one unit increase corresponds to a one standard deviation increase in temperature deviations within district (constituency). We do this to account for variation in both the variability and mean of local climates. As a result of this normalization the implied change (in degrees) of our new variable may vary from one location to the next. Figure B2 in the Appendix, for instance, displays the spatial distribution of temperature shocks as calculated at the district level.

We lag all temperature variables to ensure that outcomes are measured after observed temperature deviations. Rather than imposing assumptions on the lag structure we estimate all models employing up to three monthly lags. We match our lagged measures to households (for the IHDS) and constituencies (for electoral data) using the month-year-district and month-election-constituency triplet, respectively. After residualizing by district and year, we observe a negative correlation between one-month-lagged temperature shocks and voting for the incumbent of -0.10 for state electoral outcomes (Figure 1). We find a positive correlation between temperature and

[11] See Schultz and Mankin (2019) for potential drawbacks to this approach where civil conflict may damage infrastructure. To address this we manually confirm the operability of all weather stations for our period of analysis using the Global Climate Observing System.

turnout (0.10), peaceful protests (0.01), especially for road-obstruction protests (0.03).

Figure 1: Correlation between Temperature and Incumbent Reelection (Vidhan Sabha)



Note: The figure includes 95% confidence bands. We residualize both the y-axis and x-axis variables by controlling for district and year fixed effects.

Additional Covariates

We collect data on a number of variables that may simultaneously impact climate outcomes, political behavior, and public opinion. To proxy for urbanization we use nightlight data from the Defense Meteorological Satellite Program (DMSP) satellite platforms.[12] To measure irrigation we employ self-reported data on access to irrigation from the IHDS, and also use the standard normalized difference vegetation index (NDVI), which is a widely-used and accurate metric for quantifying the health and density of vegetation using satellite data. Further, we capture rainwater runoff, soil moisture and pollution using high-quality data collected from the European Union's Space program, Copernicus, and the NASA's Socioeconomic Data and Applications Center. Finally, we use census data to compute aggregate district-level population characteristics: population size, pop-

[12] We use the composite that estimates gas flaring in billions of cubic meters with intercalibration to reduce measurement error, and increase spatial comparability (https://worldbank.github.io/OpenNightLights/tutorials/mod1_2_introduction_to_nighttime_light_data.html).

ulation density, education, ethnic fragmentation and state capacity.[13] These confounders capture time-variant economic and policy changes, and otherwise insofar as these dimensions respond to man-made socioeconomic transformations. Table A2, in the Appendix, displays the summary statistics.

Inclusion of these variables leads to dramatic loss of observations in the case of political behavior, for example from $> 12,000$ observations to $2,800$ for voting outcomes. For this reason we exclude them from our main results for those outcomes though we include them in the robustness results presented in Appendix B.[14] Since confounders are available for all years of the IHDS panel we include them in our main specification for public opinion outcomes.

3.2 Methods

Given the panel structure of our data, we estimate fixed-effects regressions. First, for our behavioral outcomes—protests and electoral outcomes—we estimate:

$$y_{dt} = Shock_{dt-s}\beta + X_{dt}\delta + \gamma_d + \phi_t + e_{dt},$$

where y_{dt} is the outcome observed in district (constituency) d for the month-year t. $Shock_{dt-s}$ is the month-year weather shock, lagged s months from period t.[15] X is a row-vector of confounders that include variables that may affect climate and behavior. γ_d are district (constituency) fixed effects, which capture any time-invariant confounders; ϕ_t corresponds to the time period fixed effect, and e_{idt} is an stochastic error term. We estimate two-way clustered standard errors at the district (constituency) and election-period levels as treatment uptake is likely to vary along these dimensions.

Second, for our measures of public opinion we estimate:

[13] We use these district-level covariates to confirm robustness of our results only as their inclusion results in significant missingness because they are available for 20 states out of 31.

[14] Results are similar though less precisely estimated in the case of electoral behavior.

[15] Studying the cumulative effect of the shocks is unwarranted as they are unlikely to be independent from one another and thus un-identified and non-commensurable (Blackwell and Glynn, 2018).

$$y_{idt} = Shock_{dt-s}\beta + X_{dt}\delta + \gamma_i + \phi_t + e_{idt},$$

where y_{idt} is the outcome for respondent i, in district d and the month-year of the survey, t. $Shock_{dt-s}$ is the month-year weather shock, lagged s months from the month of interview. X is a row-vector of confounders similar as before. γ_i are household fixed effects; ϕ_t corresponds to a period fixed effect and e_{idt} is a stochastic error term. Similarly as before, we estimate two-way clustered standard errors at the district and survey-wave-year levels; we also drop singletons to reduce the probability of type I error.

For both specifications we test the robustness of our specification to spatial clustering and heterogeneity-robust estimators (Conley, 2010; Roth et al., 2023), among other variations (Appendix B.5).

4 Results

4.1 Behavioral outcomes

First, we consider our behavioral measures of political mobilization. Table 1 displays our main results. The models include all covariates. Each panel corresponds to a different lag between climate shock and interview date, ranging from $t-1$ to $t-3$. We choose not to place strong a priori assumptions on the lag structure of belief updating in our theory, following a range of existing studies which estimate the attitudinal and behavioral impacts of climate in which effects diminish rapidly with time (Burke et al., 2015).

For anti-incumbent voting (Column 1), we look specifically at the probability that the incumbent party is re-elected in either Vidhan Sabha (state). We focus on this measure because in India there is a well-known problem of incumbency disadvantage, which provides strong incentives for parties to remove incumbents from election tickets unless they are popular and closely aligned with the party(Uppal, 2009; Jensenius and Suryanarayan, 2022),[16] All in all, we observe than a one standard deviation shock in the local temperature leads to an statistically significant 7.6PP decline in the likelihood that the incumbent party is re-elected to the Vidhan Sabha. The effect vanishes quickly consistent with similar findings in other contexts (Egan and Mullin, 2017). We also observe a positive and precisely estimated impact of temperature on turnout rates. This effect is longer-lasting persisting for both one and two month lags. We find no effect of temperature shocks on Lok Sabha outcomes (Figure A4).

Next we consider the impacts of our temperature shock variable on protest behavior. We observe few examples of violent protest in the data though a substantively significant rate of non-violent political protest, thus we focus on the latter to avoid standard inference issues with extremely rare events. Non-violent protest behaviors are categorized by tactic, most prominently Traffic Obstructions, Strikes, and Hunger Protests. Traffic obstructions and hunger protests are particularly important for our analysis since they are regularly employed by protesting Indian farmers as a method of garnering national attention. In a recent, high-profile example, the passage of controversial agricultural laws in 2020 led to mass protests in which Indian farmers blocked key railways and highways leading into New Delhi using trucks, tractors, and harvesting equipment. Similar protests involving traffic obstruction ultimately spread throughout the country and even to other countries with significant Sikh populations. Ultimately more than thirty protesters died of exposure while camping on Indian national highways (Rueters, 2021).

Columns 3-5 in Table 1 depicts the results. We observe a positive impact of temperature shocks on for both hunger protests and traffic obstructions, which decays rapidly over time. The effect is statistically significant only in the first period. We observe a negative effect for strikes perhaps reflecting growing economic insecurity among workers in the wake of environmental pressures which may translate into reduced bargaining power with capital owners. Overall we observe that a one standard deviation shock to local temperatures leads to a statistically significant 2.4PP increase in traffic obstructions as means of protesting.

[16] In our data, the incumbent party is re-elected into office 40% of the time, whereas incumbent candidates 20%. Further, we do not find evidence of effects of temperature shocks on the latter.

Table 1: **Impact of a temperature shock on protest and electoral outcomes**

	Electoral outcomes		*Protests*		
	Incumbent reelected	*Turnout rate*	*Obstructions*	*Strikes*	*Hunger*
	(1)	(2)	(3)	(4)	(5)
		a. One month lag			
Shock	-0.076**	0.044***	0.024**	-0.036*	0.023**
	(0.034)	(0.013)	(0.011)	(0.020)	(0.011)
Observations	12692	12692	10330	10330	10330
Fixed effects	Yes	Yes	Yes	Yes	Yes
		b. Two months lag			
Shock	-0.051	0.044***	0.013	-0.025	0.010
	(0.039)	(0.014)	(0.013)	(0.020)	(0.011)
Observations	12692	12692	10331	10331	10331
Fixed effects	Yes	Yes	Yes	Yes	Yes
		c. Three months lag			
Shock	-0.024	-0.009	-0.011	-0.002	-0.011
	(0.067)	(0.024)	(0.013)	(0.020)	(0.014)
Observations	12692	12692	10330	10330	10330
Fixed effects	Yes	Yes	Yes	Yes	Yes

Note: Standard errors are clustered at the constituency and election-period. Coefficients that are significantly different from zero are denoted by the following: *10%, **5%, and ***1%. The main independent variable is a one standard deviation increase in temperature relative to district baseline.

4.2 Public Opinion Data

Next we test the results of our theory related to citizen beliefs and experiences within the community. We predict that climate shocks will exert a negative impact on confidence in state government and the police, but a positive impact on the frequency of cooperation within communities. Table 2 displays our main results controlling for the false-discovery rate induced by multiple hypothesis testing. We find consistent support for our predictions. The coefficients are signed as expected and estimated with precision, especially for shorter lags ($t-1$ and $t-2$). We observe strong recency bias as estimated effects decay quickly over time., which is consistent with the observed nature of climate shocks on opinion (Egan and Mullin, 2017). The magnitude of our estimates are also substantively significant. From approximately seventy thousand households interviewed, a one standard deviation climate shock of is expected to undermine the confidence of more than fifty hundred households—i.e., more than ten thousands working adults—in key government institutions. Likewise we observe an increase in the likelihood of self-reported cooperation to get water by about the same amount.

In Appendix B.3 we provide evidence in favor of the economic mechanisms theorized above. In this regard, we show that loss of confidence in state government is driven by residents in rural areas.[17] We also show that shocks have a negative impact on self-reported agricultural income and self-reported consumption; our measure of temperature shocks has little overall effect on government transfers. We also observe that the effects are driven by non-Hindi and those receiving government support via ration cards, as they are some of the most economically vulnerable individuals in India. Likewise, we investigate the role of non-random assignment of preparedness for environmental shocks, finding that the impacts of environmental exposure are higher in areas with low preparedness. Therefore we find evidence that the effects are driven by those that are most economically-vulnerable to these shocks.

We also probe the role of cooperation in Appendix B.2. We calculate directed controlled effects of climate change for both citizens that report cooperating and not cooperating over water resources. We find that citizens that cooperate report lower levels of conflict and more reliable access to drinking water. Lastly we assess the role of misattribution and bias in citizen learning which is a key feature of rational models of political accountability under uncertainty (Appendix B.4). Consistent with our theory, we find that for those with less information exhibit a stronger negative relationship between environmental pressures and confidence in state government. In contrast, those with the highest levels of information don't exhibit a statistically significant effect.

4.3 Robustness

In Appendix B.5 we describe a number of alternative specifications, variables, and empirical tests which we use to probe the robustness of our core findings. In particular we demonstrate the robustness of the results to: alternative definitions of long-run mean, spatial clustering, and heterogeneity-robust estimators. We also investigate the potential impacts of unobserved con-

[17] We do not carry out a similar analysis for electoral outcomes because constituencies are an amalgamation of both urban and rural areas—with a share of rural population ranging from 0% to 100%, with a median of 75%—and thus we cannot measure with precision voting outcomes for urban or rural areas. Although using night-light as proxy for urbanization we find that political mobilization is more likely in more urbanized areas, this result is not robust to using the share of rural population as a proxy for urbanization—hence evidence in this regard is inconclusive at best.

Table 2: Impact of a temperature shock on citizens' confidence in government institutions

	Confidence in state government	*Confidence in police*	*Cooperation to get water*
	(1)	(2)	(3)
a. One month lag			
Shock	-0.079***	-0.078***	0.083**
	(0.027)	(0.024)	(0.030)
R-squared	0.512	0.549	0.532
Observations	68524	69112	69454
Fixed effects	Yes	Yes	Yes
Controls included	Yes	Yes	Yes
b. Two months lag			
Shock	-0.076***	-0.058*	0.096**
	(0.024)	(0.029)	(0.037)
R-squared	0.513	0.549	0.529
Observations	68542	69130	69472
Fixed effects	Yes	Yes	Yes
Controls included	Yes	Yes	Yes
c. Three months lag			
Shock	-0.036	-0.034	0.072
	(0.027)	(0.033)	(0.051)
R-squared	0.514	0.549	0.529
Observations	68474	69062	69404
Fixed effects	Yes	Yes	Yes
Controls included	Yes	Yes	Yes

Note: Standard errors are clustered at the constituency and survey-year. Coefficients that are significantly different from zero are denoted by the following: *10%, **5%, and ***1%. Covariates include household and year fixed effects, night-light density, pollution, soil moisture, runoff and vegetation. The main independent variable is a one standard deviation increase in temperature relative to district baseline.

founding variables via sensitivity analysis, and parameter stability to the exclusion of districts and constituencies. For our individual-level outcomes, we also assess robustness to different measurement of our outcomes, selective attrition out of sample, and for support for other institutions. Across the board we find consistent support for our theoretical predictions and the robustness of our empirical results.

5 Discussion and Conclusions

While the current work emphasizes the role of temperature abnormalities, the inferential dynamics we describe are not limited to these circumstances. Natural disasters of all kinds provide opportunities for citizens to revise their political beliefs. In the wake of historic flooding during the 2022

Monsoon season, Pakistani citizens learned just how badly they had been served by an incumbent government which had for years under-invested in emergency preparedness, infrastructural quality, and even telecommunications networks (Baloch, 2022; Kugelman, 2022).[18] Similarly, following a record-breaking earthquake in Turkey the following year, headlines declared that "An act of God caused the earthquake in Turkey – murderous corruption caused so many deaths" (Letsch, 2023). The corruption in question referred to widespread deficiencies in government permitting and licensing for construction activities which resulted in the collapse of thousands newly-built residential buildings (Letsch, 2023). Related within the United States, on the heels of apocalyptic-like conditions induced by historic wildfires across Canada's east coast, Republican politicians seized the opportunity to criticize liberal politicians for their handling of forestry policy, intentionally casting doubt on the causal processes responsible for poor air quality across the eastern seaboard.[19]

Natural disasters such as those just described often receive disproportionate media coverage and popular interest. Still, there may be particular value in considering how the full range of environmental pressures associated with climate change—especially temperature—are likely to reshape citizen beliefs and resulting political behavior. Climate change represents a secular evolution in environmental conditions for societies around the world, a trend which is unprecedented in human history. Societies which have adapted over millennia to particular geographic and climatic conditions will soon face conditions far outside of their historical experience. While some predicted changes will be dramatic, others will occur slowly and remain largely unnoticed by populations with low rates of climate change awareness or understanding. Under these conditions, growing demand for state services combined with the inferential challenges we identify pose a significant threat to the stability and well-being of societies across the global south. While there is more work to be done, this paper takes a first step towards investigating what these pressures mean

[18] In the immediate aftermath of flooding, millions of Pakistani citizens were left without telecommunications access as rising waters revealed critical weaknesses in the design of national IT infrastructure (Rashid et al., 2022).

[19] When asked about a link between climate change and the Canadian wildfires, Sen Tommy Tuberville (R-Ala) scoffed: "We've had fires for all of our life, come on...this is just another situation where you've gotta do your work in forests" (D'Angelo and Bobic, 2023).

for citizens and the political systems they inhabit.

References

Acharya, A., Blackwell, M., and Sen, M. (2016). Explaining causal findings without bias: Detecting and assessing direct effects. *The American Political Science Review*, 110(3):512.

Anderson, C. A. and Bushman, B. J. (2002). Human aggression. *Annual review of psychology*, 53(1):27–51.

Ashworth, S., Bueno de Mesquita, E., and Friedenberg, A. (2018). Learning about voter rationality. *American Journal of Political Science*, 62(1):37–54.

Asselin, L.-M. (2009). *Analysis of multidimensional poverty: Theory and case studies*, volume 7. Springer Science & Business Media.

Balcazar, C. F. and Redaelli, S. (2017). Measuring housing deprivation: Methodology and an application to afghanistan. *Mimeo World Bank*.

Baloch, K. (2022). Pakistan's floods are a man-made disaster. *The Diplomat*.

Bardhan, P. (2000). Irrigation and cooperation: An empirical analysis of 48 irrigation communities in south india. *Economic Development and cultural change*, 48(4):847–865.

Barreca, A., Deschenes, O., and Guldi, M. (2018). Maybe next month? temperature shocks and dynamic adjustments in birth rates. *Demography*, 55(4):1269–1293.

Bechtel, M. M. and Hainmueller, J. (2011). How lasting is voter gratitude? an analysis of the short-and long-term electoral returns to beneficial policy. *American journal of political science*, 55(4):852–868.

Bhavnani, R. R. (2014). India National and State Election Dataset.

Birkmann, J., Liwenga, E., Pandey, R., Boyd, E., Djalante, R., Gemenne, F., Filho, W. L., Pinho, P., Stringer, L., and Wrathall, D. (2022). *Poverty, Livelihoods and Sustainable Development*, pages 1171–1274. Cambridge University Press, Cambridge, UK and New York, USA.

Blackwell, M. and Glynn, A. N. (2018). How to make causal inferences with time-series cross-sectional data under selection on observables. *American Political Science Review*, 112(4):1067–1082.

Blakeslee, D., Chaurey, R., Fishman, R., Malghan, D., and Malik, S. (2021). In the heat of the moment: Economic and non-economic drivers of the weather-crime relationship. *Journal of Economic Behavior & Organization*, 192:832–856.

Blankenship, B., Kennedy, R., Urpelainen, J., and Yang, J. (2021). Barking up the wrong tree: How political alignment shapes electoral backlash from natural disasters. *Comparative Political Studies*, 54(7):1163–1196.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Climate and Conflict. *Annual Review of Economics*, 7(1):577–617.

Carleton, T. A. and Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, 353(6304):aad9837.

Chatterjee, S., Kapur, D., Sekhsaria, P., and Subramanian, A. (2022). Agriculture federalism: New facts, constitutional vision. *Chatterjee, S., Kapur, D., Sekhsaria, P., & Subramanian, S.(2022). Agricultural Federalism New Facts, Constitutional Vision. Economic and Political Weekly*, 57(36):39–48.

Chhibber, P. K. and Verma, R. (2018). *Ideology and identity: The changing party systems of India*. Oxford University Press.

Conley, T. G. (2010). Spatial econometrics. In *Microeconometrics*, pages 303–313. Springer.

D'Angelo, C. and Bobic, I. (2023). Under apocalyptic skies, republicans blow smoke on climate change. *Huffington Post*.

Egan, P. J. and Mullin, M. (2017). Climate Change: US Public Opinion. *Annual Review of Political Science*, 20:209–227.

Government of India (2018). *Economic Survey of India,2017–18, vol. 1*, chapter Climate, climate change and agriculture, pages 100–119. Government of India, Ministry of Finance.

Grossman, G., Michelitch, K., and Prato, C. (2024). The effect of sustained transparency on electoral accountability. *American Journal of Political Science*, 68(3):1022–1040.

Grossman, G. and Slough, T. (2022). Government responsiveness in developing countries. *Annual Review of Political Science*, 25(1):131–153.

Gulati, A., Kapur, D., and Bouton, M. M. (2020). Reforming indian agriculture. *Economic & Political Weekly*, 55(11):35–42.

Healy, A. and Malhotra, N. (2009). Myopic voters and natural disaster policy. *American Political Science Review*, 103(3):387–406.

Healy, A. J., Malhotra, N., and Mo, C. H. (2010). Irrelevant events affect voters' evaluations of government performance. *Proceedings of the National Academy of Sciences*, 107(29):12804–12809.

Heutel, G., Miller, N. H., and Molitor, D. (2021). Adaptation and the mortality effects of temperature across us climate regions. *Review of Economics and Statistics*, 103(4):740–753.

Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367.

Jensenius, F. R. and Suryanarayan, P. (2022). Party system institutionalization and economic voting: Evidence from india. *The Journal of Politics*, 84(2):814–830.

Kapur, D. (2020). Why does the indian state both fail and succeed? *Journal of Economic Perspectives*, 34(1):31–54.

Kolenikov, S. and Angeles, G. (2009). Socioeconomic status measurement with discrete proxy variables: Is principal component analysis a reliable answer? *Review of Income and Wealth*, 55(1):128–165.

Kugelman, M. (2022). How bad governance exacerbated pakistan's flooding. *Foreign Policy*.

Lee, M. M. and Zhang, N. (2017). Legibility and the informational foundations of state capacity. *The Journal of Politics*, 79(1):118–132.

Letsch, C. (2023). An act of god caused the earthquake in turkey—murderous corruption caused so many deaths. *The Guardian*.

Little, A. T., Tucker, J. A., and LaGatta, T. (2015). Elections, protest, and alternation of power. *The Journal of Politics*, 77(4):1142–1156.

Lüdeke, M. K., Walther, C., Sterzel, T., Kok, M. T., Lucas, P., Janssen, P., and Hilderink, H. (2014). Understanding change in patterns of vulnerability.

Mach, K. J., Kraan, C. M., Adger, W. N., Buhaug, H., Burke, M., Fearon, J. D., Field, C. B., Hendrix, C. S., Maystadt, J. F., O'Loughlin, J., Roessler, P., Scheffran, J., Schultz, K. A., and von Uexkull, N. (2019). Climate as a risk factor for armed conflict. *Nature*, 571(7764):193–197.

Mares, D. M. and Moffett, K. W. (2019). Climate change and crime revisited: An exploration of monthly temperature anomalies and ucr crime data. *Environment and Behavior*, 51(5):502–529.

Rashid, N., Sheikh, M., and Khan, A. (2022). Pakistan disconnected: Understanding the fragility of our mobile network in the wake of the 2022 floods. *Tabad Lab*.

Roth, J., Sant'Anna, P. H., Bilinski, A., and Poe, J. (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244.

Rueters (2021). Timeline: Indian farmers' yearlong protests against farm laws. *Al Jazeera*.

Schultz, K. A. and Mankin, J. S. (2019). Is temperature exogenous? the impact of civil conflict on the instrumental climate record in sub-saharan africa. *American Journal of Political Science*, 63(4):723–739.

Shadmehr, M. and Bernhardt, D. (2011). Collective action with uncertain payoffs: coordination, public signals, and punishment dilemmas. *American Political Science Review*, 105(4):829–851.

Sinclair, B., Hall, T. E., and Alvarez, R. M. (2011). Flooding the vote: Hurricane katrina and voter participation in new orleans. *American politics research*, 39(5):921–957.

Somanathan, E., Somanathan, R., Sudarshan, A., and Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy*, 129(6):1797–1827.

Stevens, H. R., Beggs, P. J., Graham, P. L., and Chang, H.-C. (2019). Hot and bothered? associations between temperature and crime in australia. *International journal of biometeorology*, 63:747–762.

Taraz, V. (2018). Can farmers adapt to higher temperatures? evidence from india. *World Development*, 112:205–219.

Tol, R. S. (2019). Vu research portal. *Energy Economics*, 82:1–3.

Uppal, Y. (2009). The disadvantaged incumbents: estimating incumbency effects in indian state legislatures. *Public choice*, 138(1-2):9–27.

Online Appendix

A Proofs

Proof of Proposition 1

Proof. Citizen i's posterior belief given signal s_θ is,

$$\beta_\theta = pr(\overline{\theta}|s_\theta) = \frac{1}{1+\xi} \tag{A.1}$$

where,

$$\xi = \frac{(1-p)}{p} \cdot \frac{\delta f_\theta(s_\theta|\underline{\theta},\overline{\Delta}) + (1-\delta) f_\theta(s_\theta|\underline{\theta},\underline{\Delta})}{\delta f_\theta(s_\theta|\overline{\theta},\overline{\Delta}) + (1-\delta) f_\theta(s_\theta|\overline{\theta},\underline{\Delta})} \tag{A.2}$$

Re-arranging gives,

$$\xi = \frac{(1-p)}{p} \cdot \left[\left(\frac{f_\theta(s_\theta|\overline{\theta},\overline{\Delta})}{f_\theta(s_\theta|\underline{\theta},\overline{\Delta})} + \frac{(1-\delta)}{\delta} \cdot \frac{f_\theta(s_\theta|\overline{\theta},\underline{\Delta})}{f_\theta(s_\theta|\underline{\theta},\overline{\Delta})} \right)^{-1} + \left(\frac{f_\theta(s_\theta|\overline{\theta},\overline{\Delta})}{f_\theta(s_\theta|\underline{\theta},\underline{\Delta})} + \frac{(1-\delta)}{\delta} \cdot \frac{f_\theta(s_\theta|\overline{\theta},\underline{\Delta})}{f_\theta(s_\theta|\underline{\theta},\underline{\Delta})} \right)^{-1} \right] \tag{A.3}$$

By assumptions A1-A3 in the main text, each of the component ratios above increases monotonically in s_θ implying a corresponding increase in β_θ. Let β be a function which maps signals to posteriors, $\beta : s_\theta \to (0,1)$. Then β is monotonically increasing in s_θ. Finally given A4 (stochastic dominance) the expected signal given $\underline{\Delta}$ is higher than under $\overline{\Delta}$: $\mathbb{E}[s_\theta|\underline{\Delta}] > \mathbb{E}[s_\theta|\overline{\Delta}]$. But since $\beta(s_\theta)$ is monotonic we also have,

$$\mathbb{E}[\beta(s_\theta)|\underline{\Delta}] > \mathbb{E}[\beta(s_\theta)|\overline{\Delta}] \tag{A.4}$$

□

Proof of Proposition 2

Proof. Consider a symmetric cutpoint equilibrium strategy s^* such that any citizen observing $s_\theta < s^*$ chooses to mobilize and the rest remain home. After observing s_θ, it is optimal for citizen i to mobilize if and only if,

$$\mathbb{E}_\omega \left[\mathbb{E}_\theta \left[\phi(\psi,\omega),\omega)(\theta_C - \theta_L)|s_\theta, s^*\right]\right] \geq c \tag{A.5}$$

or

$$\mathbb{E}_\omega \left[\phi\left(\mathbb{E}_\theta\left[\psi|s_\theta, s^*, \omega\right], \omega\right)\right] \cdot (p - \beta(s_\theta)) \geq c \tag{A.6}$$

where, as above $\beta(s_\theta)$, is the posterior probability the incumbent is a high type given signal s_θ. Note that if $\beta(s_\theta) \geq p$ then citizen i has a dominant strategy to not mobilize as he prefers the incumbent remain in office regardless of others' actions.

To establish optimality of s^* we first show the left hand side is monotonic in the signal, s_θ, on the interval $(-\infty, s^p)$ where we define s^p as the signal which leaves the citizen with exactly his prior belief: $\beta(s^0) = p$. The proof of Proposition 1 establishes that $\beta(s_\theta)$ is increasing in s_θ so $(p - \beta(s_\theta))$ is decreasing globally. Next consider expected turnout under equilibrium strategy s^* and signal s_θ for any ω. This is,

$$\mathbb{E}_\theta\left[\psi|s_\theta, s^*, \omega\right] = \beta(s_\theta)\int_{-\infty}^{s^*} f(t|\overline{\theta},\omega)dt + (1-\beta(s_\theta))\int_{-\infty}^{s^*} f(t|\underline{\theta},\omega)dt \tag{A.7}$$

Assumption A1 in the main text ensures that $f(s|\overline{\theta},\omega)$ first order stochastically dominates $f(s|\underline{\theta},\omega)$. Thus as $\beta(s_\theta)$ increases (A.7) as a whole decreases. Since $\phi_1 > 0$ we conclude that the left hand side of (A.6) is decreasing in the signal s_θ for all signals below s^0. Thus if type $s_\theta = s^* < s^0$ is indifferent between mobilizing and not, then the equilibrium strategy is optimal for all remaining citizens.

Next we establish existence of s^* such that equation (A.6) holds with equality. Define a function

$g(s^*)$ as follows,

$$g(s^*) = \mathbb{E}_\omega \left[\phi\left(\mathbb{E}_\theta\left[\psi | s_\theta = s^*, s^*, \omega\right], \omega\right)\right] \cdot \left(p - \beta(s^*)\right) \tag{A.8}$$

Note that $g(\cdot)$ is continuous in its argument. We'll argue that there exist a pair $(\bar{s}, \underline{s})$ such that $lim_{s \to \bar{s}} g(s^*) < c$ and $lim_{s \to \underline{s}} g(s^*) > c$. For the former set $\bar{s} = s^0$. As $s^* \to s^0$ expected turnout is bounded above while $p - \beta(s^*)$ approaches zero. So $lim_{s^* \to \bar{s}} g(s^*) = 0 < c$ as desired. For the lower bound, pick any $\underline{s} \in (-\infty, s^0)$. The limit of $g(s^*)$ as $s^* \to \underline{s}$ is,

$$\lim_{s^* \to \underline{s}} g(s^*) = \mathbb{E}_\omega \left[\phi\left(\left(\beta(\underline{s} \int_{-\infty}^{\underline{s}} f(t|\overline{\theta}, \omega) + (1 - \beta(\underline{s}) \int_{-\infty}^{\underline{s}} f(t|\underline{\theta}, \omega)\right), \omega\right)\right] \left(p - \beta(\underline{s})\right) \tag{A.9}$$

Since $\underline{s} < s^0$ we have $(p - \beta(\underline{s})) > 0$. Expected turnout is also strictly positive so $g(\underline{s}) > 0$. By continuity of g there exists a $c(\underline{s})$ such that $g(\underline{s}) > c(\underline{s}) > 0$ as required. By the intermediate value theorem there exists an $s^* \in (\underline{s}, s^0)$ such that equation (A.6) holds with equality and the resulting s^* is a symmetric equilibrium of the game.

To establish the result note that by assumption A4 $f(s|\theta, \underline{\Delta})$ first order stochastically dominates $f(s|\theta, \overline{\Delta})$. So holding incumbent type and equilibrium strategy constant, the expected signal is worse during times of high environmental pressure implying greater turnout:

$$\mathbb{E}[\psi|\theta, \overline{\Delta}, s^*] = \int_{-\infty}^{s*} f(s|\theta, \overline{\Delta}) \tag{A.10}$$

$$> \int_{-\infty}^{s*} f(s|\theta, \underline{\Delta}) \tag{A.11}$$

$$= \mathbb{E}[\psi|\theta, \underline{\Delta}, s^*] \tag{A.12}$$

□

Proof of Proposition 3

Proof. For equilibrium strategy s^* citizen i optimally mobilizes if and only if,

$$\mathbb{E}_\theta\left[\mathbb{E}_\omega\left[\phi(\psi,\omega)\left(\theta_C-\theta_L\right)|s_\omega,s^*,\theta\right]\right]>c \tag{A.13}$$

or, since s is uninformative about θ_L,

$$\mathbb{E}_\theta\left[\mathbb{E}_\omega\left[\phi(\psi,\omega)|s_\omega,s^*,\theta\right]\right]\cdot(p_C-p_L)>c \tag{A.14}$$

Note that if $p_C = p_L$ then no citizen has incentive to mobilize regardless of their estimations of state capacity as they expect no difference between their welfare under the challenger as under the incumbent. In the absence of grievances, learning about state capacity does not impact mobilization.

Now suppose that $p_C > p_L$ so that there exists a prior grievance against the incumbent. We first argue that the expected utility of mobilizing is monotonic in signal s_ω. Consider the expected probability that mobilization is successful,

$$\mathbb{E}_\omega\left[\phi(\psi,\omega)|s_\omega,s^*,\theta\right]=\beta(s_\omega)\phi\left(\left(\int_{-\infty}^{s^*}f(t|\theta,\overline{\omega})dt\right),\overline{\omega}\right)+(1-\beta(s_\omega))\,\phi\left(\left(\int_{-\infty}^{s^*}f(t|\theta,\underline{\omega})dt\right),\underline{\omega}\right) \tag{A.15}$$

By identical arguments to Proposition 1 $\beta(s_\omega)$ is increasing in its argument. Moreover by assumption A1 in the main text $f(s|\theta,\overline{\omega})$ first order stochastically dominates $f(s|\theta,\underline{\omega})$. Thus the expected probability of successful mobilization - and therefore expected utility from mobilization - is decreasing in the signal, s_ω. Then if there is a signal s^* such that the citizen observing s^* is indifferent between mobilizing and not, then it is optimal for all other citizens to follow the equilibrium strategy.

To show existence of s^* note that,

$$\lim_{s^*\to\infty} g(s^*) = \mathbb{E}_\theta\left[\phi\left(\int_{-\infty}^{\infty} f(t|\theta,\overline{\omega}),\overline{\omega}\right)\right](p_C - p_L) \tag{A.16}$$

$$= p_C - p_L \tag{A.17}$$

So $p_C - p_L > c$ ensures that $lim_{s^*\to\infty} g(s^*) > c$. Next, note that,

$$\lim_{s^*\to-\infty} g(s^*) = \mathbb{E}_\theta\left[\phi\left(0,\underline{\omega}\right)\right](p_C - p_L) \tag{A.18}$$

$$= 0 \tag{A.19}$$

So $lim_{s^*\to\infty} g(s^*) = 0 < c$. By the intermediate value theorem then there exists an s^* such that a citizen observing s^* is indifferent between mobilizing and not. Finally as in Proposition 2 first order stochastic dominance of $f(s|\omega,\Delta)$ (A4) establishes the proposition.

□

Proof of Proposition 3

Proof. With $\overline{\tau} > \underline{\tau}$ an equilibrium strategy is a pair of type-specific cutpoints (s^H, s^L). Any citizen of type τ observing $s > s^\tau$ will mobilize while others stay home. Suppose that $s^L > s^H$ indicating a greater propensity to mobilize for high types. A citizen of type τ_i optimally mobilizes if and only if,

$$\mathbb{E}_\omega\left[\mathbb{E}_\theta\left[\mathbb{E}_\gamma\left[\phi(\psi,\omega)\tau_i(\theta_C - \theta_L)|s_\gamma\right]\right]\right] \geq c \tag{A.20}$$

or,

$$\mathbb{E}_\omega\left[\mathbb{E}_\theta\left[\phi(\mathbb{E}[\psi|s_\gamma,(s^L,s^H)],\omega)\right]\right]\tau_i(p_C - p_L) \geq c \tag{A.21}$$

The signal affects the benefits of mobilization only via expected turnout. Conditioning on (θ, ω) this is,

$$\mathbb{E}_{\gamma}[\psi | s_{\gamma}, (s^L, s^H), \theta, \omega] = \beta(s_{\gamma}) \left[\overline{\gamma} \int_{s^H}^{\infty} f(t|\theta, \omega) dt + (1 - \overline{\gamma}) \int_{s^L}^{\infty} f(t|\theta, \omega) dt \right] + \tag{A.22}$$

$$\big(1 - \beta(s_{\gamma})\big) \left[\underline{\gamma} \int_{s^H}^{\infty} f(t|\theta, \omega) dt + (1 - \underline{\gamma}) \int_{s^L}^{\infty} f(t|\theta, \omega) dt \right] \tag{A.23}$$

By the same arguments as Proposition 1 $\beta(s_{\gamma}$ is increasing in the signal s_{γ}. Since $\overline{\gamma} > \underline{\gamma}$ and $s^L > s_H$ expected turnout is increasing in s_{γ}. So if (s^H, s^L) are indifferent types with $s^L > s^H$ then the equilibrium strategy profile is optimal for all citizens. To confirm our conjecture consider the indifferent type defined by equality,

$$\mathbb{E}_{\omega} \left[\mathbb{E}_{\theta} \left[\phi(\mathbb{E}[\psi | s_{\gamma}, (s^L, s^H)], \omega) \right] \right] \tau_i (p_C - p_L) = c \tag{A.24}$$

Since expected turnout is increasing in s_{γ} and $\overline{\tau} > \underline{\tau}$ it must be that the indifferent type $\overline{\tau}$ observes a lower signal than indifferent type $\underline{\tau}$. So $s^L > s^H$.

To establish existence define $g(s^H)$ as,

$$g(s^H) = \mathbb{E}_{\omega} \left[\mathbb{E}_{\theta} \left[\phi(\mathbb{E}[\psi | s^H, (s^L, s^H)], \omega) \right] \right] \overline{\tau} (p_C - p_L) \tag{A.25}$$

for the high types threshold and analogously for the low type. Consider again the expected turnout component of $g(s^H)$,

$$\mathbb{E}_{\gamma}[\psi | s^H, (s^L, s^H), \theta, \omega] = \beta(s^H) \left[\overline{\gamma} \int_{s^H}^{\infty} f(t|\theta, \omega) dt + (1 - \overline{\gamma}) \int_{s^L}^{\infty} f(t|\theta, \omega) dt \right] + \tag{A.26}$$

$$\big(1 - \beta(s^H)\big) \left[\underline{\gamma} \int_{s^H}^{\infty} f(t|\theta, \omega) dt + (1 - \underline{\gamma}) \int_{s^L}^{\infty} f(t|\theta, \omega) dt \right] \tag{A.27}$$

As $s^H \to -\infty$ this quantity approaches $\underline{\gamma} + (1 - \underline{\gamma}) \int_{s^L}^{\infty} f(t|\theta, \omega) dt \equiv c^H$. As $c^H \to \infty$ it must also be the case that $s^L \to \infty$ since s^L is strictly larger in any equilibrium. So expected turnout approaches $0 < c$.

Consider the analogous exercise for the low type. Expected turnout is,

$$\mathbb{E}_{\gamma}[\psi|s^L,(s^L,s^H),\theta,\omega] = \beta(s^L)\left[\overline{\gamma}\int_{s^H}^{\infty} f(t|\theta,\omega)dt + (1-\overline{\gamma})\int_{s^L}^{\infty} f(t|\theta,\omega)dt\right] + \tag{A.28}$$

$$\left(1-\beta(s^L)\right)\left[\underline{\gamma}\int_{s^H}^{\infty} f(t|\theta,\omega)dt + (1-\underline{\gamma})\int_{s^L}^{\infty} f(t|\theta,\omega)dt\right] \tag{A.29}$$

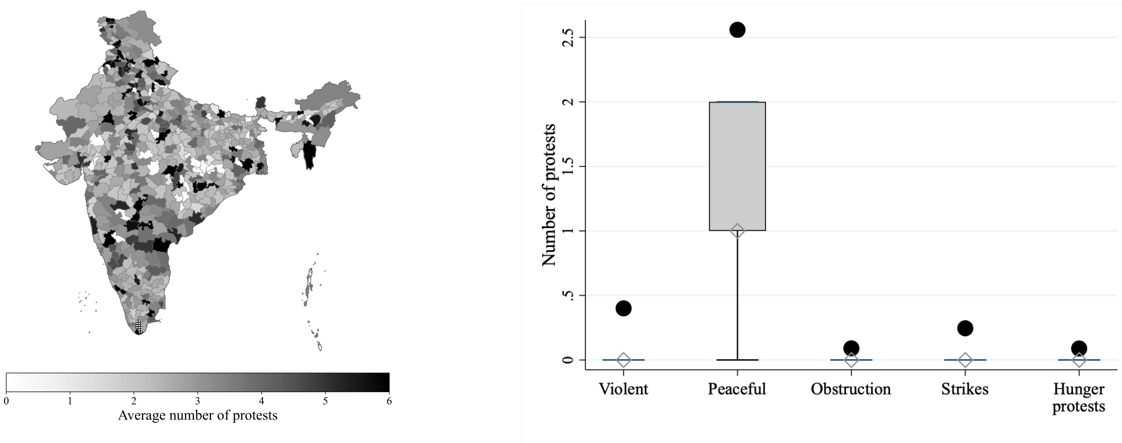
As $s^L \to \infty$ expected turnout approaches $\overline{\gamma}\int_{s^H}^{\infty} f(t|\theta,\omega)dt \equiv c^L$. As $s^L \to -\infty$ it must also be that $s^H \to -\infty$. So expected turnout approaches $1 > c$. Noting that $c^H > c^L$ setting $c \in (c^L, c^H)$ establishes existence of both indifferent types. $\square$

B Empirical appendix

B.1 Descriptives

Figure B. 1: Distribution of protest counts

(a) Spatial distribution **(b) Box plot**



Note: The maxima for the type of protests are 42, 277, 10, 4, 8, 51, 97, from left to right in panel b, respectively.

Figure B. 2: Distribution of average temperature shock

(a) Spatial distribution **(b) Kernel density distribution**

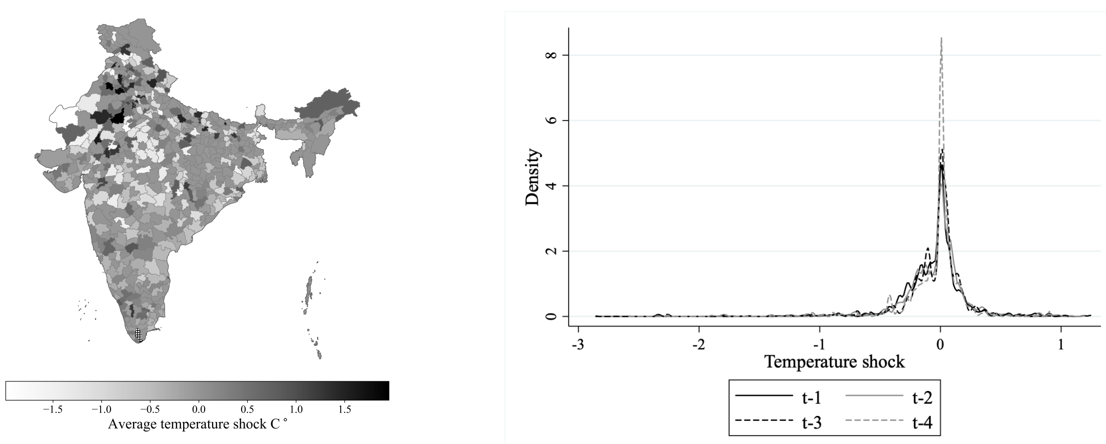
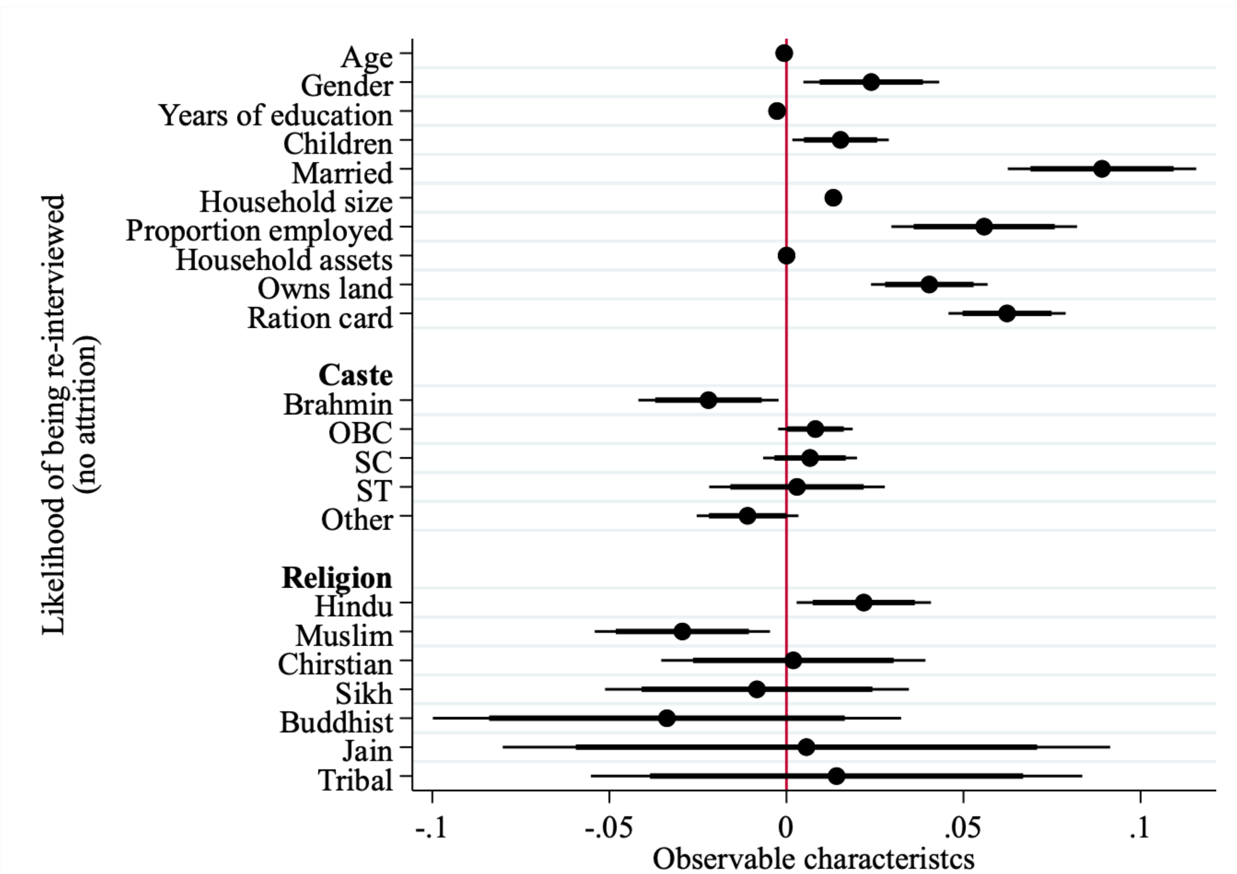


Figure B. 3: Balance check for attrition



Note: 90% and 95% confidence intervals wherein standard errors are spatially clustered using a 500km bandwidth.The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Table B. 1: Public opinion questions in IHDS

Variable name	Question	Options	Value	Share
Conflict between inhabitants	In this village/neighborhood, do people generally get along with each other or is there some conflict or a lot of conflict.	No conflict	0	65.4
		Some conflict	1	28
		Lot of conflict	1	6.6
Cooperation to get water	In some communities, when there is a water supply problem, people bond together to solve the problem. In other communities, people take care of their own families individually. What is your community like.	Solves individually	0	35.4
		Bond together	1	64.6
Conflict between communities	In this village/neighborhood, how much conflict would you say there is among the communities/jatis that live here.	No conflict	0	56.1
		Some conflict	1	30.3
		Lot of conflict	1	13.6
Confidence politicians	Confidence in politicians to fulfill promises.	Hardly any confidence at all	0	54.6
		Only some confidence	1	35.2
		A great deal of confidence	1	10.2
Confidence police	Confidence in the police to enforce the law.	Hardly any confidence at all	0	25.9
		Only some confidence	1	50.1
		A great deal of confidence	1	24
Confidence state government	Confidence in the state government to look after the people.	Hardly any confidence at all	0	21.9
		Only some confidence	1	50.5
		A great deal of confidence	1	27.6
Confidence news	Confidence in newspapers to print the truth.	Hardly any confidence at all	0	8.5
		Only some confidence	1	51.5
		A great deal of confidence	1	40
Confidence village government	Confidence in village panchayats/nagarpalika to implement public projects.	Hardly any confidence at all	0	19.6
		Only some confidence	1	49.5
		A great deal of confidence	1	31
Confidence schools	Confidence in schools to provide good education.	Hardly any confidence at all	0	8.6
		Only some confidence	1	33.9
		A great deal of confidence	1	57.5
Confidence hospitals	Confidence in hospitals and doctors to provide good treatment.	Hardly any confidence at all	0	10.7
		Only some confidence	1	35.9
		A great deal of confidence	1	53.3

Note: Additional information can be found at https://www.icpsr.umich.edu/web/DSDR/studies/22626 and https://www.icpsr.umich.edu/web/DSDR/studies/36151

Table B. 2: Summary statistics

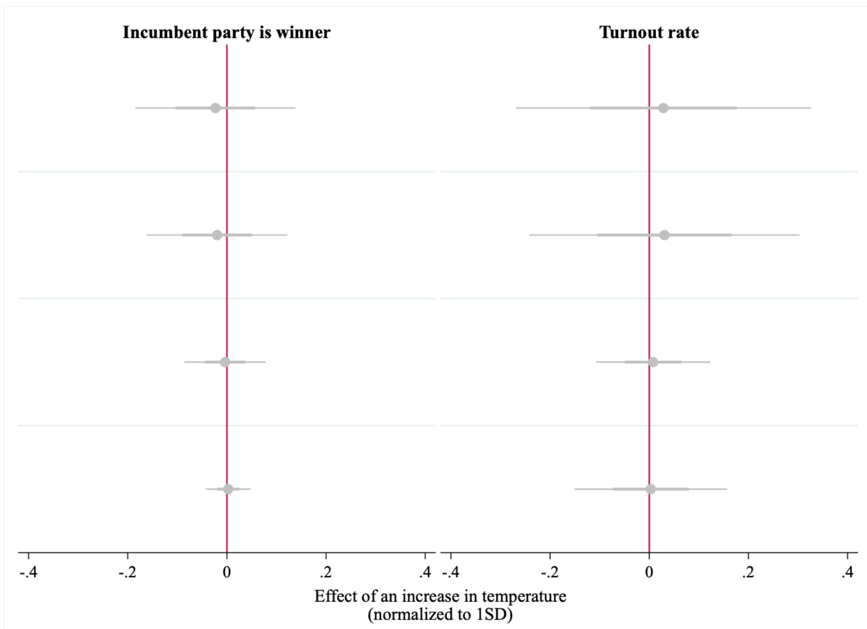
	Mean	Standard deviation	Min	Max	Median	Obs.
IHDS round (% second round)	0.47	0.5	0	1	0	75649
Confidence in institutions						
State government (%)	0.78	0.41	0	1	1	74920
Police (%)	0.74	0.44	0	1	1	75230
Politicians (%)	0.45	0.5	0	1	0	75280
Village government (%)	0.8	0.4	0	1	1	74855
News (%)	0.91	0.28	0	1	1	72556
Conflict/cooperation						
Cooperation (%)	0.65	0.48	0	1	1	75424
Conflict between communities	0.35	0.48	0	1	0	75341
Conflict between communities	0.44	0.5	0	1	0	75358
Indexes						
Confidence in government	0.75	0.24	0	1	0.8	75470
Confidence in security forces	0.75	0.24	0	1	0.8	75470
Conflict/cooperation	0.47	0.24	0	1.4	0.4	75563
Economic characteristics						
Household consumption (thou. rupees, 2005=100)	0	0.01	0	0.43	0	75569
Farming income (thou. rupees, 2005=100)	0.01	0.03	-0.32	1.6	0	75648
Government transfers (thou. rupees, 2005=100)	0	0	0	0.18	0	75648
Temperature shock:						
t-1	-0.12	1	-3.09	2.44	-0.11	74975
t-2	-0.01	1	-2.35	2.34	-0.02	74975
t-3	0.05	1	-2.62	2.26	0.04	74975
t-4	0.07	1	-2.82	2.44	0.12	74975
Media consumption						
Listens radio	0.64	0.48	0	1	1	74677
Watches tv	0.62	0.49	0	1	1	74619
Reads news	0.63	0.48	0	1	1	74595

Table B. 3: Summary statistics

	Mean	Standard deviation	Min	Max	Median	Obs.
District-level covariates						
Average nighlight intensity, pre-shock	8.77	11.64	0.07	62.88	5.39	75649
Presence of irrigation, pre-shock (%)	0.21	0.41	0	1	0	75649
NDVI index	138.38	39.62	53.74	255	134.06	65467
Pollution	56.42	40.29	9.19	279.65	43.52	75649
Runoff	-7.17	104.29	-1000	1000	-1.53	75547
Soil moisture	3.18	116.72	-1000	1000	-2.86	75649
Myers index	14.93	5.95	2.19	30.51	14.41	75649
Total population (thou.)	3078642	3143821	158120	27200000	2088567	70577
Population density	1.32	4.39	0.01	42.25	0.4	70577
Ethnic fragmentation index	32.02	23.07	3.13	100	25.45	70577
Illiteracy (%)	1.25	0.58	0.06	3.45	1.2	72840
Public good provision index*	60.38	18.35	0	95.24	61.9	25378
Household (head) characteristics						
Age	48.69	13.4	18	100	48	75649
Sex	0.88	0.32	0	1	1	75649
Education (years)	6.04	4.96	0	17	6	75471
Caste	0.17	0.37	0	1	0	75649
Religion	0.82	0.38	0	1	1	75649
Urban area	0.83	0.38	0	1	1	75649
Has children	0.66	0.47	0	1	1	75649
Is married	0.92	0.27	0	1	1	75649
Household size	5.08	2.44	1	38	5	75649
No. workers	2.05	1.33	0	13	2	75649
Wealth index	13.57	6.39	0	30	13	75635
Owns land	0.57	0.5	0	1	1	75648
Provided ration card by government	0.85	0.35	0	1	1	75626
Social capital	7.66	12.7	0	100	0	75563

Note: The unit of observation is the head of household.
* Monetary values are measured in constant rupees of 2011, spatially deflated.

Figure B. 4: Impact of Temperature Shocks on Electoral Outcomes (Lokh Sabha)



Note: Point estimates display 95% and 90% confidence intervals wherein standard errors are at the constituency and election-month. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include proxies for urbanization (night-light density) and for the presence of water and vegetation.

B.2 Cooperation and Water outcomes

We evaluate the role of cooperation in water outcomes. We do this this by performing directed controlled estimations for each category of cooperation (i.e., zero and one) to avoid standard concerns regarding sequential ignorability in mediation analysis.[B.1] We use several measures in the IHDS that capture access to water, as well as measures regarding the absence of cooperation—such as community conflict. First, we observe that for the full sample, hours of piped water fall immediately after a climate shock, confirming our conjecture of increased scarcity (Figure B5). Second, we observe that this negative impact of climate shocks on hours of piped water appears only for those citizens who do not report cooperation (Figure B6, panel a). Finally we observe a statistically-weak negative effect pf climate on self-reported conflict. Though again this is present only for those citizens who report cooperating with one another over water resources (Figure B6, panel b).

B.3 Economic Mechanism & Government Transfers

Next we investigate the impacts of temperature shocks on self-reported economic well-being.[B.2] We observe a negative impact on both consumption and agricultural income though these effects appear only for two and three month lags. The latter appears to be more robust and precisely estimated (Figure B7). We observe a small increase in government transfers, with the caveat that government assistance is about a tenth of farming income. We observe suggestive evidence that a fall in observed economic outcomes captures much of the variation of the effect of climate on public opinion using demediation analysis (Acharya et al., 2016), but we refrain from reporting these results given that we cannot rule out problems regarding violations of sequential ignorability; thus this is a plausible mechanism.

[B.1] This is tantamount to interacting every regressor with the mediator.

[B.2] The relationship between temperature abnormalities and economic output is the subject of an active research program (Tol, 2019; Carleton and Hsiang, 2016). The tests above serve as plausibility probe of our theorized mechanism rather than precise estimate of these impacts which are highly complex and contingent.

B.3.1 Heterogeneity

We anticipate the greatest effects for agricultural communities, thus we explore differences in the levels of treatment uptake by investigating the effects area of residence (urban v. rural) (Figure B8), on agriculture-dependent households and other (Figure B9), those interviewed during the growing season and otherwise (Figure B10). Results appear to be driven by rural households and - marginally - by those engaged in agricultural production. These effects stand to reason because not only rural areas are the ones more likely to be directly impacted by climate change, specially economically. These pressures may have complex follow on effects for other markets, urban consumers, and even international trade. For instance, the impact on agricultural-goods prices can take time to reach other communities because prices are *sticky* (a well-known economic stylized fact), and might be insufficient to generate a discernible reaction.

Similarly, we test the moderating effects of benefits received under the National Food Security Act (NFSA). Under the NFSA, all state governments in India have to identify households that are eligible for ration cards—those below or close to the poverty line–to purchase subsidized food grain from the Public Distribution System. We find that beneficiary households are not more resilient than non-beneficiaries (Figure B11). This is consistent with Healy and Malhotra (2009), insofar as we observe little evidence that such participation in ex-ante redistributive programs is effective blunting the impacts of temperature shocks, not to mention that these households are self-select into the program by virtue of being more economically vulnerable.

Along these lines, government preparedness for environmental shocks is not randomly assigned, thus we investigate if treatment uptake can differ by geographical locations. Specifically, if investments in broader levels of preparedness are correlated with more general investments in state capacity, we can condition our estimates on a measure of government capacity to assess this. We perform this analysis employing a standard measure of government capacity as "legibility" (Lee and Zhang, 2017). We compute the index such that lower values indicate lower state capacity. The results of our analysis show that higher government capacity is associated with a smaller (conditional) average treatment effect. Thus we find the impacts of environmental exposure are higher in areas with low preparedness (Figure B12).

Lastly, we explore if the level of treatment uptake is different based on religion and caste. The extent to which the state government should provide special protections for marginalized communities is a matter of debate given India's long-socio-hierarchical tradition (Gulati et al., 2020; Chhibber and Verma, 2018), hence these marginalized communities—such as non-Hindi and scheduled castes—may be more vulnerable to temperature shocks and thus express stronger grievances. We observe that households that are not Hindus exhibit a marginally higher treatment uptake though we continue to also observe treatment effects in the predicted directions for Hindu respondents also (Figure B13).

B.4 The Role of Information

Next we explore the possibility of misattribution and bias in citizen learning in the wake of environmental shocks. We do this by considering how a respondent's information environment and information processing ability affects the degree and longevity of their belief updating. If the effects identified above represent accurate citizen learning about their political environments, then citizens with better access to information or high levels of education should demonstrate stronger and more long-lived effects than their counterparts. In contrast, if the effects identified above represent misattribution, then citizens with better access to information or high levels of education should show smaller and more short-term effects compared with other citizens.

We investigate heterogeneity in effect estimates by level of educational attainment and degree of media consumption.[B.3] To do this we estimate a robust-to-scale order-consistent index of each respondent's information environment using polychoric Principal Component Analysis (e.g., Kolenikov and Angeles 2009), and estimate the moderating impacts of this measure.

The factor loads of the index are shown in Table B4, column (1). Since a standard variance-decomposition of the index indicates that education explains most the variation in it, we also com-

[B.3] The IHDS contains questions asking each respondent to describe the frequency with which they read newspapers, listen to the radio, watch television, and how much do households spend in media consumption (e.g., cable and internet).

pute the index excluding education: Table B4, column (2). However, the normalized distributions for both indexes are fairly similar (Figure B14). All in all, we observe that the factor loads display ordering consistency insofar as they all reflect the same direction (positive) for larger values of the variable (e.g., Asselin 2009), thus they capture the latent information on the informational environment.

Our results are depicted in Figure B15. In it we plot the estimated marginal effect of a one standard deviation increase in temperature at each level of our information environment index. We observe significant heterogeneity according to a respondent's information environment, especially for confidence in state government. This is consistent with misattribution playing a role in citizen updating in the wake of climate pressures. Those with less information demonstrate a strong negative relationship between environmental pressures and confidence in state government while the same estimate for those with more information is statistically indistinguishable from zero. We observe no consistent moderating relationship for confidence in police and an inverse relationship for cooperation around water resources, as expected.[B.4]

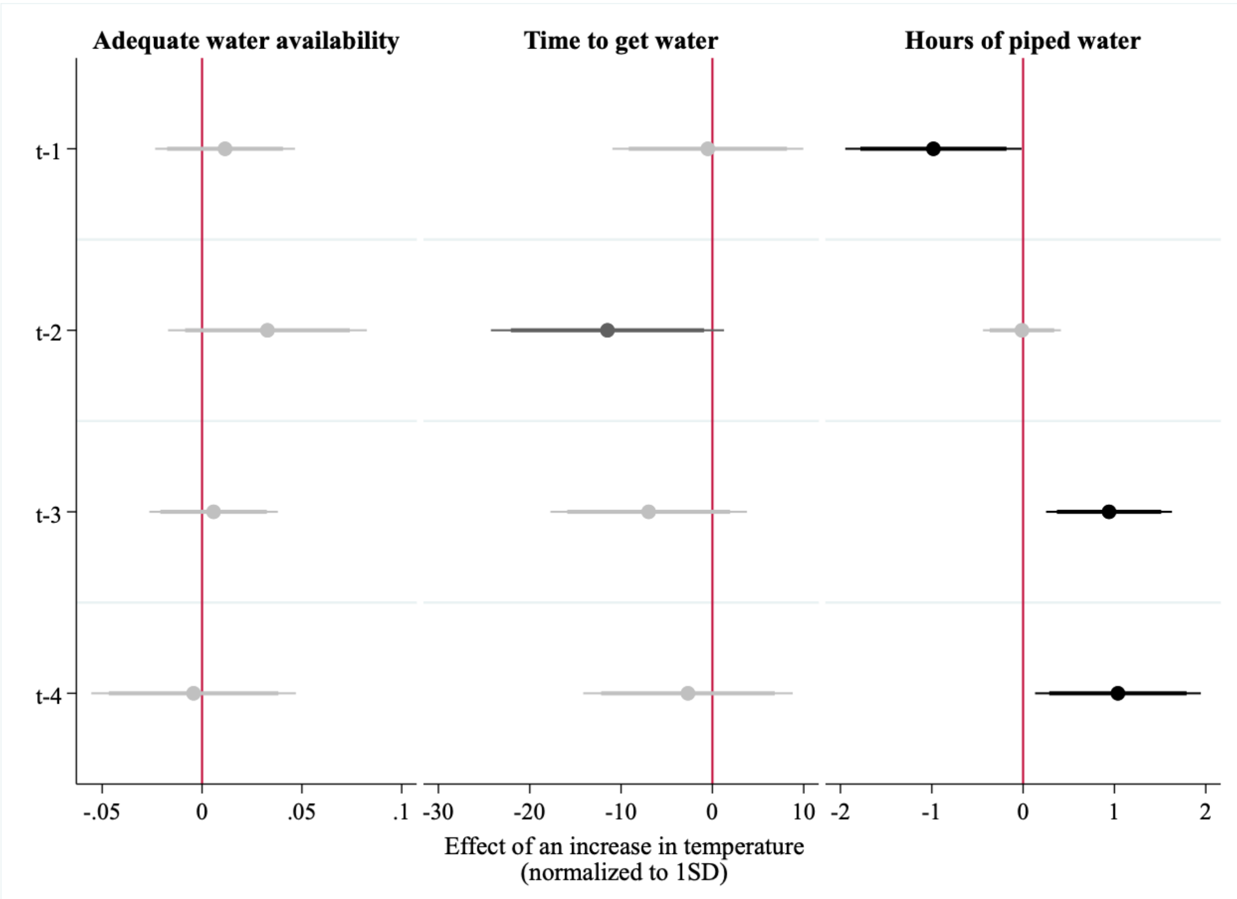
Table B. 4: Factor loads for Polychoric Principal Component Analysis

Variable		Factor loads
Years of education		0.427795
Log(media spending + 1)		0.381249
Watches	No	-0.34082
Tv	Yes	0.204617
Reads	No	-0.59713
news	Yes	0.333209
Listens	No	-0.49202
radio	Yes	0.264077
Member of	No	-0.01382
Agr. Society	Yes	0.244382

Note: First principal component has all positive factor loads, which satisfies global ordering consistent y as defined by Balcazar and Redaelli (2017).

[B.4] We observe consistent results when we evaluate each variable independently, although estimates are noisier given lower variation. In these explorations, we observe that the effect of the treatment vanishes much more slowly with little information.

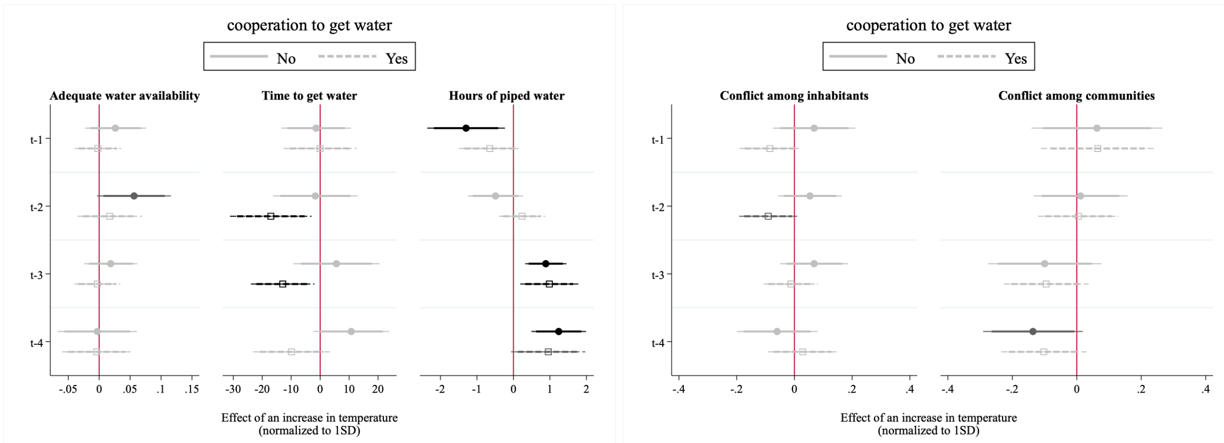
Figure B. 5: Impact of temperature shocks on water outcomes



Note: The shaded area is a 95% confidence interval wherein standard errors are clustered at the district level and survey-year.The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation. Directed controlled effects are estimated by restricting the sample to an specific value of the post-treatment variable and estimating the results for that sub-sample.

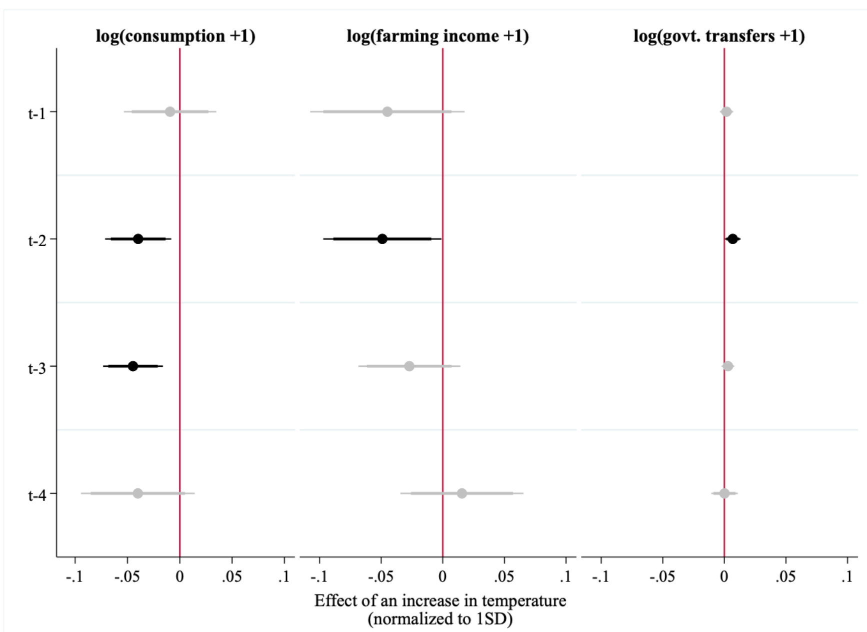
Figure B. 6: Impact of temperature shocks on confidence in institutions by cooperation (Directed controlled effects)

(a) Water outcomes **(b) Self-reported conflict**



Note: The shaded area is a 95% confidence interval wherein standard errors are clustered at the district level and survey-year.The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation. Directed controlled effects are estimated by restricting the sample to an specific value of the post-treatment variable and estimating the results for that sub-sample.

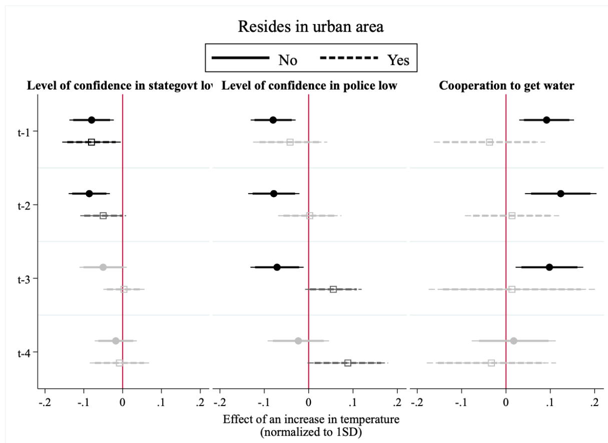
Figure B. 7: Impact of temperature shocks on household economic outcomes



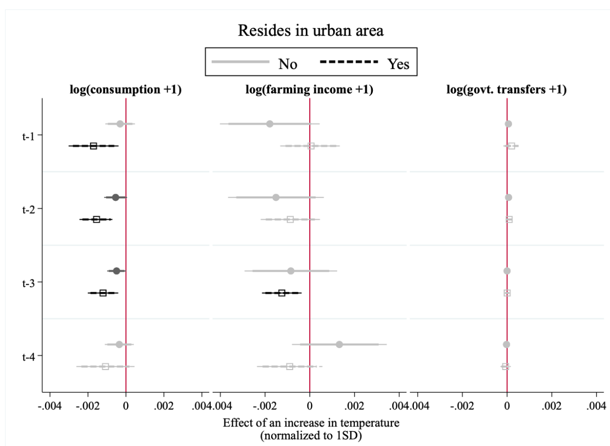
Note: 90% and 95% confidence intervals wherein standard errors are at the district and survey-year level.The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 8: Impact of temperature shocks on confidence by area of residence

(a) Confidence in government institutions



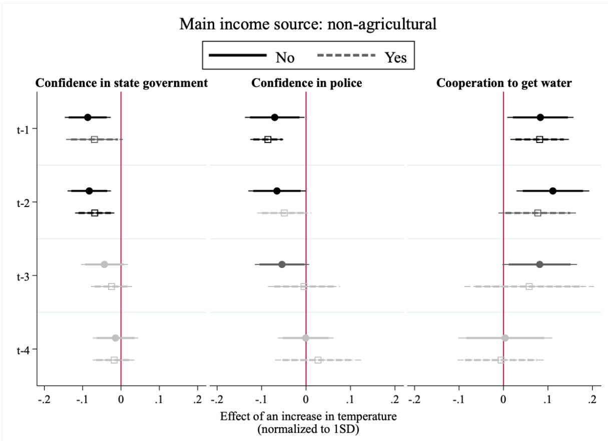
(b) Households' economic outcomes



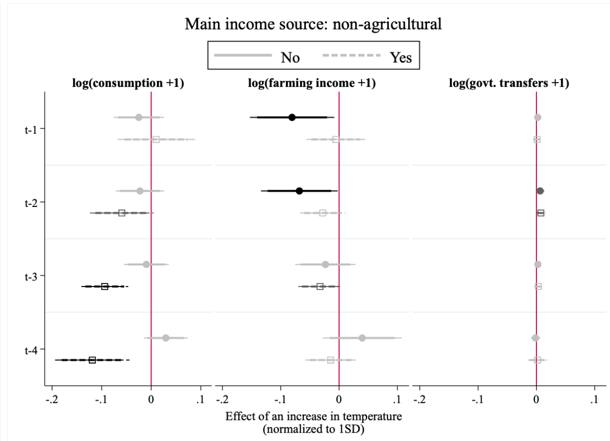
Note: Point estimates display 95% and 90% confidence intervals wherein standard errors are at the district and survey-year level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 9: Impact of temperature shocks on confidence by dependence on agriculture

(a) Confidence in government institutions



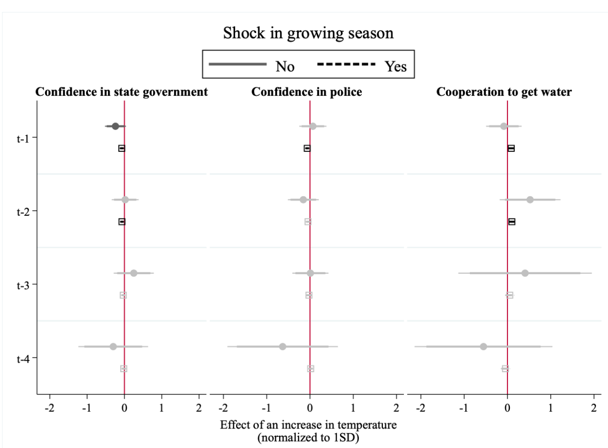
(b) Households' economic outcomes



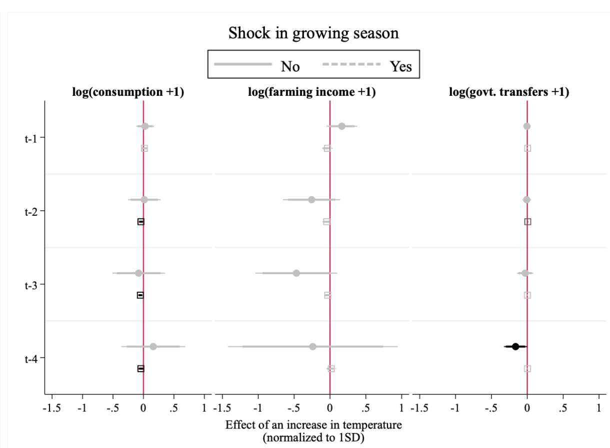
Note: Point estimates display 95% and 90% confidence intervals wherein standard errors are at the district and survey-year level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 10: Impact of temperature shocks on confidence in institutions (Moderated by seasonality)

(a) Confidence in government institutions



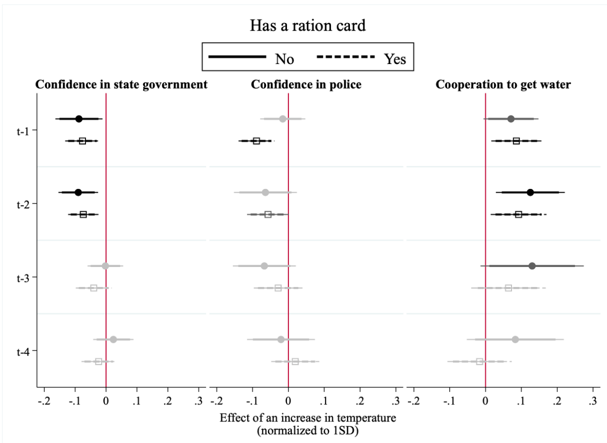
(b) Households' economic outcomes



Note: The shaded area is a 95% confidence interval wherein standard errors are at the district and survey-year level.The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 11: Impact of temperature shocks by ration card status

(a) Confidence in institutions



(b) Households' economic outcomes

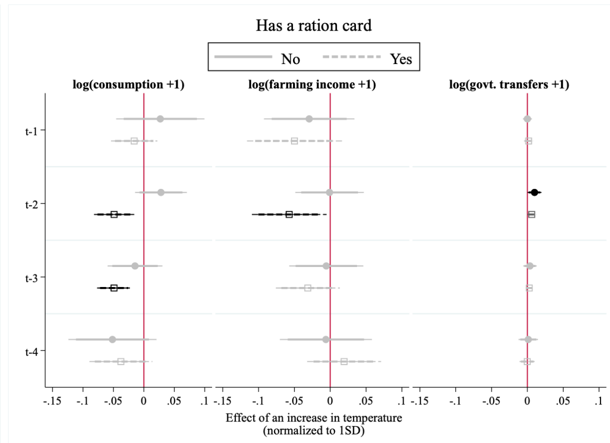
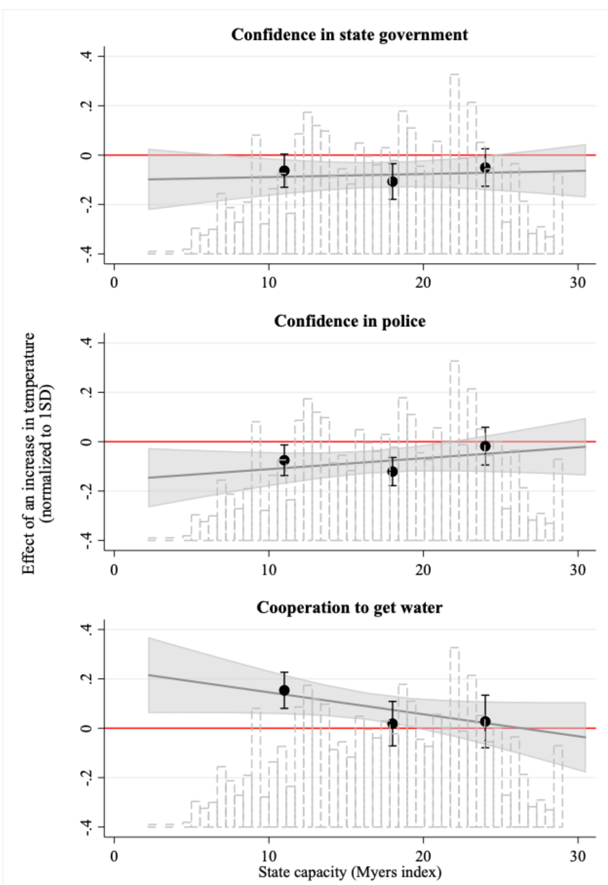
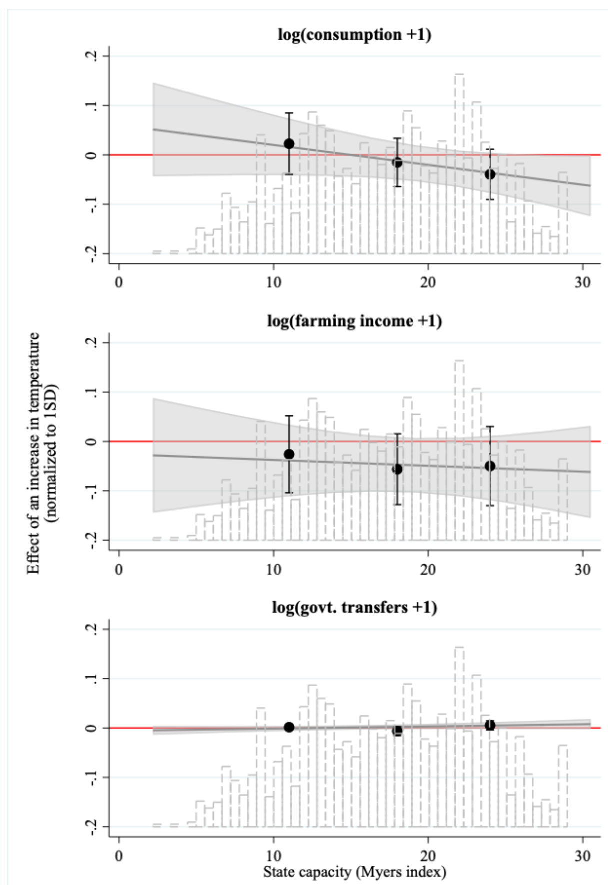


Figure B. 12: Impact of temperature shocks on citizens' by state capacity

(a) Confidence in government institutions



(b) Household outcomes



Note: The shaded area is a 95% confidence interval wherein standard errors are at the district and survey-year level.The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 13: Impact of temperature shocks by select sociodemographic attributes

(a) Religion (b) Caste

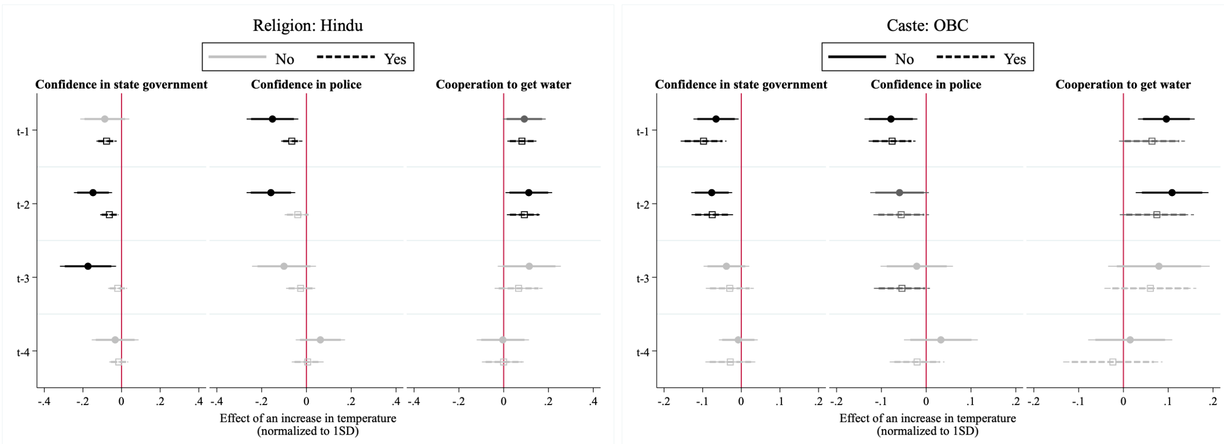


Figure B. 14: Distribution of information index

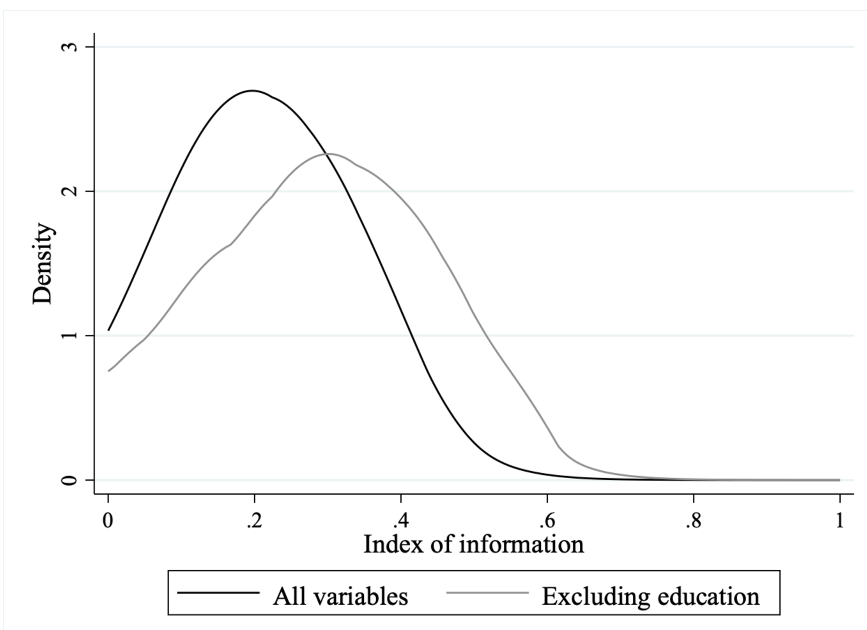
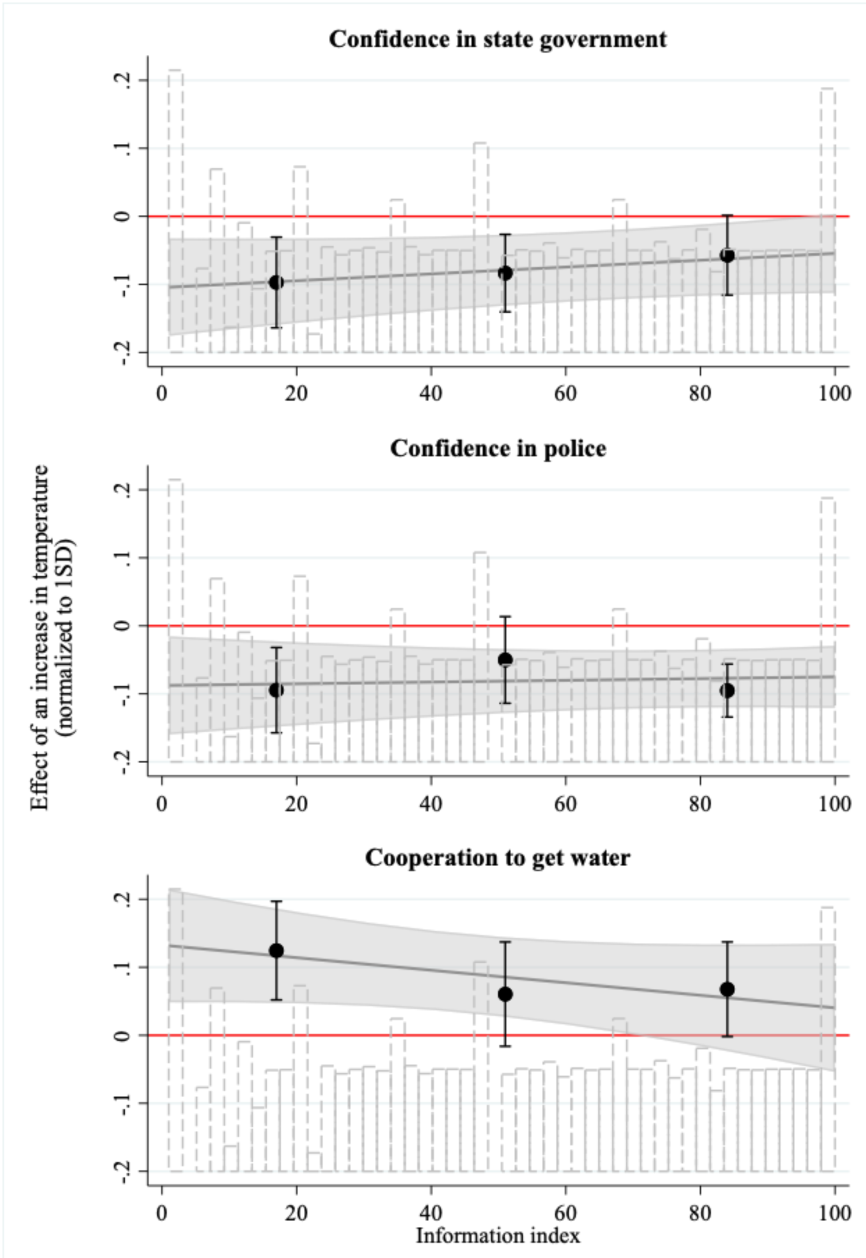


Figure B. 15: Confidence in government institutions
(by Index of Information Environment)



Regression of temperature shocks on confidence in Information Environment Index. Index created via polychoric principal components analysis. Errors are clustered at the district and survey-year levels. Covariates include household and year fixed effects, night-light density, pollution, soil moisture, run-off and vegetation.

B.5 Overview of Robustness Results

To explore the robustness of our results we consider a number of alternative variables and specifications. First we re-estimate Tables 1 and 2 using Conley standard errors to account for spatial correlation, and also heterogeneity-robust estimators (Figures B17 and B16).[B.5] Then we use alternative measures of long-run temperature. These alternative measures include 5, 10 and 20 year windows prior to survey administration (Figure B18). All in all, our main results are largely robust. We also show that results are driven largely by positive temperature shocks (Figure B19).

To investigate the possibility of confounding variables, we first show that our estimates are not sensitive to the inclusion of confounding variables described in the text (Table B5). Next we conduct a sensitivity analysis. We find that to pose a significant threat to inference any potential confounder would need to have a substantially larger partial R2 than that observed for any of the other variables already included in our analysis (Figure B20). We also find that our main results are not contingent to a district or constituency using Jackknife (Figure B21).

We also carry out additional robustness tests on the individual-level data: We start by taking up the possibility of selective attrition out of sample. Our results are robust to including household weights and to including the households who were not re-interviewed during the same survey round (Figure B22). The same holds when results are estimated controlling for observable characteristics likely to be associated with non-random attrition (Figures B3), however we do not report these results as they may exhibit post-treatment bias. We also observe similar effects for migrant and non-migrant households that remain within-sample (i.e. that migrate within district, rather than across districts) (Figure B23).

We also analyze the impact of temperature in confidence on other, similar, government institutions: the village government and the political class in general (Figure B24, panel a). Our results provide little evidence for an effect on the village government, but we do find an effect on the political class that is weaker in nature vis-á-vis the effect of temperature on confidence on the state

[B.5] Although we show results for 500km bandwidths, our results are robust to different smaller (e.g., 250km) and larger (e.g., 1000km) bandwidths.

government. This is important because the latter outcome does not make any distinctions on the role/type of the politician, which implies that people are pooling together observations of politicians across the spectrum (those that they may consider responsible or not). This provides further credence to the idea that voters are more likely to punish politicians they may hold responsible, as the effect we observe is attenuated. We also observe no effect of climate shocks on reported rates of conflict either within or across communities, consistent with the idea that in some contexts conditions of scarcity may lead to renewed cooperation rather than the outbreak of new conflict (Figure B24, panel c); see also Section B.2. Nevertheless, we show below that our results are also robust to considering these alternative outcomes algonside our main outcomes in an index measure.

We also estimate a series of placebo tests demonstrating that climate shocks have no effects on assessments of schools, hospitals, or news media (Figure B24); the private sector competes with the government in the provision of these services thus it is harder to attribute responsibility to the government in these cases. Across the board these alternative tests suggest strong evidence for our theory and robustness of our empirical results.

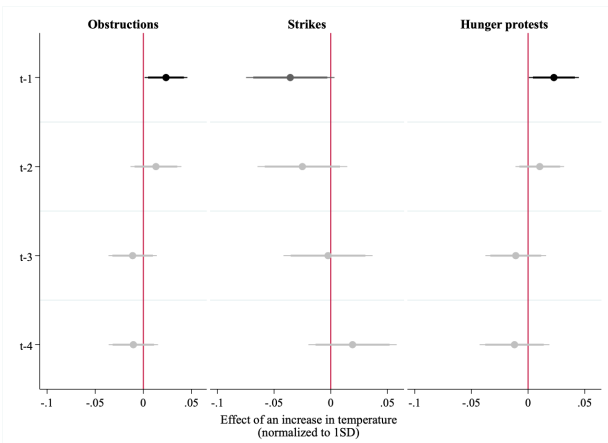
Finally, we use alternative measures to prove further the robustness of our results. First, we employ alternative dichotomization scheme where so that a one corresponds to “a great deal” of confidence while zero corresponds to “some” or “hardly any” confidence (Table B1). We observe statistically weaker results (Figure B25, panel a), suggesting that most of the action comes from individuals changing their opinions from “some” to “hardly any’. We also construct an index of confidence in government institutions (i.e., confidence in state government, politicians and village government), an index of confidence in security forces (i.e., confidence in the police and military), and an index of cooperation (i.e., cooperation to get water and absence of community conflict), using polychoric Principal Component Analysis (e.g., Kolenikov and Angeles 2009), making sure that the factor loads display ordering consistency (e.g., Asselin 2009). Our results remain qualitatively similar when employing these resulting variables (Figure B25, panel b).

Table B. 5: Robustness to Main Confounders

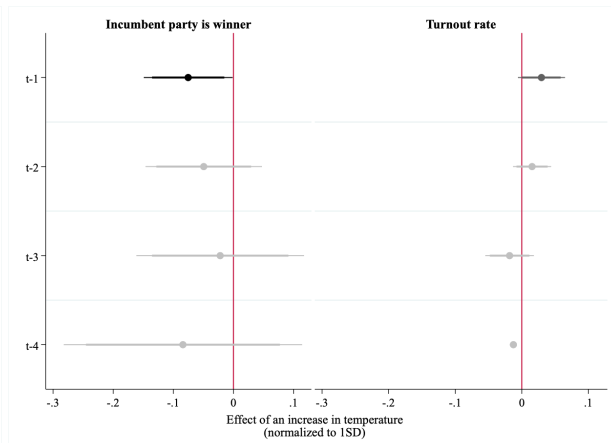
	Electoral outcomes		***Protests***		
	Incumbent reelected	***Turnout rate***	***Obstructions***	***Strikes***	***Hunger***
	(1)	(2)	(3)	(4)	(5)
a. One month lag					
Shock	-0.141*	-0.090	0.024**	-0.036*	0.023**
	(0.060)	(0.043)	(0.011)	(0.020)	(0.011)
R-squared	0.628	0.862	0.096	0.192	0.153
Observations	2882	2882	10330	10330	10330
Fixed effects	Yes	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes	Yes
b. Two months lag					
Shock	0.115	-0.028	0.013	-0.025	0.010
	(0.063)	(0.039)	(0.013)	(0.020)	(0.011)
R-squared	0.629	0.859	0.096	0.192	0.153
Observations	2816	2816	10331	10331	10331
Fixed effects	Yes	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes	Yes
c. Three months lag					
Shock	0.011	-0.023	-0.011	-0.002	-0.011
	(0.038)	(0.017)	(0.013)	(0.020)	(0.014)
R-squared	0.617	0.866	0.098	0.193	0.153
Observations	2844	2844	10330	10330	10330
Fixed effects	Yes	Yes	Yes	Yes	Yes
Controls included	Yes	Yes	Yes	Yes	Yes

Figure B. 16: Impact of temperature shocks on main outcomes
(Conley standard errors)

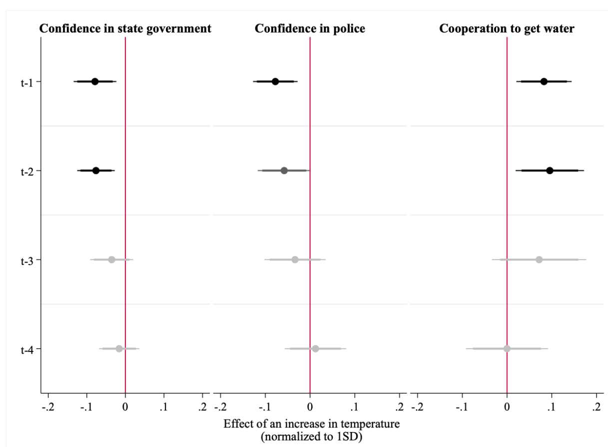
(a) Protests



(b) Vidhan Sabha



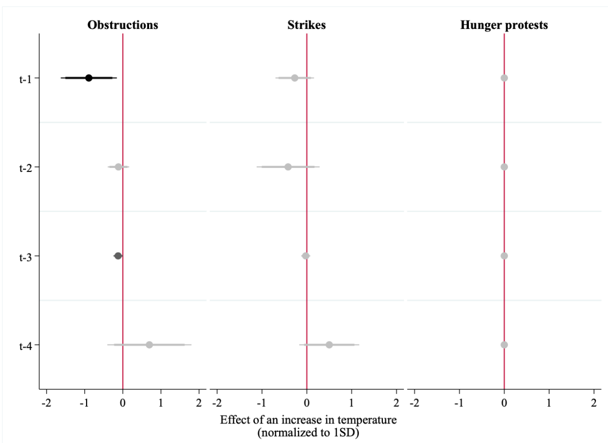
(c) Confidence in institutions



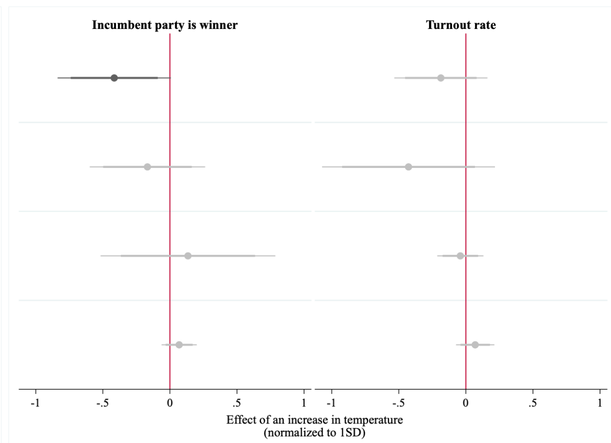
Note: The shaded area is a 95% confidence interval wherein standard errors are spatially clustered using a standard 500km bandwidth with a one-period serial correlation. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation. Additional controls include: literacy, ethnic fractionalization, the myers index, and crime.

Figure B. 17: Impact of temperature shocks on main outcomes (heterogeneity-robust estimators)

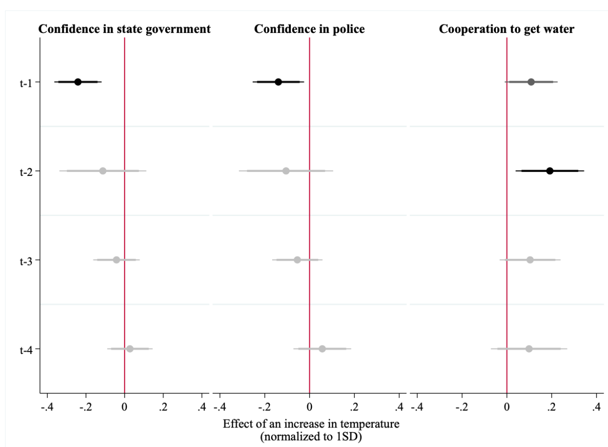
(a) Protests



(b) Vidhan Sabha



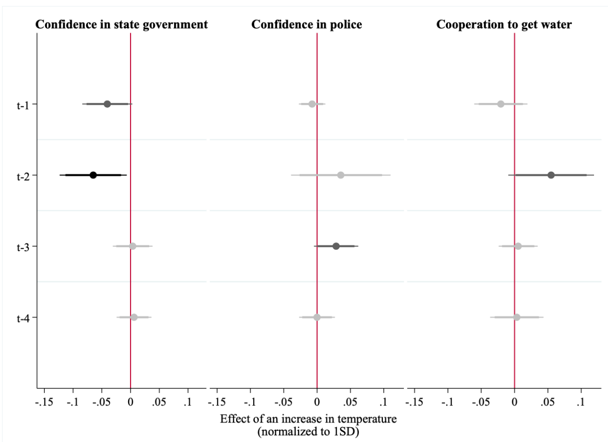
(c) Confidence in institutions



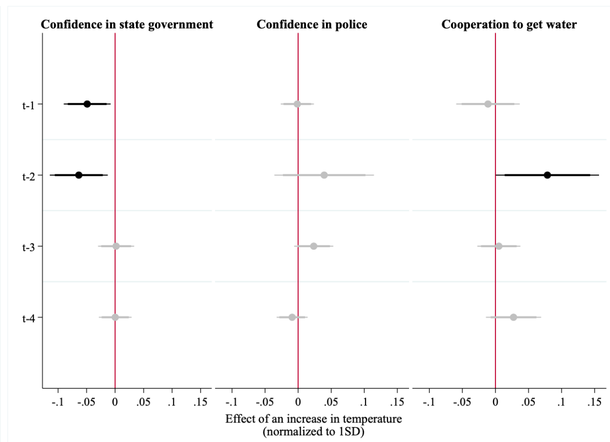
Note: The shaded area is a 95% confidence interval wherein standard errors are at the district (constituency) and survey-year (election-period) level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 18: Alternative Definitions of Long-Run Mean

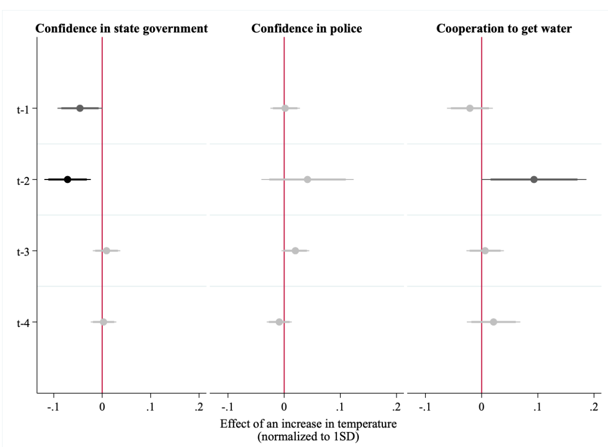
(g) Confidence in institutions (5 years before interview)



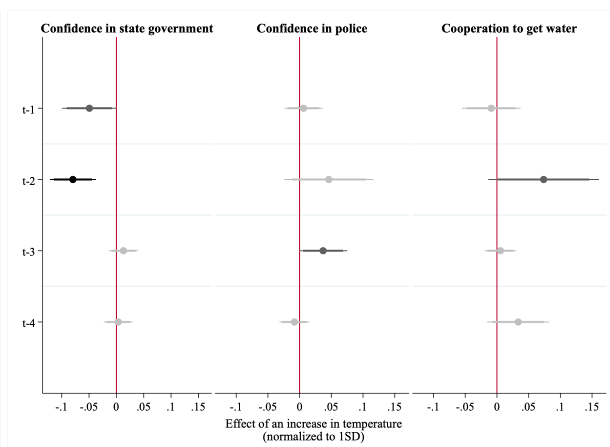
(h) Confidence in institutions (10 years before interview)



(i) Confidence in institutions (20 years before interview)



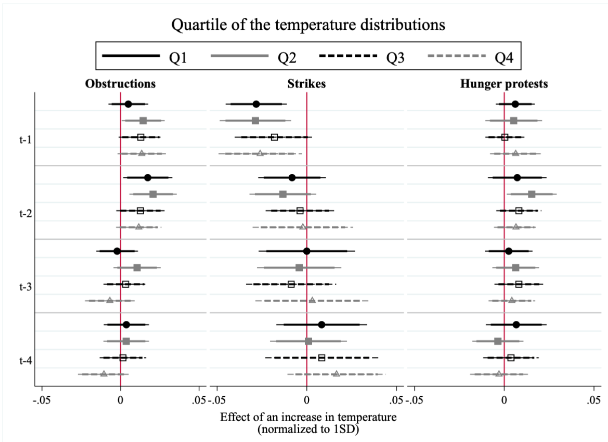
(j) Confidence in institutions (First 16 years of life)



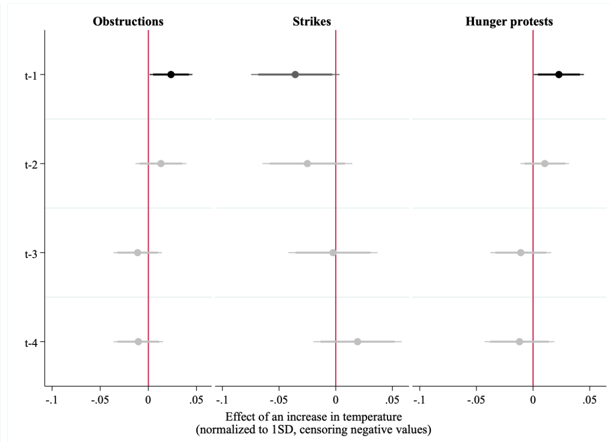
Note: The shaded area is a 95% confidence interval wherein standard errors are at the district (constituency) and survey-year (election-period) level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 19: Non-monotonic impact of temperature shocks on main outcomes

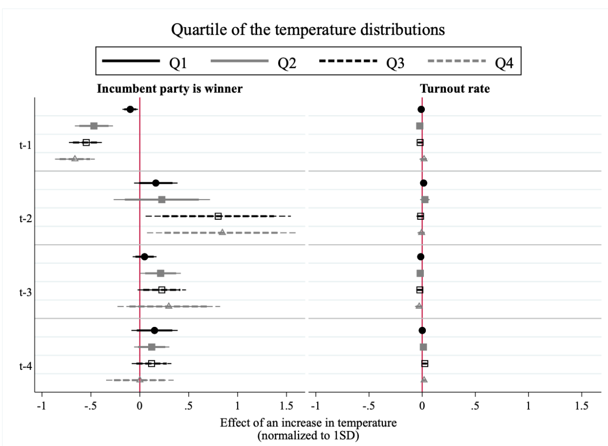
(a) Protests (Non-monotonic)



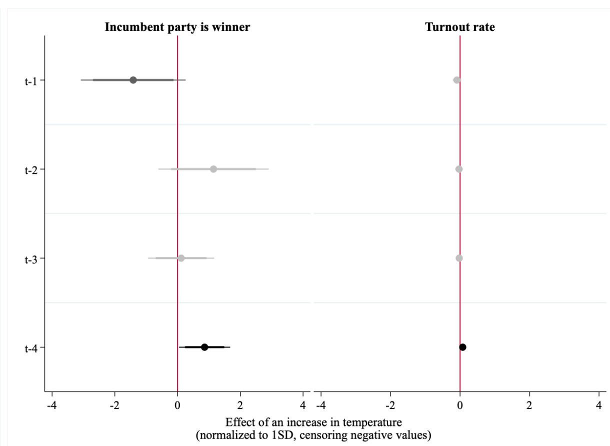
(b) Protests (Censored to positive values)



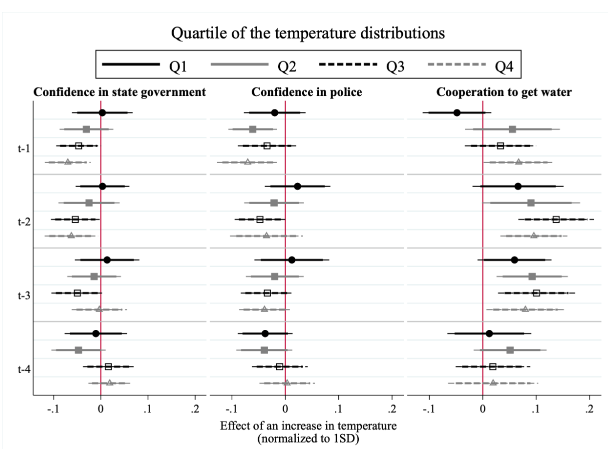
(c) Vidhan Sabha (Non-monotonic)



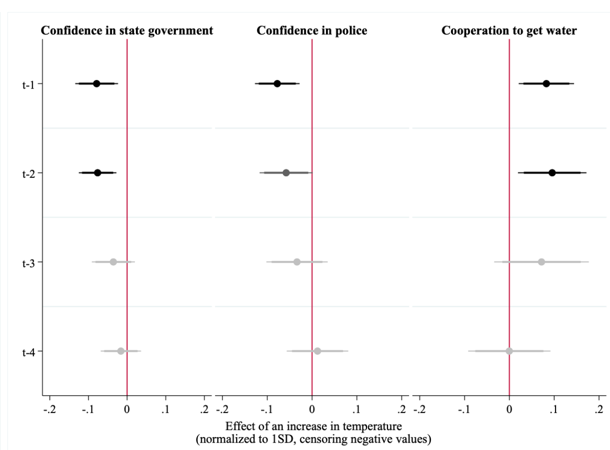
(d) Vidhan Sabha (Censored to positive values)



(e) Confidence in institutions (Non-monotonic)



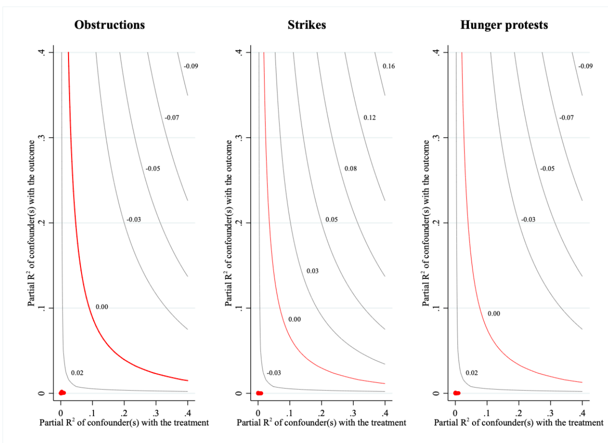
(f) Confidence in institutions (Censored to positive values)



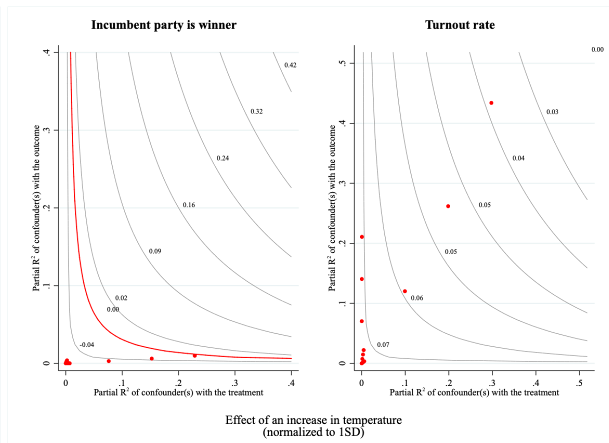
Note: The shaded area is a 95% confidence interval wherein standard errors are at the district (constituency) and survey-year (election-period) level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 20: Impact of temperature shocks on main outcomes (sensitivity analysis)

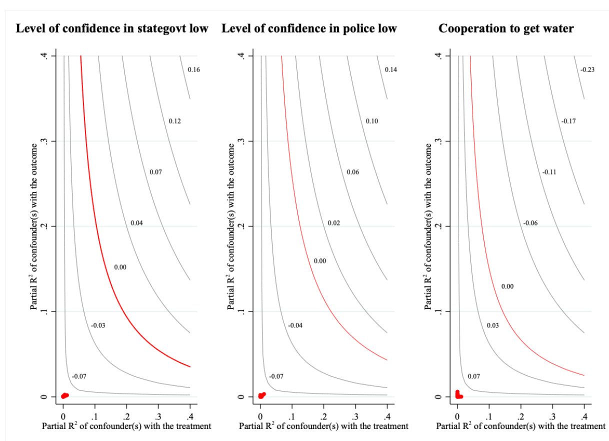
(a) Protests



(b) Vidhan Sabha



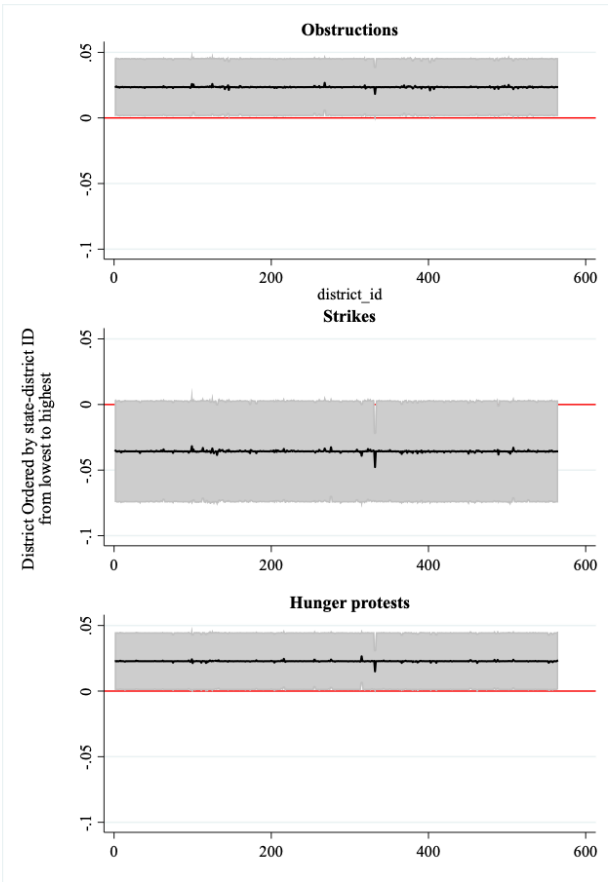
(c) Confidence in institutions



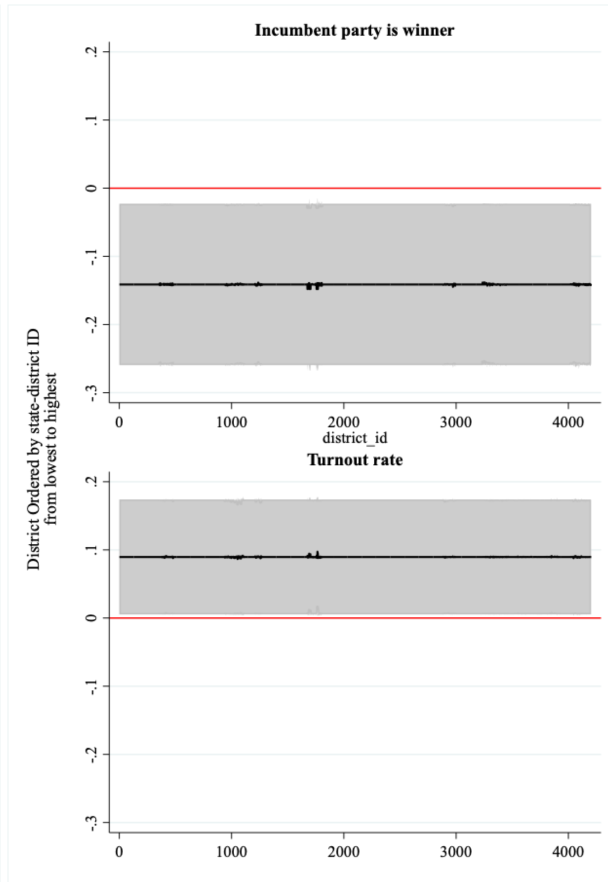
Note: The shaded area is a 95% confidence interval wherein standard errors are at the district (constituency) and survey-year (election-period) level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff, vegetation, population size, population density, education, ethnic fragmentation and state capacity. The patterns showcased herein hold for all other lags, from $t-1$ to $t-4$.

Figure B. 21: Impact of temperature shocks on main outcomes (parameter stability)

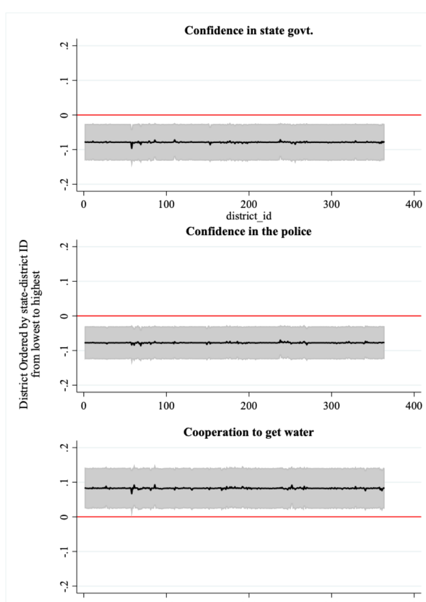
(a) Protests



(b) Vidhan Sabha



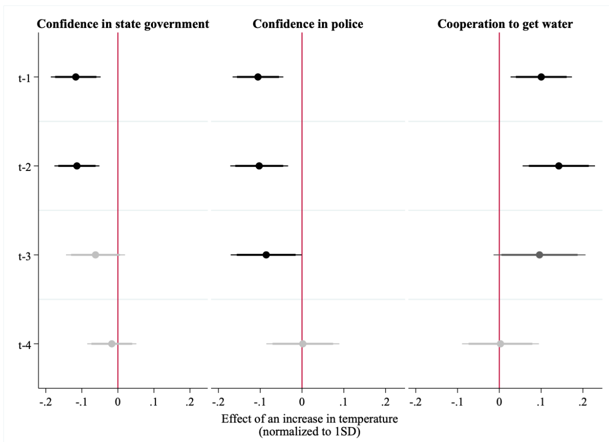
(c) Confidence in institutions



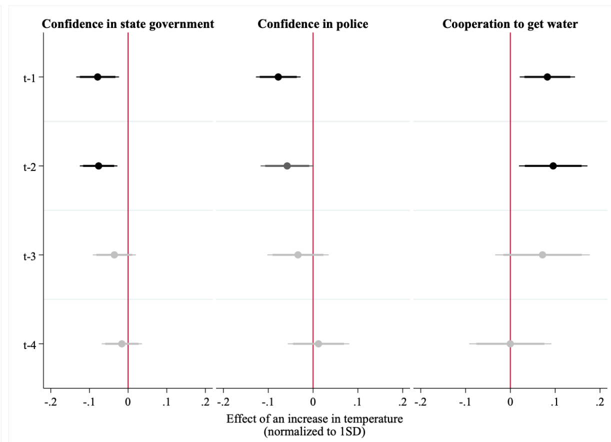
Note: The shaded area is a 95% confidence interval wherein standard errors are at the district (constituency) and survey-year (election-period) level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation. The patters showcased herein hold for all other lags, from $t-1$ to $t-4$.

Figure B. 22: Impact of temperature shocks on confidence in institutions (robustness to sampling)

(a) Controlling for sampling frame



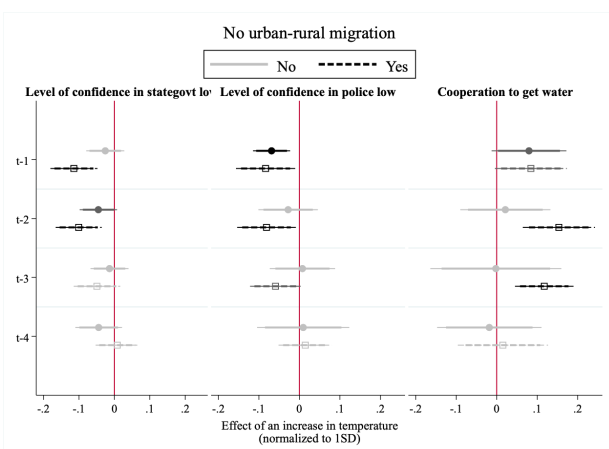
(b) Dropping singletons



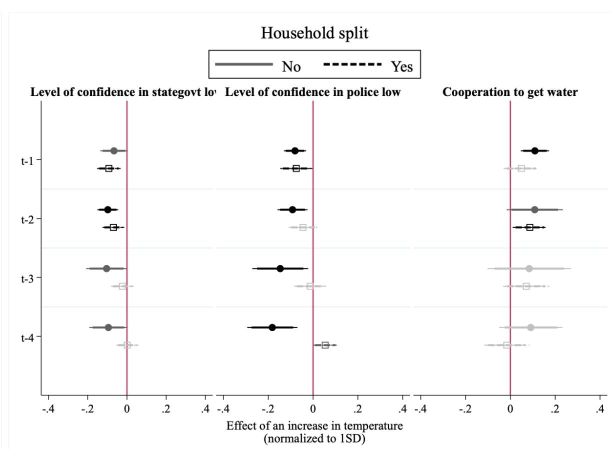
Note: The shaded area is a 95% confidence interval wherein standard errors are at the district and survey-year level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff, vegetation, population size, population density, education, ethnic fragmentation and state capacity. The patters showcased herein hold for all other lags, from $t-1$ to $t-4$.

Figure B. 23: Impact of temperature shocks on confidence in institutions (by migration status and split-household status)

(a) Migrant households



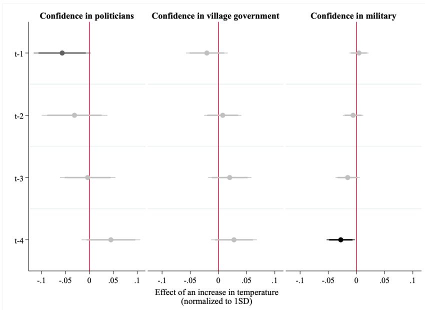
(b) Split households



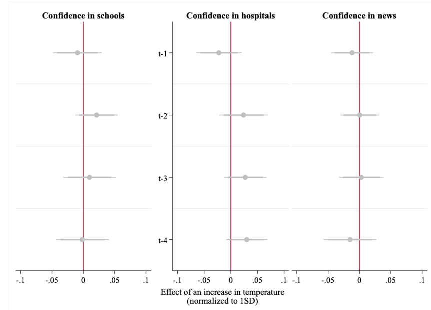
Note: The shaded area is a 95% confidence interval wherein standard errors are at the district and survey-year level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include household and year fixed effects, and proxies for man-made microclimates: night-light density, pollution, soil moisture, runoff and vegetation.

Figure B. 24: Impact of a temperature shock on citizens’ confidence in other institutions

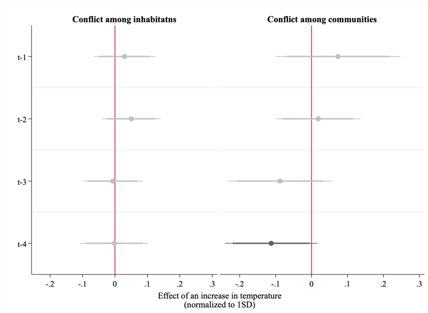
(a) Other government institutions



(b) Placebos



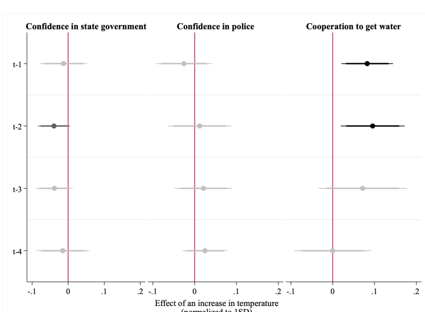
(c) Self-reported conflict



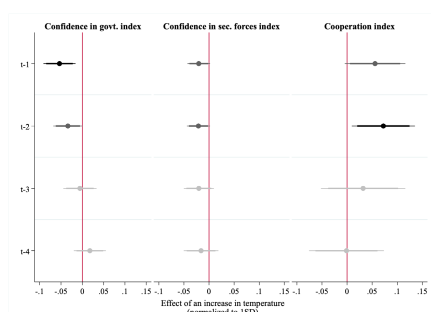
Note: Point estimates display 95% and 90% confidence intervals wherein standard errors are at the district and survey-year level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include proxies for urbanization (night-light density) and for the presence of water and vegetation.

Figure B. 25: Impact of a temperature shock on indices (alternative outcome measures)

(a) Alternative dichotomization



(b) Index



Note: Point estimates display 95% and 90% confidence intervals wherein standard errors are at the district and survey-year level. The main independent variable corresponds to a temperature shock measured in Celcius, standardized to a one standard deviation shock within district. The controls in each regression include proxies for urbanization (night-light density) and for the presence of water and vegetation.

C External validity

We select India as our case study in part due to its severe vulnerability to the impacts of climate change. However, this does not mean that India is unique, limiting our capacity of drawing inferences outside of its the context.[F.1] Our inferences are tied mainly to clearly specified mechanisms, which depart from standard assumptions in models of incomplete information rather than relying solely in specific point estimates (Section 2). Our scope conditions indicate also that there should be some level of uncertainty about whether "bad" outcomes from climate means either "bad climate" or "bad policy" – as such citizens cannot distinguish the Government's degree of responsibility for observed outcomes. Overall, our results shows evidence for these mechanisms (Section 4). Thus our inferences are potentially transportability outside of India.[F.2]

To add more precision, we identify those countries that are likely to display the behavioral conditions herein. To do this we use numerous indicators gleaned from the World Bank's statistical indicators, the World Bank's Database of Political Institutions, and the Variaties of Democracy Project, to show that India is similar to many lower-middle-income and low income states on a number of indicators associated with the country's politics and socio-demographics.[F.3]

To select the indicators, we use various variables associated to climate change vulnerability,[F.4] and perform an automated sub-selection of indicators to reduce the amount of missing data that

[F.1] In India for example, the central government was blamed by Tamil Nadu's farmers for Karnataka's refusal to open the flood gates of the Mekedatu dam to provide water toTamil Naidu during the 2017 drought, sparking protests due to poor government response. Similarly, in Ghana, during 2023, heavy rains increased the volume of water in the Akosombo dam close to its limit, which led the government-controlled electricity company to release water of their reservoirs. However, government negligence in this process caused widespread floods that affected downstream communities, which received little assistance from the government, leading affected citizens to blame the government for the floods. Other similar examples can be found, such as the Greek, Algerian, Nigeria and Maui droughts and wildfires caused by extreme and dry temperatures, during 2023, and even the floods in western Germany during 2021.

[F.2] Findley, Michael G., Kyosuke Kikuta, and Michael Denly. "External validity." *Annual Review of Political Science* 24 (2021): 365-393.

[F.3] The World Bank's income groups are based on the GNI per capita in constant USD. GNI measures are expressed in United States dollars (USD), and are determined using conversion factors derived according to the Atlas method: `https://datahelpdesk.worldbank.org/knowledgebase/articles/378832-what-is-the-world-bank-atlas-method`. We also considered other data sources for our exercise but the amount of missing data for our analysis was considerable, so they were excluded by our algorithm below.

[F.4] Assa, Jacob, and Riad Meddeb. "Towards a multidimensional vulnerability index." United Nations Development Programme. 2023. See also: Marzi, Sepehr,... "Assessing future vulnerability and risk of humanitarian crises using climate change and population projections within the INFORM framework." Global Environmental Change 71 (2021): 102393.

is common in these data bases. We define our period of analysis: 2000-2014, circa the period of study of our main analysis in the manuscript : 2005-2012. The selected variables are shown in Table C1.

We use the variables in Table C1 to perform a Cluster Analysis, in order to find comparable countries to India. For this endeavor we choose Ward's Linkage using the L2 norm to measure dissimilarity between countries in a multidimensional space.[F.5] We also use Duda–Hart $Je(2)/Je(1)$ and $pseudo-T2$ to define the optimal number of clusters, minimizing the dissimilarity within groups and maximizing it between groups.[F.6]

We find that the largest $Je(2)/Je(1)$ stopping-rule value is 0.8, corresponding to six groups, with a $pseudo-T2$ of 4.2 – which is among the smallest using 15 potential clustering groups (Table C2). In this regard, a combination of a high $Je(2)/Je(1)$ with a low $pseudo-T2$ indicate more distinct clusters, while increasing within-cluster homogeneity.

We find that India is classified with 18 other lower-middle-income and low income countries, but not all of them (Table C3). We observe that India is clustered with countries from East Asia and the Pacific, South Asia, Latin America, and especially with those from Sub-Saharan Africa. We further validate our data-driven groupings by looking at the means in every indicator: We find that India is similar to the average low- and lower-middle-income countries in regards to the distribution of resources, and the quality of some of its political institutions. Likewise, these countries show in general a big agricultural sector, employing most of their population.

Importantly, India displays higher levels of political accountability and lower levels of corruption, which should ameliorate problems in the provision of public goods. Thus India could be a comparatively challenging case to test our theory.

To further address concerns about case selection tied to the India's agricultural capacity, we also investigate various indicators for agricultural productivity and resilence. Since doing this reduces the amount of observations affecting the clustering outcomes due to missing data, we display these

[F.5] There is widespread agreement that this approach outperforms other linkage algorithms for creating clusters: Ferreira, Laura, and David B. Hitchcock. "A comparison of hierarchical methods for clustering functional data." Communications in Statistics-Simulation and Computation 38, no. 9 (2009): 1925-1949.

[F.6] Everitt, Brian S., Sabine Landau, Morven Leese, and Daniel Stahl. Cluster analysis. John Wiley & Sons, 2011.

indicators for the same countries identified from our cluster analysis, above (Table C4).

We observe that agricultural productivity and the contribution of the agricultural sector in India to total GDP, is similar to that in lower-middle-income countries; low-income countries depend more on this sector. However, the extent of low water productivity and withdrawals is more severe in India. Countries such as Sri Lanka, Armenia, Kyrgyz Republic and Tajikistan, do show similar levels of water productivity and water stress, and even of agricultural productivity (Table C5), but do not display the type of institutions that India demonstrates – hence they are excluded from the groupings by our cluster analysis.

All in all, numerous countries meet the scope conditions of our theory to varying degrees. Thus holding constant certain idiosyncrasies of the Indian case, this country is generally similar to other developing countries for relevant political and socio-demographic indicators. Therefore it is likely that our conclusions herein bear implications for other countries outside of India.[F.7]

[F.7] Our current work in progress in both Latin America and Africa supports these claims. However, presenting these results is outside of the scope of this paper and is part of our future work.

Table F. 1: Selected indicators

Dimension	Indicator	Description	Source
Agriculture	Agricultural land (% of land area)	Share of land area that is adequate for agricultural production.	**WDI**
	Arable land (% of land area)	Arable land includes land defined by the FAO as land under temporary crops, temporary meadows for mowing or for pasture, land under market or kitchen gardens, and land temporarily fallow.	
Distribution of power	Exclusion by Urban-Rural Location index	Extent to which Individuals are denied access to services or participation in governed spaces based on their identity or belonging to a particular group.	**V-Dem**
	Political group equality in respect for civil liberties	A political group is defined as those who are affiliated with a particular political party or candidate, or a group of parties/candidates. Civil liberties are understood to include access to justice, private property rights, freedom of movement, and freedom from forced labor.	
	Power distributed by social group	A social group is differentiated within a country by caste, ethnicity, language, race, region, religion, or some combination thereof. Social group identity is contextually defined and cross-cut, so that a given person could be defined in multiple ways, i.e., as part of multiple groups.	
	Power distributed by socioeconomic position	This indicator is concerned with the political effects of this inequality. Specifically, we are concerned with the extent to which wealth and income translates into political power.	
	Power distributed by urban-rural location	Urban areas are defined as populatio density exceeding a threshold of 150 persons per square kilometer; there is access to a sizeable settlement of 50,000 people or more within some reasonable travel time.	
Inequality	Educational equality	Extent is high quality basic education guaranteed to all, sufficient to enable them to exercise their basic rights as adult citizens. Basic education refers to ages typically between 6 and 16 years of age.	**V-Dem**
	Equal access index	Extent to which all groups should enjoy equal de facto capabilities to participate, to serve in positions of political power, to put issues on the agenda, and to influence policymaking.	
	Equal distribution of resources index	Extent to which resources both tangible and intangible are distributed in society.	
	Equal protection index	Extent to which the protection of rights and freedoms across social groups is guranteed by the state.	
	Health equality	Extent to which high quality basic healthcare guaranteed to all, sufficient to enable them to exercise their basic political rights as adult citizens.	

Dimension	Indicator	Description	Source
Institutions	Control of Corruption: Estimate	Extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as ”capture” of the state by elites and private interests.	**WDI**
	Electoral democracy index	Extent to which the ideal of electoral democracy in its fullest sense is achieved.	**V-Dem**
	Executive embezzlement and theft	Extent to which the executive, or their agents, steal, embezzle, or misappropriate public funds or other state resources for personal or family use.	
	Freedom of association thick index	Extent to which parties, including opposition parties, allowed to form and to participate in elections, and to what extent are civil society organizations able to form and to operate freely.	
	Particularistic or public goods	Extent to which the profile of social and infrastructural spending in the national budget is particularistic.	
	Political System	Political system is parliamentary, assembly-elected president or presidential.	**DPI**
	Rule of Law: Estimate	Extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	**WDI**
	Social class equality in respect for civil liberty	Extent to which the level of civil liberties is generally the same across socioeconomic groups. Civil liberties are understood to include access to justice, private property rights, freedom of movement, and freedom from forced labor.	**V-Dem**
	Social group equality in respect for civil liberties	Extent to which all social groups, as distinguished by language, ethnicity, religion, race, region, or caste, enjoy the same level of civil liberties. Civil liberties are defined as above	
	Voice and Accountability: Estimate	Extent to which a country’s citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.	**WDI**
Sociodemographics	Employment in agriculture (% of total employment) (modeled ILO estimate)	Persons of working age who were engaged in any activity to produce goods or provide services for pay or profit. The agriculture sector consists of activities in agriculture, hunting, forestry and fishing.	**WDI**
	Net migration	Net total of migrants during the period, that is, the number of immigrants minus the number of emigrants, including both citizens and noncitizens.	
	Population density (people per sq. km of land area)	Population density is midyear population divided by land area in square kilometers.	
	Rural population (% of total population)	People living in rural areas as defined by national statistical offices.	

Table F. 2: Statistics from cluster analysis

No clusters	Je(2)/Je(1)	pseudo T-squared
2	0.81	7.51
3	0.84	5.99
4	0.83	5.76
5	0.67	6.79
6	0.81	3.59
7	0.69	5.40
8	0.58	4.27
9	0.65	3.58
10	0.71	2.88
11	0.60	3.95
12	0.84	3.29
13	0.75	3.67
14	0.47	4.46
15	0.69	2.66

Note: We use Duda–Hart diagnostics on clusters computed using the L2 norm Ward Linkage.

Table F. 3: Country comparisons

Dimension	Indicator	India	Aggregates: Low income	Aggregates: Lower middle income	Aggregates: Low & lower middle income	Lower middle income countries: Bolivia	Indonesia	Cote d'Ivoire	Papua New Guinea	Solomon Islands	Lower income countries: Benin	Burundi	Comoros	Liberia	Malawi	Mali	Mozambique	Nepal	Niger	Sierra Leone
Agriculture	Agricultural land (% of land area)	60.55 (0.04)	46.12 (1.33)	27.34 (2.20)	39.86 (1.27)	34.40 (0.09)	28.44 (0.45)	63.97 (0.48)	2.64 (0.05)	3.43 (0.13)	31.38 (0.54)	71.89 (0.27)	71.07 (0.21)	16.37 (0.37)	55.63 (0.86)	33.25 (0.20)	49.58 (0.33)	29.14 (0.10)	33.25 (0.66)	50.84 (1.38)
	Arable land (% of land area)	53.29 (0.14)	17.40 (0.91)	5.09 (0.46)	13.30 (0.72)	3.60 (0.12)	12.18 (0.13)	9.25 (0.20)	0.58 (0.02)	0.65 (0.03)	22.66 (0.23)	38.26 (0.45)	34.93 (0.00)	4.55 (0.13)	34.54 (0.83)	4.77 (0.18)	6.42 (0.21)	15.60 (0.16)	11.75 (0.21)	18.39 (1.33)
Distribution of power	Exclusion by Urban-Rural Location index	0.26 (0.00)	0.58 (0.01)	0.59 (0.02)	0.59 (0.01)	0.38 (0.03)	0.35 (0.00)	0.61 (0.00)	0.91 (0.00)	0.85 (0.00)	0.46 (0.00)	0.61 (0.00)	0.40 (0.00)	0.80 (0.01)	0.64 (0.00)	0.76 (0.00)	0.58 (0.00)	0.59 (0.02)	0.47 (0.01)	0.53 (0.01)
	Political group equality in respect for civil liberties	1.91 (0.07)	0.55 (0.04)	0.88 (0.07)	0.66 (0.04)	1.12 (0.06)	0.00 (0.00)	1.13 (0.03)	1.44 (0.00)	1.61 (0.00)	0.40 (0.00)	0.19 (0.13)	0.62 (0.00)	0.36 (0.11)	-0.05 (0.00)	0.78 (0.00)	0.40 (0.00)	-0.35 (0.24)	1.21 (0.00)	1.04 (0.03)
	Power distributed by social group	1.12 (0.04)	1.26 (0.04)	1.28 (0.05)	1.27 (0.03)	0.73 (0.05)	1.12 (0.04)	1.75 (0.08)	1.21 (0.00)	1.79 (0.00)	1.92 (0.03)	0.42 (0.06)	1.44 (0.09)	0.93 (0.18)	1.08 (0.02)	2.51 (0.02)	1.25 (0.00)	1.30 (0.08)	1.33 (0.03)	1.33 (0.07)
	Power distributed by socioeconomic position	1.24 (0.04)	0.93 (0.03)	0.70 (0.08)	0.85 (0.04)	2.12 (0.16)	0.11 (0.00)	0.99 (0.04)	0.26 (0.00)	0.19 (0.01)	1.04 (0.02)	1.39 (0.12)	1.61 (0.04)	0.83 (0.10)	0.70 (0.03)	0.92 (0.08)	0.58 (0.02)	1.36 (0.07)	1.26 (0.07)	0.52 (0.03)
	Power distributed by urban-rural location	0.83 (0.01)	-0.60 (0.05)	0.54 (0.05)	-0.22 (0.05)	0.83 (0.10)	0.33 (0.01)	-0.32 (0.00)	0.44 (0.00)	1.23 (0.00)	0.08 (0.00)	-0.53 (0.00)	-0.85 (0.00)	-0.88 (0.00)	-0.52 (0.00)	-1.72 (0.01)	-0.58 (0.01)	-0.07 (0.29)	-0.43 (0.00)	-0.63 (0.01)
Inequality	Educational equality	-1.22 (0.03)	-0.73 (0.06)	-0.92 (0.04)	-0.79 (0.04)	-0.84 (0.14)	-0.51 (0.02)	-0.96 (0.03)	-1.41 (0.00)	-1.01 (0.04)	0.77 (0.17)	-0.86 (0.03)	0.12 (0.01)	-0.97 (0.14)	-1.07 (0.02)	-1.18 (0.03)	-0.99 (0.01)	-0.98 (0.02)	-0.58 (0.05)	-0.52 (0.09)
	Equal access index	0.79 (0.01)	0.74 (0.01)	0.68 (0.01)	0.72 (0.01)	0.78 (0.02)	0.68 (0.01)	0.83 (0.01)	0.54 (0.00)	0.59 (0.01)	0.86 (0.01)	0.67 (0.01)	0.75 (0.01)	0.76 (0.02)	0.70 (0.01)	0.85 (0.01)	0.72 (0.00)	0.80 (0.01)	0.75 (0.01)	0.71 (0.00)
	Equal distribution of resources index	0.34 (0.01)	0.39 (0.01)	0.35 (0.01)	0.38 (0.01)	0.43 (0.02)	0.46 (0.00)	0.29 (0.01)	0.19 (0.00)	0.34 (0.01)	0.58 (0.02)	0.41 (0.01)	0.42 (0.00)	0.26 (0.02)	0.35 (0.01)	0.42 (0.01)	0.33 (0.00)	0.38 (0.01)	0.43 (0.01)	0.40 (0.02)
	Equal protection index	0.67 (0.01)	0.68 (0.01)	0.67 (0.01)	0.68 (0.01)	0.70 (0.01)	0.71 (0.01)	0.57 (0.01)	0.61 (0.00)	0.74 (0.02)	0.91 (0.00)	0.52 (0.01)	0.76 (0.01)	0.59 (0.03)	0.69 (0.01)	0.90 (0.01)	0.73 (0.01)	0.82 (0.01)	0.84 (0.01)	0.37 (0.02)
	Health equality	-0.54 (0.05)	-0.76 (0.04)	-0.86 (0.05)	-0.79 (0.03)	-0.34 (0.10)	-0.53 (0.02)	-1.12 (0.03)	-1.65 (0.00)	-1.00 (0.03)	-0.52 (0.04)	-0.33 (0.04)	-0.49 (0.02)	-1.72 (0.08)	-1.05 (0.03)	-0.23 (0.01)	-1.01 (0.02)	-0.58 (0.03)	-0.57 (0.04)	-0.79 (0.07)
Institutions	Control of Corruption: Estimate	-0.44 (0.02)	-0.71 (0.02)	-0.69 (0.04)	-0.70 (0.02)	-0.63 (0.05)	-0.82 (0.04)	-0.99 (0.07)	-1.02 (0.04)	-0.17 (0.07)	-0.66 (0.03)	-1.10 (0.06)	-0.77 (0.03)	-0.84 (0.07)	-0.59 (0.06)	-0.67 (0.04)	-0.55 (0.02)	-0.71 (0.03)	-0.77 (0.04)	-0.91 (0.03)
	Electoral democracy index	0.73 (0.01)	0.49 (0.01)	0.57 (0.01)	0.51 (0.01)	0.73 (0.01)	0.70 (0.01)	0.45 (0.02)	0.51 (0.01)	0.49 (0.02)	0.66 (0.01)	0.30 (0.02)	0.49 (0.03)	0.52 (0.05)	0.49 (0.01)	0.55 (0.03)	0.47 (0.01)	0.37 (0.04)	0.57 (0.03)	0.50 (0.03)
	Executive embezzlement and theft	0.58 (0.00)	-0.73 (0.04)	-0.41 (0.09)	-0.62 (0.04)	-0.36 (0.09)	-0.12 (0.02)	-0.93 (0.16)	-1.26 (0.07)	-0.66 (0.14)	-0.19 (0.02)	-0.92 (0.20)	-0.43 (0.02)	-0.75 (0.12)	-1.52 (0.03)	-1.21 (0.06)	-0.59 (0.01)	-0.81 (0.04)	-0.48 (0.07)	-0.89 (0.07)
	Freedom of association thick index	0.80 (0.00)	0.77 (0.01)	0.81 (0.01)	0.78 (0.01)	0.86 (0.01)	0.82 (0.00)	0.76 (0.01)	0.86 (0.00)	0.79 (0.01)	0.89 (0.00)	0.47 (0.02)	0.75 (0.02)	0.75 (0.04)	0.82 (0.01)	0.79 (0.01)	0.79 (0.00)	0.74 (0.03)	0.81 (0.01)	0.80 (0.01)
	Particularistic or public goods	1.15 (0.00)	1.14 (0.04)	0.52 (0.07)	0.93 (0.04)	0.71 (0.11)	1.10 (0.06)	0.03 (0.26)	0.22 (0.00)	0.03 (0.12)	2.14 (0.06)	0.45 (0.03)	0.68 (0.09)	0.75 (0.05)	1.73 (0.04)	1.32 (0.00)	1.12 (0.05)	0.88 (0.07)	1.12 (0.13)	1.70 (0.12)
	Political System	2.00 (0.00)	0.12 (0.03)	0.72 (0.10)	0.32 (0.04)	0.00 (0.00)	0.33 (0.13)	0.00 (0.00)	2.00 (0.00)	2.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.13 (0.09)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	1.33 (0.26)	0.00 (0.00)	0.00 (0.00)
	Rule of Law: Estimate	0.05 (0.03)	-0.70 (0.03)	-0.75 (0.04)	-0.72 (0.02)	-0.82 (0.07)	-0.67 (0.04)	-1.26 (0.07)	-0.86 (0.02)	-0.43 (0.12)	-0.50 (0.04)	-1.20 (0.06)	-1.00 (0.04)	-1.17 (0.10)	-0.21 (0.03)	-0.35 (0.06)	-0.66 (0.03)	-0.69 (0.05)	-0.61 (0.03)	-1.03 (0.04)
	Social class equality in respect for civil liberty	1.01 (0.01)	1.02 (0.07)	0.92 (0.02)	0.98 (0.04)	1.09 (0.03)	1.09 (0.02)	0.71 (0.01)	0.66 (0.00)	0.94 (0.08)	2.24 (0.01)	0.48 (0.05)	1.14 (0.00)	0.67 (0.02)	1.11 (0.04)	2.16 (0.07)	1.08 (0.03)	1.91 (0.10)	1.57 (0.03)	-0.47 (0.11)
	Social group equality in respect for civil liberties	0.69 (0.01)	1.53 (0.04)	0.98 (0.06)	1.35 (0.04)	0.86 (0.15)	0.80 (0.02)	0.27 (0.10)	1.18 (0.00)	1.82 (0.09)	2.14 (0.02)	1.15 (0.03)	1.68 (0.03)	0.96 (0.15)	1.66 (0.06)	2.02 (0.01)	1.69 (0.05)	1.24 (0.07)	2.50 (0.01)	1.00 (0.09)
	Voice and Accountability: Estimate	0.43 (0.01)	-0.34 (0.03)	-0.23 (0.04)	-0.30 (0.02)	-0.01 (0.03)	-0.08 (0.04)	-1.04 (0.06)	-0.09 (0.04)	0.07 (0.05)	0.22 (0.04)	-0.95 (0.07)	-0.45 (0.06)	-0.54 (0.13)	-0.29 (0.05)	0.09 (0.07)	-0.13 (0.02)	-0.66 (0.08)	-0.32 (0.05)	-0.38 (0.08)
Socio - demographics	Employment in agriculture (% of total employment) (modeled ILO estimate)	53.52 (1.25)	67.74 (0.99)	44.71 (1.33)	60.06 (1.03)	35.38 (1.19)	40.90 (1.03)	48.73 (0.58)	29.77 (1.37)	45.76 (0.75)	46.45 (1.17)	89.49 (0.50)	49.65 (1.81)	48.86 (0.99)	70.57 (0.92)	66.90 (0.84)	78.09 (0.78)	69.97 (0.75)	77.33 (0.48)	65.78 (0.97)
	Net migration	-4.00e+05 (68151.10)	-33056.77 (6660.48)	-23415.32 (6138.98)	-29842.95 (4890.08)	-13918.20 (540.75)	-76547.40 (7502.53)	-1.13e+05 (9778.69)	43452.33 (1395.16)	-2380.87 (132.53)	3627.87 (2383.00)	24107.47 (14151.64)	-2462.80 (120.66)	10714.13 (14422.51)	-20739.87 (2642.82)	-32383.67 (8735.17)	-32369.73 (8308.16)	-2.62e+05 (20645.95)	-5893.20 (2070.41)	32467.73 (17123.66)
	Population density (people per sq. km of land area)	399.32 (7.09)	109.20 (8.27)	41.16 (4.42)	86.52 (6.03)	8.98 (0.18)	125.18 (1.92)	62.40 (1.64)	15.34 (0.56)	18.15 (0.50)	77.20 (2.74)	317.77 (14.52)	333.36 (8.11)	37.84 (1.57)	144.62 (4.81)	11.64 (0.45)	27.36 (0.89)	184.43 (1.75)	11.94 (0.52)	82.38 (2.85)
	Rural population (% of total population)	70.06 (0.40)	72.28 (0.84)	61.94 (1.89)	68.83 (0.89)	34.96 (0.54)	52.54 (0.92)	53.92 (0.50)	86.92 (0.02)	81.24 (0.52)	58.40 (0.60)	90.08 (0.30)	72.00 (0.04)	53.21 (0.43)	84.72 (0.13)	66.32 (0.93)	69.05 (0.42)	84.18 (0.39)	83.77 (0.01)	62.19 (0.42)

Note: The table reports country-means for the period 2000-2014. Standard errors are in parentheses.

Table F. 4: Country comparisons, agricultural productivity

Indicator	India	Aggregates Low income	Lower middle income	Low & lower middle income	Lower middle income countries Bolivia	Indonesia	Cote d'Ivoire	Papua New Guinea	Solomon Islands	Lower income countries Benin	Burundi	Comoros	Liberia	Malawi	Mali	Mozambique	Nepal	Niger	Sierra Leone
Agriculture, forestry, and fishing, value added (% of GDP)	17.99 (0.46)	34.47 (0.86)	18.65 (0.90)	29.23 (0.79)	11.33 (0.39)	14.31 (0.30)	16.77 (0.42)	25.54 (2.31)	32.10 (0.79)	25.82 (0.27)	39.40 (0.88)	29.71 (0.15)	59.96 (3.79)	26.42 (0.79)	33.10 (0.70)	23.63 (0.69)	32.57 (0.80)	37.01 (0.81)	51.07 (0.87)
Annual freshwater withdrawals, agriculture (% of total freshwater withdrawal)	90.78 (0.10)	67.47 (2.27)	57.78 (3.83)	64.62 (1.97)	91.69 (0.08)	80.33 (0.66)	43.24 (1.08)	0.28 (0.01)		33.84 (2.03)	78.82 (0.20)	47.00 (0.00)	8.62 (0.09)	86.25 (0.13)	97.94 (0.03)	74.05 (0.38)	98.00 (0.06)	77.58 (2.82)	22.05 (0.24)
Level of water stress: freshwater withdrawal as a proportion of available freshwater resources	65.56 (0.33)	6.38 (0.41)	6.34 (0.93)	6.37 (0.40)	1.16 (0.01)	21.49 (1.09)	6.09 (0.14)	0.12 (0.00)		0.98 (0.00)	10.25 (0.03)	0.83 (0.00)	0.26 (0.00)	17.31 (0.12)	7.93 (0.04)	1.38 (0.06)	8.32 (0.01)	4.83 (0.25)	0.48 (0.00)
Cereal yield (kg per hectare)	2582.73 (68.67)	1409.20 (48.06)	2934.98 (123.98)	1917.79 (68.14)	1931.72 (59.46)	4560.18 (104.44)	1875.38 (56.35)	4109.31 (102.97)	2989.64 (258.78)	1254.92 (41.15)	1262.40 (18.54)	1323.87 (7.53)	1190.43 (51.39)	1660.93 (139.80)	1236.83 (75.23)	771.92 (57.54)	2354.19 (51.43)	420.23 (16.29)	1344.77 (80.50)
Water productivity, total (constant 2015 US$ GDP per cubic meter of total freshwater withdrawal)	2.02 (0.15)	17.57 (1.86)	17.01 (1.52)	17.41 (1.39)	11.12 (0.54)	3.55 (0.05)	23.49 (1.45)	38.32 (1.60)		64.21 (3.06)	8.77 (0.41)	77.70 (2.69)	16.45 (0.90)	4.71 (0.29)	1.85 (0.09)	8.05 (0.36)	1.86 (0.09)	5.68 (0.05)	15.06 (1.30)

Note: The table reports country-means for the period 2000-2014. Standard errors are in parentheses.

Table F. 5: Country comparisons, water stress and productivity

Indicator	India	Sri Lanka	Armenia	Kyrgyz Republic	Tajikistan
Agriculture, forestry, and fishing, value added (% of GDP)	17.99 (0.46)	12.23 (1.01)		24.86 (2.07)	21.79 (0.57)
Annual freshwater withdrawals, agriculture (% of total freshwater withdrawal)	90.78 (0.10)	88.34 (0.44)	66.93 (1.27)	93.06 (0.10)	89.74 (1.62)
Level of water stress: freshwater withdrawal as a proportion of available freshwater resources	65.56 (0.33)	90.88 (0.04)	49.86 (2.54)	53.63 (1.44)	74.21 (1.01)
Cereal yield (kg per hectare)	2582.73 (68.67)	3594.01 (53.05)	2239.11 (151.21)	2651.27 (57.68)	2383.25 (163.96)
Water productivity, total (constant 2015 US$ GDP per cubic meter of total freshwater withdrawal)	2.02 (0.15)	4.23 (0.31)	3.05 (0.14)	0.59 (0.04)	0.45 (0.04)

Note: The table reports country-means for the period 2000-2014. Standard errors are in parentheses.