Can Crises Affect Citizen Activism? Evidence from a Pandemic*

October 7, 2025

Abstract

We ask whether major crises can be catalysts for civic activism. Using state-level variation in COVID-19 peaks in India and quasi-random participation in an online survey (March–July 2021), we measure willingness to act against healthcare fraud by supporting an NGO advocating transparency. Comparing respondents surveyed before and after their state's COVID-19 peak, we find a significant rise in anti-corruption activism post-peak. This surge appears driven by heightened perceptions of healthcare corruption, greater awareness of rights, increased risk tolerance, and more optimistic beliefs about others' willingness to act. Our findings suggest crises can mobilize citizens toward collective action for accountability.

JEL codes: D73, D83, I15
Keywords: crisis, corruption, health sector, activism, COVID-19

*We acknowledge financial support from the UK government's Global Integrity Anti-Corruption Evidence (GI-ACE) program, through DFID Accountability Initiative. The data used in this paper are part of a larger study, which included random allocation of subjects to different anti-corruption treatment conditions. We pre-registered the larger experimental study on AsPredicted in March 2021. The data collection for the larger study happened in two waves, due to the need to generate survey responses in wave 1 that would allow us to incentivize belief elicitation in wave 2. The larger study employs data from the second wave of data collection. In this paper, we employ data from the first wave of the data collection and from the Control condition of the second wave.

1 Introduction

Direct lived experiences may be powerful motivators for belief formation and decision-making (Malmendier, 2021). By impacting large segments of the population, major crises caused by economic shocks, natural disasters, violent conflicts or health epidemics, may induce persisting changes in individual-level and society-level beliefs, expectations and behaviors.[1] The COVID-19 pandemic stands as an unparalleled global crisis, due to its profound impact on virtually every aspect of life worldwide. Similar to other catastrophic events, the pandemic also facilitated corruption in settings characterized by weak institutions, lack of transparency in the disbursement of emergency health funds, and little oversight over the use of such funds (Gallego et al., 2020; Rose-Ackerman, 2021; Vrushi and Kukutschka, 2021).

In this paper, we investigate whether, by amplifying difficulties in accessing medical care and by forcing large segments of the population to directly confront corruption within the healthcare system, the pandemic increased individuals' willingness to engage in anti-corruption activism in India. We exploit state-level variation in the timing of the second COVID-19 wave, between April and July 2021, and data from an online survey experiment that we administered throughout India between March and July 2021. The second wave of the pandemic occurred in India largely unexpectedly in April 2021, and the number of daily cases peaked nationally on May 8, 2021. The resulting loss of lives is unprecedented in history (Jha et al., 2022), causing widespread grief that touched nearly every family, regardless of socioeconomic status.[2]

The online survey aimed to capture experiences with the healthcare system, and individual willingness to engage in activism to curb fraud and corruption in hospitals. We implemented the study through Qualtrics, which manages large survey panels in India. We partnered with a Non-Government Organization (NGO) working on increasing transparency and accountability in the health sector. Importantly, the data collection was opened and closed multiple times by the Qualtrics team over the implementation period across the country (at the same time), to meet pre-determined quota and data quality checks. This generated quasi-random variation in the timing of individual participation in the survey, which allows us to compare, within a state, the preferences and decisions of individuals who participated

[1] Studies in psychology and neuroscience suggest that "emotional events often attain a privileged status in memory" (LaBar and Cabeza, 2006) and prior experiences influence how individuals learn (Sharpe et al., 2021; Spunt and Adolphs, 2017; Isen et al., 1978).

[2] According to the World Health Organization dashboard, India had a cumulative 44,997,326 total cases as of 11 September 2023, second only to the United States, and the third highest death count. In particular, the second wave (April-July 2021) in India witnessed the highest surge in the world. India became the first country to report over 400,000 new cases in a single day on April 30, 2021 (see Media Report).

in the survey before and those who participated after the COVID-19 peak.[3]

In the survey, we first elicit individuals' support for a (hypothetical) anti-corruption social movement, by asking for their willingness to "participate in a protest against corruption in the delivery of health services." We then give subjects the chance to take real action against fraud and corruption in the health sector. Specifically, at the end of the survey, we ask subjects whether they would be willing to sign a petition to the Ministry of Health to demand more accountability in the health sector, or make a donation to the NGO working to increase accountability and reduce corruption, or watch a 5 minute informational video on ways to take action against fraud in the health sector. These are very common forms of online or "armchair" activism, i.e., engagement with social causes without in-person participation. They are less costly than in-person activism, but can drive change by generating significant support for NGOs advocating for social causes, either through donations[4] or by pressuring key decision-makers in the private and public sectors (Colmer et al., 2023; Daubanes and Rochet, 2019).

Data from our sample of nearly 900 Indian men, of which about 35% surveyed before the COVID-19 peak in their state of residence, and 65% surveyed after the peak, show evidence of a substantial and statistically significant increase in subjects' willingness to take action against healthcare corruption after being exposed to the second wave of the pandemic. We document a 9% increase in willingness to protest against healthcare corruption, a 31% increase in stated willingness to take action by either signing a petition, making a donation to an NGO or watching an how-to-act video, and a 42% increase in actual engagement in one of these forms of activism. Our survey data indicate that this increase in willingness to engage in anti-corruption activism likely stems from: (1) an increase in perceived corruption in the health sector, (2) greater awareness of own rights and entitlements regarding health provision, (3) increased risk tolerance and (4) a positive shift in individual beliefs about others' willingness to take action. We find suggestive evidence that the impact of the crisis may have persisted in the longer-term. Using data on self-reported willingness to protest from an online survey we conducted 14 months after our initial study (following the same procedures), we find a 7.8 pp increase in subjects' (hypothetical) willingness to protest relative to pre-crisis. We interpret this with caution as longer-term estimates are more vulnerable to time-varying state-level factors and other confounding influences.

Our paper adds to the literature on how personal experiences of society-wide negative shocks can affect individual beliefs, preferences and behaviors, both at the micro- and the

[3]Our study design is sometimes referred to as an "unexpected event during study design". See Muñoz et al. (2020) for a review of this methodology.

[4]For instance, in the US, immediately after the Supreme Court's decision to overturn Roe vs Wade, in June 2022, donations to Planned Parenthood increased by 40 times compared to a regular day.

macro-level. For instance, Malmendier and Nagel (2011) show that individuals' experiences of macro-economic shocks have long-term effects on risk attitudes and investment decisions, and Belloc et al. (2016) document that in the Middle Ages experiencing earthquakes facilitated the transition from autocratic to self-governed institutions in Italy. A large literature on the microeconomics of violent conflicts provides evidence on the impact of war victimization on individual attitudes and preferences, including civic engagement and political participation (Bauer et al., 2016; Shai, 2022; Bellows and Miguel, 2009; Blattman, 2009; Akbulut-Yuksel et al., 2020). Recent work on environmental disasters show that exposure to such disasters (e.g, wildfires) impacts individual preferences over the size of government and climate activism (Coury, 2025; Coury and Winichakul, 2025; Xu, 2025).

While there exists a large body of work on the effects of major health shocks on economic activity, health outcomes, and human capital development (see Beach et al. (2022) for a recent review of this literature), investigations of impacts on individual preferences and attitudes are scarce. Klemm and Mauro (2022) find that, in the US the COVID-19 pandemic increased support for progressive tax reforms, with the results being driven by individuals who experienced serious illness or job losses. Recent studies show that exposure to an epidemic over an individual's formative years reduces confidence in scientists, leading to lower vaccine take-up (Eichengreen et al., 2021) and to lower confidence in both political institutions and the healthcare system (Saka et al., 2022). Evidence of long-term effects of pandemics is also provided by Aassve et al. (2021), who show that the descendants of Spanish Flu survivors, who immigrated to the US, inherited a lower level of social trust. Additionally, recent work has shown that the COVID-19 pandemic had lasting impacts on preferences, e.g., work preferences (Chen et al., 2023), political preferences (Baccini et al., 2021), and confidence in the press and in governmental organizations (Brodeur et al., 2021).[5]

The primary challenge in the investigations of the impact of global health shocks on preferences lies in the identification of causal effects. This is due to the widespread and simultaneous diffusion of a pandemic across a population, and the non-random implementation of response strategies by national and local governments. We overcome these challenges by employing survey data collected as the second wave of the pandemic unexpectedly unfolded in India, and by leveraging time and spatial variation in exposure to the pandemic, together with quasi-randomness in the timing of survey participation.

Finally, we contribute to the literature on ways to counter corruption by leveraging participatory mechanisms and citizen involvement. The implementation of effective anti-corruption systems in setting where corruption is widespread is challenging. While top-

[5] For a review of the literature on the socioeconomic consequences of the COVID-19 pandemic see Brodeur et al. (2021).

down monitoring and accountability systems have proven effective (see, e.g., Ferraz and Finan, 2008; Olken, 2007; Zhang, 2023) their implementation is often hindered by poor institutions, lack of transparency and collusion between monitors and agents.[6] In these environments, pressure from service recipients through bottom-up monitoring (Afridi et al., 2024; Bjorkman and Svensson, 2009; Serra, 2012) and social activism, often facilitated by advances in information and communication technologies (Jha and Sarangi, 2023) and by the outreach activities of dedicated NGOs, may be necessary to achieve change. Our study shows that global negative shocks, by heightening individual experiences of corruption and creating a sense of urgency for efficient service delivery hindered by corruption, can alter individual preferences for anti-corruption activism. Notably, while widespread media coverage of the pandemic—both globally and within India—highlighted inefficiencies in the health sector and the resulting large loss of lives, this alone was not enough to drive activism. Our findings show that direct personal experience, particularly exposure to the second wave during one's own state's peak, was the key driver of change. This occurred through increased information on own rights and entitlements, more severe perceptions of corruption, and changes in beliefs about others' willingness to join an anti-corruption social movement.

In the next section, we discuss India's health sector and the timeline of the pandemic in the country. The data and methodology are elaborated upon in Section 3. Section 4 presents the results, including robustness checks. We conclude in Section 5.

2 Background and Context

2.1 India's Health Sector

The Indian healthcare system suffers from chronic under investment in key infrastructure and a high level of out-of-pocket expenditure, especially in poorer states (Garg and Karan, 2009; Das et al., 2016; Banerjee et al., 2008).[7] In fact, the healthcare system is characterized by substantial state-level variation in healthcare spending as a proportion of budget, capacity of hospital beds, and availability of health personnel and testing centers (Choutagunta et al., 2021). Moreover, the private sector has recently become a dominant player in healthcare provision, with minimum government regulation. This has led to nearly 70% of all health expenses occurring in the private sector, a substantially larger number than the average of

[6] For a review of issues related to corruption in developing countries, see Banerjee et al. (2012); Pande (2011); Serra and Wantchekon (2012).

[7] According to the World Bank, India spent only USD 63.75 on health care per capita, versus a world average of USD 1,121.81 in 2019. Similarly, the share of out-of-pocket expenditure was roughly 55% of current health expenditure in India, whereas the world average was about 18%.

46% observed in low and middle countries.[8]

Capacity and budgetary constraints, insufficient regulation and lack of oversight contribute to the proliferation of fraud and corruption in healthcare provision (Kumar, 2003).[9] Although corruption has been an enduring issue within the Indian healthcare sector, the COVID-19 pandemic significantly exacerbated its scope and impact. The absence of a regulatory framework posed a significant obstacle for states seeking to enforce accountability measures against corrupt individuals within healthcare facilities.[10]

Corruption took place in the form of overcharging for COVID-related services, favoritism in service provision, and even the administration of fake vaccines for a fee.[11]

2.2 Pandemic Timeline

The first wave of the COVID-19 pandemic was marked by a strict nationwide lockdown with restrictions on domestic and international travel, stretching from 25 March 2020 to 31 May 2020, with the caseload peaking nationally around September 2020. In stark contrast, the second wave of the pandemic, which reached India during spring 2021, was marked by general unpreparedness and lack of coordinated efforts to keep the upsurge of COVID-19 cases under control. Moreover, the management of disease control and vaccinations shifted from the federal to the state governments (Press Information Bureau, 2021) between the two waves.

The 7-day moving average of the confirmed daily case-load surged from 65,144 on April 1 to about 392,331 by May 8, 2021, at its peak (World Health Organisation, 2022). According to news reports, in the absence of a nationwide lockdown, most states issued a complete or partial lockdown (Indian Express, 2021). Despite such localized lockdowns, each state showed similar increases in daily confirmed cases. Nevertheless, the different states reached their peak at different times, between April and July 2021. Specifically, ten states peaked before the national peak (May 8), nineteen states peaked on or after the national peak, but still in the month of May, one state peaked in June and one in July.[12]

[8] For more details, see data from World Bank.

[9] See also the Transparency International Health Sector Corruption report Transparency International - Health Sector Corruption.

[10] For instance, the Clinical Establishments Act (2010), which provides for the registration and regulation of clinical establishments and prescribes minimum standards of facilities, had not been adopted at the time of the pandemic. For more press coverage of the limited implementation of this act, see: The Print and The Tribune.

[11] For news coverage, see here.

[12] In the Online Appendix A, we report the specific COVID-19 7-day moving average peak dates in each Indian state in Table A1.

3 Data and Methodology

3.1 Data

We conducted an online survey of adult Indian men implemented by Qualtrics between March and July 2021.[13] The study was framed as a general survey focused on understanding people's behavior and attitude during the pandemic, rather than health sector 'corruption' per se, in order to avoid priming the subjects.

The survey opened and closed on random dates between March and July 2021 throughout the country.[14] To identify the unanticipated COVID-19 wave and subsequent peaks in national and state-level daily caseloads, we utilize publicly available administrative data.[15] In Figure 1, we show the distribution of subjects according to the date of case peak experienced in their respective states of residence (in grey) and the timing of the survey (in red).[16] Depending on each respondent's random date of survey, we create a dummy variable that indicates whether the subject participated in the survey on or before the peak-date of daily COVID cases in his state of residence.[17]

Following a battery of initial questions on demographics and experience with healthcare, we measured subjects' support for a social movement aimed at fighting corruption in the health sector. Specifically, we elicited individuals' agreement/disagreement with a statement related to their personal willingness to take part in a (hypothetical) protest aimed at fighting malfeasance/irregularities in the health sector during the pandemic. This constitutes our (hypothetical) outcome measure of willingness to protest.[18] Once subjects reached the end

[13] We recruited only men to avoid gender disparities arising from access to computer/mobile devices, healthcare and intra-household decision-making. Participation was conditional on monthly household income of INR 60,000 or less. Therefore, our average survey respondent is younger, more educated and belongs to wealthier households than the average Indian urban man.

[14] Qualtrics maintains a large pool of subjects who are representative of relatively younger, economically better-off and urban Indian population. Qualtrics sends a link to the potential respondents and waits for the sample to reach the target quota. Subjects in this survey did not get to see when the survey link would be on or for how long it would remain active. Typically, it took between 1 and 4 days to collect the target data. For detailed information on the dates the survey was open and closed by the Qualtrics team, see Table A2 in the Online Appendix.

[15] See: `https://www.covid19india.org/`.

[16] Throughout the paper, "peak" refers to the peak in daily new confirmed cases of COVID. Our main results are robust to using the peak in daily deaths instead. Additionally, our results hold when replacing state-level peaks in COVID cases with the national peak. We also show the statewise count of subjects interviewed before and after their respective peak dates in columns 2 and 3 of Table A1 in the Online Appendix.

[17] The national peak in daily cases was on May 8, 2021. The state-wise peaks in daily cases are provided in Table A1 in the Online Appendix.

[18] Willingness to engage in anti-corruption activism may be a sensitive issue for some individuals. Sensitivity bias in survey responses is attenuated in online surveys, as study participants remain anonymous to researchers.

of the survey, we thanked them for their participation (following standard practice in online surveys) and then we invited them to "think about the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic." We included a brief description of a nation-wide NGO that we partnered with - the All India Drug Action Network (AIDAN). AIDAN is a collective of medical and legal professionals that has been pressurizing local and federal government to better regulate health care in India, fostering transparency in pricing and providing redressal to patients who have been illegally overcharged. We then asked subjects whether they wanted to support AIDAN's activities or exit the survey. Subjects were randomly assigned to different forms of online activism, which we designed in collaboration with AIDAN. Specifically, they could either sign a petition to the Health Ministry (*Petition Treatment*), or donate part or all of their survey earnings to AIDAN (*Donation Treatment*), or watch an informational video on AIDAN's activities and ways to get involved (*Video Treatment*),[19] or choose among the three actions (*Choice Treatment*).

Subjects assigned to the *Petition Treatment* were given the chance to sign a petition addressed to the Union Health Minister of India. If subjects clicked on "Petition," they were shown a new page, which disclosed the full 200-word long letter, which we designed in close collaboration with AIDAN. The letter placed demands on the government to (1) fast-track the adoption of regulatory laws of health establishments, (2) adopt a clear communication of treatment protocols and implementation of prescription audits, and (3) implement district level grievance redress systems for patients. At the bottom of the petition, subjects were given the chance to sign by writing down their name (first or full or leave empty), knowing that the petition, once all signatures had been collected, would be sent to the Health Minister. Subjects could also decide not to sign the petition and instead select the "Exit Survey" button, which appeared at the bottom of the same page.

Subjects assigned to the *Donation Treatment* were given the same information about the non-profit organization (AIDAN) as in the Petition Action Treatment, once they reached the final survey page. They were then given the option to either donate a percentage of their bonus earnings – generated via the belief elicitation and a risk preference task – to the organization, or to exit the survey. If they selected the "Donation" button, they were shown a new page where they were asked to select their desired donation level, out of 10 possible levels, i.e., 10 percent, 20 percent, 30 percent, and so on and so forth, up to 100 percent of their bonus earnings.[20] Importantly, 0 percent was also listed as a possibility, meaning that subjects could still decide to not make a donation to the organization prior to exiting the

[19] See Online Appendix B for the decision screens shown to the participants.

[20] We deducted the contribution from subjects' earnings and donated the amount to AIDAN after completion of the study.

survey.

Subjects in the *How-To-Act Video Treatment* received the same information at the end of the survey, but were given the chance to watch a 5-minute informational video about AIDAN's activities, including examples on how the organization helps citizens fight corruption in the health sector. The video also provided information on how citizens can assist AIDAN's efforts to promote transparency and accountability, for instance by sharing information on their own experience with illegal practices in the health sector and by collectivizing in the fight against corruption. Like in the other treatments, subjects were first given the chance to select either "Exit Survey" or "Video", and then, once the video started in the next page, they could still exit the survey at any time. We included an invisible time tracker to record how long the participants watched the 5-minute video.

Finally, subjects randomly assigned to the *Choice Treatment* received the same information about AIDAN, but were presented with the three actions - Petition, Donation, Video – and asked whether they would like to take up one of them - but only one - or exit the survey.

Our design resembles solicitations of activism from NGOs through email or social media. Such solicitations typically include a link to a petition, donation or video campaign page. Interested subjects first click the link to gather more information on the initiative, and then, once on the action page, decide whether to take action. Similarly, our design leads to two measure of anti-corruption activism: (i) individual initial willingness to act by selecting the activism option presented to them at the end of the survey (the equivalent to clicking the link provided in an email) rather than exiting, and (ii) actual activism, i.e., the decision to sign the petition, or donating part of their earnings to the NGO, or watching the full 5 minute how-to-act video, once on the action page.

Our analysis is therefore based on three outcome variables: (1) the hypothetical willingness to protest against corruption in the provision of health service, elicited through a survey question; (2) stated willingness to take action, as measured by the decision to not exit the survey and instead receive more information on one of the forms of activism presented to subjects, and (3) actual activism, measured by the decision to engage in one of the three forms of activism – signing the petition with a name, donating a positive amount or watching the full 5-minutes of the how-to-act-video.[21] For the latter two measures, due to our small sample size, we pull together the subsamples of survey participants who were asked to engage in each of the available forms of activism. We replicate the analysis for each form of activism separately and report the estimates in the Appendix.

We consider our measures of willingness to act and actual activism as a *real-effort* be-

[21]For examples of online survey-based studies using a petition or a donation to measure individual preferences see for instance Alesina et al. (2018); Settele (2019); Bursztyn et al. (2020).

havioral, rather than *hypothetical*, measures since subjects had to incur a cost when they chose to engage in these actions instead of exiting the survey.[22] We therefore expect them to be less likely affected by social desirability bias and more likely to reflect individual true preferences regarding anti-corruption activism. While our "willingness to protest" measure is hypothetical and self-reported, it is still contextually important because, due to our study methodology (online survey), we could not include protesting in our real-effort elicitation of activism.

3.2 Empirical Methodology

3.2.1 Estimation Strategy

Our main estimating equation is the following:

$$Y_{ist} = \gamma + \beta_0 \; Post_{ist} + \beta_1 X_{ist} + \alpha_s + \varepsilon_{ist} \tag{1}$$

where $\mathrm{Y_{ist}}$ is one of the three outcome variables defined above - hypothetical willingness to protest, willingness to act, and the decision to engage in actual online activism. $\mathrm{Post_{ist}}$ is a dummy variable equal to 1 if the subject i's survey date t was after the 7-day moving average peak in daily COVID cases in his state of residence s, and 0 otherwise.[23] Hence, β_0 is our main coefficient of interest, capturing the effect of the second wave of pandemic on outcomes. $\mathrm{X_{ist}}$ is a vector of individual characteristics, such as age, education, marital status, religion (1- Hindu; 0- otherwise), caste (1-SC (Schedule Caste), ST (Scheduled Tribe) or OBC (Other Backward Classes) subjects; 0 otherwise), income (1 if household income is below INR 30K in previous month; 0 otherwise), assets (count of assets owned by a subject from a list of 10 common household assets), household composition, (i.e., having children, living with parents and living with an elderly person), mode of participation by phone and frequency of participation in online surveys.[24] We also include state fixed effects α_s and an idiosyncratic error term $\varepsilon_{\mathrm{ist}}$. Throughout, we define the peak in terms of the 7-day moving

[22] By not exiting the survey subjects incurred the opportunity cost of time. By signing the petition they further incurred the cost of being identified by the Ministry of Health, and possibly receiving individual punishment. By making a donation, subjects incurred a pecuniary cost. By watching the 5-minute video, they incurred the opportunity cost of longer time spent on the survey. Recent work by Chapman et al. (2025) questions the reliability of qualitative self-assessments of preferences, as opposed to incentivized elicitations. We note that our behavioral measures of activism go beyond self-reported elicitation, capturing costly actions rather than stated intentions alone.

[23] Bol et al. (2021) have also adopted a similar estimation strategy while measuring trust in government during COVID-19. For a recent review of studies using similar strategy, see Muñoz et al. (2020).

[24] SC, ST, or OBC groups indicate subjects are who are socio-economically deprived individuals in India.

average.[25] Standard errors are clustered at the state-month level to account for unobserved heterogeneity over time and space.

Note that equation 1 does not contain time fixed effects. Although the survey was fielded over a four-month period, it was only open for a limited number of days, spread irregularly before and after each state's peak. Including calendar-time fixed effects would absorb nearly all of this limited temporal variation, leaving insufficient degrees of freedom to identify the effect of interest. To account for this, we supplement our analysis by estimating equation 1 at successive bandwidths around the timing of the shock, capturing the impact dissemination over time during the study period. Specifically, we estimate whether the impact of the crisis differs with the distance – measured in days – between the time of the survey and the time of the state-level peak. We therefore define a model with a running variable, *Days*, ranging from -112 to 93, with 0 corresponding to the day of the peak, and 1 indicating the first day after the peak, as follows:[26]

$$Y_{ist} = \gamma + \beta_0 \; Post_{ist} + \beta_1 \; D_{ist} + \beta_2 \; D_{ist} \; \times \; Post_{ist} + \beta_3 X_{ist} + \alpha_s + \varepsilon_{ist} \tag{2}$$

where $\mathrm{D_{ist}}$ (i.e., the *Days* variable) denotes the difference in days between the interview date t and the peak date for subject i residing in state s. In this model, $Post_{ist}$ indicates the immediate impact of exposure to the peak, whereas the interaction term $D_{ist} \times Post_{ist}$ tests whether the impact became weaker or stronger over time. We also check for trends, explicitly, later.

Given the number of outcome variables, we correct the p-values associated with individual hypotheses by employing the step-down multiple testing method developed by Romano and Wolf (2005). Finally, we examine whether the impact of the crisis on activism is long-lasting. To do so, we augment our sample with additional survey data collected following the same procedure between August and November 2022, i.e., more than one year after our primary data collection. However, from this new survey wave we only have the hypothetical willingness to protest as our measure of activism.

3.2.2 Threats to Identification and Robustness Checks

Since the experience of the pandemic or its timing is unlikely to be random, we utilize the quasi-random staggering of the time of the survey data collection within a state of residence, jointly with state-level variation in the timing of the pandemic, to assess the impact of the

[25] Note that in the absence of centralized lock-downs, we can consider the stringency of localized lock-downs as a factor that varied at the state-level, and is absorbed by the state fixed effects.

[26] For example, if the peak in subject's state of residence was on 9 May 2021 and he was interviewed on 10 May, then the Days variable would be equal to 1.

crisis on anti-corruption activism. Note that given our data, we cannot measure the change in willingness to act for a *given* individual; rather, we compare different individuals who were surveyed pre- and post-peak within the same state.

For causal estimation, we require that conditional on observables, assignment to pre or post periods is independent of the outcomes. We assume that this is the case given the quasi-randomness of the timing of the survey implementation by the Qualtrics team. Specifically, subjects could not select into either pre or post group, because the survey was opened and closed for several brief time spans (in all states across the country at the same time), which was unpredictable from the respondents' viewpoint. Respondents were given only one opportunity to take the survey. Therefore, we consider the assignments of individuals to a pre or a post group as good as random.[27] This does not necessarily mitigate concerns about unobserved differences and therefore needs further elaboration. In Table 1, we test and show that the pre and the post samples are similar in terms of observable characteristics, with only 2 out of 12 variables (marital status and being a disadvantaged Caste) being significantly different across groups. Additionally, as a robustness check, we repeat the main analysis after implementing entropy balancing (Hainmueller, 2012). This is a weighting process used to create balanced samples in observational studies with a binary treatment where the control group data can be re-weighted to match the co-variate moments in the treatment group. Column 4 of Table 1 confirms that after re-weighting, we see balance in all individual characteristics.[28]

We also check whether the quality of the data generated by the pre- and post-peak samples is consistent. Specifically, we compare recruitment speed and subject comprehension. The former is the number of Qualtrics surveys completed per minute during the time the survey was open. The latter is the rate at which participants failed attention checks. In the Online Appendix, we show (Figure A1) that these two measures are not statistically different in the pre and post groups. As a further test of whether other simultaneous events may confound our results, for instance by affecting the selection of participants in the survey, we check whether the state-level unemployment rate differs pre- and post- peak. To this end, we use the nation-wide CMIE-CPHS data (CMIE, 2023) for 227,200 adult males residing in Indian states between March - July 2021. We re-run equation 1 with individual-level employment as the outcome variable. We find no evidence of significant changes in employment rates

[27]Given that our survey period is fairly short, i.e., ranging from March 24 to July 26th, 2021, it is unlikely that other major systematic changes occurred in that time frame, besides the COVID-19 crisis.

[28]In contrast to most other matching methods, entropy balancing involves a re-weighting scheme that directly incorporates co-variate balance into the weight function that is applied to the sample units. An advantage of this method is that unlike the traditional coarsened exact matching, entropy balancing does not require huge data sets, and does not cause large portions of the sample to drop.

following the state-level COVID-19 peaks.[29] Finally, we provide several robustness checks in Section 4.1 to further assure that our estimation strategy provides causal estimates, including testing for any confounding trends.

We note that our identification strategy does not assume that subjects interviewed before the peak did not expect the peak to occur. While this may be true in the states that were affected by the second COVID-19 wave early on, once the rapid increase of COVID-19 cases was covered by news outlets, it is possible that subjects surveyed before the peak in their state of residence expected the peak to occur soon. In our analysis of heterogeneous effects, we check whether the impact of the crisis on activism is larger for subjects in early-peak than those in late-peak states.

4 Main Results

We report results from estimating equation 1 in Panel A of Table 2. For each of our measures of activism (willingness to protest, willingness to take action, and decision to take action), we report estimates without controls (columns (1), (3), and (5)) and with controls (columns (2), (4) and (6)). The estimates show that the willingness to protest against corruption increases by 7.5 percentage points (pp) after exposure to the COVID-19 peak (columns (1) and (2)). This translates into a 9% increase over the pre-peak mean of 83.2% of respondents willing to protest. Similarly, the willingness to take action at the end of the survey increases by 11.6pp after the pandemic peak (column (4)), which corresponds to a 31% increase over the pre-peak mean of 37.2%. Finally, column (6) show that the likelihood of taking an action increases by 9.8pp, i.e., 42% over the pre-peak mean of 23.3%. These estimates are robust to the Romano-Wolf correction for multiple hypothesis testing as shown in the p-values reported in Panel A. Our results are robust to entropy balancing, as shown in columns (1), (2), and (3) of Table A4.

In Panel B of Table 2, we estimate equation 2. For the hypothetical measure of willingness to protest neither the estimate for immediate effect nor exposure over time, is statistically significant (columns (1) and (2)). However, we find that the immediate impact of exposure to state peak on the real-effort willingness and decision to act is substantial. Columns (3) to (6) show that the immediate impact of the peak was an increase in willingness to act and in the likelihood to take action by 24pp and 16pp, respectively. The estimated coefficient of the interaction term *Days x Post* is statistically significant and positive in columns (3) to (6), suggesting that the impact of the peak on activism increases by between 0.8 and 0.5pp for each day post peak. The negative coefficient of the non-interacted *Days* variable

[29] See Table A3 in the Online Appendix.

indicates that as the peak of COVID-19 came nearer, preferences for activism gradually decreased, although the latter impact loses statistical significance at conventional levels when implementing entropy balancing.[30]

To graphically illustrate our results, we dis-aggregate the pre and post time periods as distance (in months) from the month containing the state peak. The time paths for our three measures of activism, shown in Figure A2 in the Online Appendix, confirm that our three measures of activism increased steadily in the 3 months following the state-level peak.

To delve into the types of actions which drive our findings above, in Panels A and B of Table 3. We dis-aggregate the results by each type of action at the extensive (Panel A) and intensive margins (Panel B) and estimate the effect of the peak on the take-up of petition, donation and how-to-act video actions when offered individually (columns (1) - (3)) or jointly (column (4)). We find that the overall significant increase in action taken is attributable to the increased likelihood of donating or taking any of the three actions (columns (2) and (4), Panel A). The willingness to donate to AIDAN increases by 18.0 pp, while the willingness to take any one of the three actions rises by 15.4 pp. The impact of the peak on willingness to sign a petition (column (1)) or watch how-to-act video (column (3)) is insignificant. On the intensive margin (Panel B), the amount of donation (column (2)) or any action actually taken, i.e. signing the petition, donating any amount or watching the video (column (4)), Panel B) increases significantly.

Overall, our results show that the pandemic's intensity significantly impacted individuals' willingness to take action that could improve accountability in the delivery of health services. In particular, individuals were more likely to donate to our partner NGO which has been engaged in voicing concerns related to regulating the health sector. These findings indicate that we are capturing meaningful changes in activism.[31]

4.1 Robustness

We acknowledge the possibility that time varying characteristics at the state level may be confounding our results since we are unable to include time fixed effects due to our short panel. We conduct several robustness checks to address this and other concerns with our empirical analysis below.

Randomization Inference and Pre-trends: To address the possibility that pre-peak trends drive our results, we first conduct a placebo test. Figure 2 plots the results of a

[30]Full results are available upon request.

[31]The findings above, for state peaks in COVID cases, are qualitatively unchanged when we instead estimate the effect of COVID deaths on our measures of activism. Results are available on request.

randomization inference test (Heß, 2017) aimed at checking the impact of a false positive exposure effect created by chance. We assign a randomly selected 'placebo peak date' to each state within the time interval of our study, replicating the process 1,000 times. The estimates in Panel A of Table 2 are larger than the placebo effects, confirming that our results are not false positives. We also check for pre-trends by plotting residuals of our estimated equation for up to 100 days prior to the COVID peak in each state. We do not observe a systematic trend in any of the three outcomes (Figure 3).

Bandwidths: We vary the bandwidth around the state-level peak by ± 1 day(s) to test the sensitivity of our results to the length of the time periods around the pandemic peak. Recall that our overall time window is 125 day, i.e., from March 24 (when the data collection began) to July 26, 2021, when it ended. We begin with employing the smallest bandwidth possible (given the short time frame of our study) around the COVID-19 peak, which is 18 days before and 18 days after the peak. This ensures that we have enough observations to ensure balance in covariates between pre and post groups at every bandwidth.[32] Subsequently, we keep increasing the bandwidth by one day up to the maximum available span of ± 112 days, depending on the state, to ensure that we are able to compare citizen activism around all state peaks in our sample. The results, presented in Figure 4, show that the estimated impact of exposure to peak is consistently positive and stable over time, for all our outcomes. The observed stability also indicates that time trends or other events during our time frame of analysis are unlikely to be driving the estimated effects.

Furthermore, as illustrated in Figure 1 previously, most responses occurred well before or well after the peak dates. Analysis of the timing of survey responses relative to peak dates reveals that only 16 out of 898 responses fell within ± 4 days of the peak, indicating minimal risk of strategically timed participation. Given that an individual is unlikely to know in real time when their state has reached the peak, this design of using $\pm$ days around the peak appropriately mitigates concerns about strategic timing of survey response.

Outliers: We remove each of the 31 states in our sample one at a time and rerun the analysis in Panel A of Table 2 (following Bol et al. (2021)) to address the possibility that some specific states are driving our findings. Our results, shown in Figure A3, are unchanged, indicating that no specific state or its trends explain our findings.

Clustering: Since the timing of the COVID-19 peak varied at the state level, as a robustness

[32] Since we have small sample sizes for narrow bandwidths, we cannot adjust the standard errors by clustering at the state-month level.

check, we estimate equation 1 by changing the level of clustering from state-month to state level and using the wild cluster-bootstrap method (Roodman et al., 2019) to correct for the small number of clusters (31 states). Our estimates are robust (see Table A5 in the Online Appendix).

4.2 Potential Mechanisms

In this section we explain the observed impact of the crisis on activism through individuals' (1) beliefs and awareness and (2) preferences and attitudes. The increased incidence of health shocks and deaths may have affected individuals' beliefs about others' willingness to take action. To the extent that one's own activism is complementary to how many others are also willing to act, beliefs may have an impact on the probability of taking action. In addition, the increased probability of needing health services may have affected their awareness of own rights and entitlements in the health sector. The magnitude of the crisis could have also led to more information on the prevalence of corruption in the provision of health services, and reduced individuals' tolerance of such corruption. Finally, the crisis could have impacted pro-social attitudes and risk preferences. Specifically, individuals may have become more willing to cooperate with others for the common good, and more prone to take on the risk of retribution that could result from engaging in anti-corruption activism.

Our survey allows us to generate a number of important measures of individuals' beliefs and attitudes. First, we record perceptions about others' support for the social cause by eliciting incentivized beliefs on the percentage of other survey participants who answered "yes" to the statement "I am willing to raise my voice and participate in a protest against corruption in the provision of health service".[33]

Second, we construct an information index that captures individuals' awareness of their rights and fraud in the health system. This index aggregates responses to two questions: one on knowledge of ongoing rates for intensive care beds in hospitals and another on whether respondents believed they had been illegally overcharged by healthcare professionals during a hospital stay. A separate corruption perception index measures individuals' views on corruption in the health sector, incorporating responses to three questions: (i) personal experience of bribery in the health sector during the pandemic, (ii) perception of corruption prevalence in the sector, and (iii) whether respondents believe corruption has increased or decreased since April 2020. Since self-reported corruption experiences and perceptions may not fully

[33]Survey data (wave 1) from a smaller group of subjects (approximately 200 Indian men surveyed a week prior to main survey), who shared similar characteristics with those in the main survey (wave 2), were collected beforehand to determine the true percentage of subjects agreeing with this statement in the main study (wave 2).

reflect individuals' tolerance of corruption, we construct a distinct corruption tolerance index based on four questions: (i) the extent to which paying a bribe is seen as justifiable, (ii) whether avoiding fare on public transportation is justifiable, (iii) whether doctors overcharging patients is justifiable, and (iv) perceived social pressure to report overcharging or bribery by a doctor.

We employ two measures to capture individual preferences related to risk and prosociality. Risk tolerance is measured on a scale from 0 to 10, where 0 indicates complete unwillingness to take risks and 10 represents a high willingness to take risks.[34] The prosociality index aggregates responses to questions assessing trust, altruism, and retaliatory tendencies (i.e., the inclination to punish unfair treatment). The survey questions for these variables are adapted from Falk et al. (2018).

To explore the mechanisms underlying the observed rise in activism, we employ equation 1 using each of the previously defined indices as the dependent variable. The findings are reported in Table 4, where columns (1) - (3) show impacts on beliefs and awareness, while columns (4) - (6) display estimates for individuals' preferences and attitudes. Since all indices are standardized around the mean in the pre-peak period, the estimated coefficients in columns (2) to (6) of Table 4 are expressed in standard deviations from the corresponding means.[35] The estimates reported in Table 4 indicate that the health crisis positively influenced subjects' beliefs regarding others' willingness to act against corruption in the health sector (column (1)). Specifically, beliefs about others' willingness to protest increased by 5.9 pp, representing a 10.26% rise over the pre-peak mean. The crisis also heightened awareness of healthcare rights and perceptions of the incidence of corruption in the health sector (columns (2) and (3)) by 0.20 and 0.22 standard deviations (SD), respectively, statistically significant at the 1 percent and 5 percent levels. Overall, these effective sizes align with the impacts we find on activism in Table 2. Furthermore, our analysis of attitudes and preferences reveals that individuals' risk tolerance increased by 0.15 SD (column (4)). This finding is consistent with existing literature showing evidence of increased risk tolerance following natural disasters (Islam et al., 2020). In the specific context of COVID-19, Tsutsui and Tsutsui-Kimura (2022) reports a similar pattern, showing increased risk tolerance among individuals in Japan after exposure to the virus. Our estimates are robust to correcting p-values for multiple hypothesis testing using the Romano and Wolf (2016) procedure.

While our estimates indicate that the health crisis led to a significant increase in the

[34] Note that we measured risk attitudes through a survey question via self-assessment. Dohmen et al. (2011) find that such generalized self-assessed survey measure of risk is stable and correlated with real world outcomes.

[35] Further details on how these survey-generated variables are created are provided in the Online Appendix C.

individuals' perceptions of others' willingness to act, as well as their own perceptions of corruption and information about rights and entitlements in the health sector, we do not find evidence of significant changes in corruption tolerance and pro-sociality (columns (5) and (6)). One possible explanation is that while information, corruption perceptions and willingness to take risk are susceptible to changes through life experiences, pro-social preferences and attitudes toward corruption are individuals traits that are less likely to change.

4.3 Heterogeneous Impacts

In this section, we assess whether there are differential impacts of the health crisis on activism based on whether a state experienced the COVID-19 peak relatively early on or later in the second wave (relative to national peak in the full sample). It could be argued that the early peak states were more likely caught off-guard by the second wave of the pandemic, leading to greater casualties.[36] We plot the month-by-month time paths of our activism outcomes for the early and late peak sub-samples in Figure A4 in the Online Appendix. In line with our expectations, we see stronger evidence of a positive impact of the crisis on activism in the early-peak than the late-peak states.

We also ask if the estimated impacts differ by pre-existing state-level characteristics, such as corruption and health infrastructure. To capture ex-ante levels of corruption at the state level, we use the Transparency International India (2019) report, which covers 20 Indian states. We create a dummy variable which equals 1 for *high corruption states* and 0 otherwise.[37] The estimates are reported in Table A6 (Panel A) in the Online Appendix. Note that the *high corruption* state indicator are captured at the state level and are time-invariant, hence these are perfectly collinear with state fixed effects. Therefore, we only report the interaction coefficient in the table. While there is insignificant impact of being in a high corruption state on willingness to protest and actual action taken (columns (1) and (3), Panel A), the impact on the willingness to act is driven by respondents residing in these states (column (2) of Panel A) as shown by the significant positive coefficient on the interaction term.

Utilizing data on hospitals from Kapoor et al. (2020), and data on state-level population for 2020 from Government of India (2019) we compute *hospital density*, i.e., the number of (public *and* private) hospitals per 100,000 people residing in a state. We interact this variable with the 'Post' dummy in Table A6 (Panel B) in the Online Appendix. We find

[36] Table A1 in the Online Appendix provides the full list of dates when state level peaks occurred.

[37] The high corruption states, as indicated in the report, are Punjab, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Karnataka, Telangana and Tamil Nadu. The states not included in the report are excluded from this analysis, reducing the number of observations to 848. For more details about the report, see Transparency International India.

suggestive evidence that the impact of the crisis on willingness to take action and actual activism tend to be higher in states with high hospital density (column (2) and (3), Panel B) although willingness to protest (column (1)) is not significantly different across this dimension). These findings suggest that respondents residing in states where they were more likely to either experience or interact with the health sector, were also the states which show higher willingness to act against corruption.

In addition, we conduct heterogeneity tests by baseline demographic characteristics that could be associated with differential impact on willingness to protest or act as a result of being exposed to the peak of the second wave of COVID. We find suggestive evidence that the crisis had a greater effect on activism among younger individuals (below 45 years), those without an elderly co-resident, and Hindu individuals (the dominant religious group).[38] These results are presented in Table A7.

4.4 Longer-term Impacts

Does the increased willingness to take action against corruption persist over time? Between October and November 2022, about 14 months after the primary data collection, we conducted another online survey, following the same procedures as in March-July 2021. The one difference is that we only elicited the hypothetical measure of activism.

We refer to the additional sample of 849 survey participants from 2022 (along with 309 participants from the pre-peak period in 2021) as our *long-term sample*. The combined set of both samples (898 plus 849) constitutes our *full sample*. We replicate the analysis from Panel A of Table 2 for both the long-term and full samples. While the effects persist over time, they are smaller in magnitude. Participants' self-reported likelihood of joining an anti-corruption protest increased by 9.4 percentage points ($p<0.01$) in the full sample, but the increase was reduced to 7.8 percentage points ($p<0.01$) in the long-term sample.[39]

4.5 Addressing Potential Identification Challenges

A potential concern with our identification strategy is that the pool of online survey participants may differ systematically between the pre- and post-COVID peak periods. To address this, we began by comparing pre and post-peak samples along observable characteristics and

[38] No other demographic characteristics were found to have a significant impact on anti-corruption activism.

[39] It is important to note that our long-term effects should be interpreted as suggestive. The short fieldwork period of the main study allows for an as-if random assignment to treatment without the need for adjustments related to time-sensitive concerns or the risk of simultaneous events—factors that are more likely to affect the long-term sample.

find only minor differences that disappear once entropy-balancing is applied (see Table 1). We further verified, using CMIE-CPHS data on over 200,000 adult men, that employment outcomes did not change significantly around state-level peaks during the study period, suggesting that broader labor market shifts did not alter survey composition (see Table A3). Lastly, placebo tests with randomly assigned "fake peaks" also generate null effects, strengthening the case that the results are not driven by spurious sample differences (see Figure 2). While some unobserved traits such as working hours cannot be directly measured, these checks increase confidence, that our results capture genuine behavioral changes rather than a shift in sample composition. However, we acknowledge that our tests may not address all potential causes of compositional change in the pre and post samples.

A second possible concern is that the "untreated" or pre-peak respondents may have anticipated the pressure on the healthcare system and the ensuing corruption. Such anticipation would likely bias our estimate downward, since the pre-peak group would exhibit higher levels of baseline activism. Consistent with this interpretation, we observe stronger effects in early-peaking states where anticipation was less likely.

Third, although the timing of survey-availability was controlled by Qualtrics and unpredictable to respondents, it remains possible that more motivated or less time-constrained individuals were relatively more likely to participate post-peak. To examine this, we compared recruitment speed and attention check (see Figure A1) performance across groups and found no systematic differences. Our results are also robust to dropping one state at a time (see Figure A3) and to alternative clustering strategies (see Table A5), reducing the likelihood that a small subset of highly engaged participants drives the findings. Nonetheless, we acknowledge that selection on unobservables cannot be entirely ruled out and present this as a limitation. Finally, participants in our sample were surveyed only once, and Qualtrics sent brief invitations and closed the link once quota was met. This feature reduces concerns about repeated invitations generating additional selection.

Taken together, these checks and clarifications suggest that while some concerns about unobserved selection cannot be fully eliminated, the combination of quasi-random survey timing, state-level variation in exposure, and our extensive robustness exercises support the interpretation that the documented increase in activism can be attributed to the pandemic.

5 Conclusion

Did the lived experience of malfeasance in the health sector, during the second wave of the pandemic in India, lead to an increase in individuals' willingness to engage in activism? By exploiting state level variation in the occurrence of COVID-19 peaks, and quasi-randomness in the timing of subjects' participation in our survey, we find evidence consistent with a significant increase in anti-corruption activism immediately, as a result of the health crisis.

Our analysis of potential mechanisms shows that the crisis positively impacted individuals' information about their rights and entitlements, their risk tolerance, their perceptions of corruption in the health sector, and their beliefs about others' willingness to take action. This suggests that the experiences during the pandemic may have strengthened individual and collective motivations to engage in activism. We acknowledge that the observed increase in activism may partially reflect a general behavioral rebound or "pandemic fatigue" effect, wherein individuals sought to reassert agency after prolonged lock-downs or broader frustration with institutional performance rather than outrage at malfeasance per se. However, note that the second-wave of the pandemic in India occurred during a period of easing of lock-downs and increased mobility relative to the stringent lockdown at the beginning of the pandemic in March 2020.

Overall, our findings provide insights on how personal experiences of negative shocks may catalyze participation in social movements aimed at addressing society-wide problems that the crisis either exacerbated or made more evident to the public. Our data, being health-sector focused, do not allow for placebo or spillover tests in other domains. Future research should explore the applicability of our findings across different countries and contexts, where institutional and systemic malfeasance may have been heightened by similar society-wide crises.

References

Aassve, A., G. Alfani, F. Gandolfi, and M. Le Moglie (2021). Epidemics and Trust: The Case of the Spanish Flu. Health Economics 30(4), 840–857.

Afridi, F., S. Bhattacharya, A. Dhillon, and E. Solan (2024). Electoral Competition, Electoral Uncertainty and Corruption: Theory and Evidence from India. Journal of Economic Behavior and Organization, forthcoming.

Akbulut-Yuksel, M., D. Okoye, and M. Yuksel (2020). Social Changes in Impressionable Years and Adult Political Attitudes: Evidence from Jewish Expulsions in Nazi Germany. Economic Inquiry 58(1), 184–208.

Alesina, A., A. Miano, and S. Stantcheva (2018). Immigration and Redistribution. Technical report, National Bureau of Economic Research.

Baccini, L., A. Brodeur, and S. Weymouth (2021). The COVID-19 Pandemic and the 2020 US Presidential Election. Journal of Population Economics 34, 739–767.

Banerjee, A., R. Hanna, and S. Mullainathan (2012). 27. Corruption. Princeton University Press.

Banerjee, A. V., E. Duflo, and R. Glennerster (2008). Putting a Band-Aid on a Corpse: Incentives for Nurses in the Indian Public Health Care System. Journal of the European Economic Association 6(2-3), 487–500.

Bauer, M., C. Blattman, J. Chytilová, J. Henrich, E. Miguel, and T. Mitts (2016). Can War Foster Cooperation? Journal of Economic Perspectives 30(3), 249–274.

Beach, B., K. Clay, and M. Saavedra (2022). The 1918 Influenza Pandemic and Its Lessons for COVID-19. Journal of Economic Literature 60(1), 41–84.

Belloc, M., F. Drago, and R. Galbiati (2016). Earthquakes, Religion, and Transition to Self-Government in Italian Cities. The Quarterly Journal of Economics 131(4), 1875–1926.

Bellows, J. and E. Miguel (2009). War and Local Collective Action in Sierra Leone. Journal of Public Economics 93(11-12), 1144–1157.

Bjorkman, M. and J. Svensson (2009). Power to the People: Evidence from a Randomized Field Experiment on Community-based Monitoring in Uganda. The Quarterly Journal of Economics 124(2), 735–769.

Blattman, C. (2009). From Violence to Voting: War and Political Participation in Uganda. American Political Science Review 103(2), 231–247.

Bol, D., M. Giani, A. Blais, and P. J. Loewen (2021). The Effect of COVID-19 Lockdowns on Political Support: Some Good News for Democracy? European Journal of Political Research 60(2), 497–505.

Brodeur, A., D. Gray, A. Islam, and S. Bhuiyan (2021). A Literature Review of the Economics of COVID-19. Journal of Economic Surveys 35(4), 1007–1044.

Brodeur, A., I. Grigoryeva, and L. Kattan (2021). Stay-at-Home Orders, Social Distancing, and Trust. Journal of Population Economics 34(4), 1321–1354.

Bursztyn, L., G. Egorov, and S. Fiorin (2020). From Extreme to Mainstream: The Erosion of Social Norms. American Economic Review 110(11), 3522–3548.

Chapman, J., P. Ortoleva, E. Snowberg, L. Yariv, and C. Camerer (2025). Reassessing Qualitative Self-assessments and Experimental Validation. Technical report, National Bureau of Economic Research.

Chen, Y., P. Cortes, G. Kosar, J. Pan, and B. Zafar (2023). The Impact of COVID-19 on Workers' Expectations and Preferences for Remote Work. In AEA Papers and Proceedings, Volume 113, pp. 556–561. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Choutagunta, A., G. Manish, and S. Rajagopalan (2021). Battling COVID-19 with Dysfunctional Federalism: Lessons from India. Southern Economic Journal 87(4), 1267–1299.

CMIE (2023). Unemployment Rate in India. `https://unemploymentinindia.cmie.com/kommon/bin/sr.php?kall=wsttimeseries&index_code=050050000000&dtype=total`. Online; accessed 14 April 2023.

Colmer, J. M., M. F. Evans, and J. Shimshack (2023). Environmental Citizen Complaints.

Coury, M. (2025). Climate risk and preferences over the size of government: Evidence from california wildfires. Review of Economics and Statistics 107(3), 697–710.

Coury, M. and P. Winichakul (2025). Climate disasters, social media, and climate activism. mimeo.

Das, J., A. Holla, A. Mohpal, and K. Muralidharan (2016). Quality and Accountability in Health Care Delivery: Audit-Study Evidence from Primary Care in India. American Economic Review 106(12), 3765–99.

Daubanes, J. and J.-C. Rochet (2019). The Rise of NGO Activism. American Economic Journal: Economic Policy 11(4), 183–212.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner (2011). Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences. Journal of the European Economic Association 9(3), 522–550.

Eichengreen, B., C. G. Aksoy, and O. Saka (2021). Revenge of the Experts: Will COVID-19 Renew or Diminish Public Trust in Science? Journal of Public Economics 193, 104343.

Falk, A., A. Becker, T. Dohmen, B. Enke, D. Huffman, and U. Sunde (2018). Global Evidence on Economic Preferences. The Quarterly Journal of Economics 133(4), 1645–1692.

Ferraz, C. and F. Finan (2008). Exposing Corrupt Politicians: The Effects of Brazil's Publicly Released Audits on Electoral Outcomes. The Quarterly Journal of Economics 123(2), 703–745.

Gallego, J. A., M. Prem, and J. F. Vargas (2020). Corruption in the Times of Pandemia. Available at SSRN 3600572.

Garg, C. C. and A. K. Karan (2009). Reducing Out-of-pocket Expenditures to Reduce Poverty: A Disaggregated Analysis at Rural-urban and State Level in India. Health Policy and Planning 24(2), 116–128.

Government of India (2019). Rural Health Statistics. `https://hmis.nhp.gov.in/downloadfile?filepath=publications/Rural-Health-Statistics/RHS%202019-20.pdf`. Online; accessed 12 October 2022.

Hainmueller, J. (2012). Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. Political Analysis 20(1), 25–46.

Heß, S. (2017). Randomization Inference with Stata: A Guide and Software. The Stata Journal 17(3), 630–651.

Indian Express (2021). Indian Express. `https://indianexpress.com/article/india/covid-19-second-wave-heres-a-list-of-states-that-have-imposed-lockdowns-7306634/`. Online; accessed 18 April 2022.

Isen, A. M., T. E. Shalker, M. Clark, and L. Karp (1978). Affect, Accessibility of Material in Memory, and Behavior: A Cognitive Loop? Journal of Personality and Social Psychology 36(1), 1.

Islam, A., C. M. Leister, M. Mahmud, and P. A. Raschky (2020). Natural Disaster and Risk-Sharing Behavior: Evidence from Rural Bangladesh. Journal of Risk and Uncertainty 61(1), 67–99.

Jha, C. K. and S. Sarangi (2023). How Advances in Information and Communication Technologies Impact Corruption? The Political Economy of Corruption, 172–188.

Jha, P., Y. Deshmukh, C. Tumbe, W. Suraweera, A. Bhowmick, S. Sharma, P. Novosad, S. H. Fu, L. Newcombe, H. Gelband, et al. (2022). COVID Mortality in India: National Survey Data and Health Facility Deaths. Science, eabm5154.

Kapoor, G., S. Hauck, A. Sriram, J. Joshi, E. Schueller, I. Frost, R. Balasubramanian, R. Laxminarayan, and A. Nandi (2020). State-Wise Estimates of Current Hospital Beds, Intensive Care Unit (ICU) Beds and Ventilators in India: Are We Prepared for a Surge in COVID-19 Hospitalizations? MedRxiv.

Klemm, A. and P. Mauro (2022). Pandemic and Progressivity. International Tax and Public Finance 29(2), 505–535.

Kumar, S. (2003). Health Care Is among the Most Corrupt Services in India. BMJ: British Medical Journal 326(7379), 10.

LaBar, K. S. and R. Cabeza (2006). Cognitive Neuroscience of Emotional Memory. Nature Reviews Neuroscience 7(1), 54–64.

Malmendier, U. (2021). FBBVA Lecture 2020: Exposure, Experience, and Expertise: Why Personal Histories Matter in Economics. Journal of the European Economic Association 19(6), 2857–2894.

Malmendier, U. and S. Nagel (2011). Depression Babies: Do Macroeconomic Experiences Affect Risk Taking? The Quarterly Journal of Economics 126(1), 373–416.

Muñoz, J., A. Falcó-Gimeno, and E. Hernández (2020). Unexpected Event during Survey Design: Promise and Pitfalls for Causal Inference. Political Analysis 28(2), 186–206.

Olken, B. A. (2007). Monitoring Corruption: Evidence from a Field Experiment in Indonesia. Journal of Political Economy 115(2), 200–249.

Oppenheimer, D. M., T. Meyvis, and N. Davidenko (2009). Instructional Manipulation Checks: Detecting Satisficing to Increase Statistical Power. Journal of Experimental Social Psychology 45(4), 867–872.

Pande, R. (2011). Can Informed Voters Enforce Better Governance? Experiments in Low-income Democracies. Annu. Rev. Econ. 3(1), 215–237.

Press Information Bureau (2021). PIB. `https://pib.gov.in/PressReleasePage.aspx?PRID=1710190`. Online; accessed 16 April 2022.

Romano, J. P. and M. Wolf (2005). Stepwise Multiple Testing as Formalized Data Snooping. Econometrica 73(4), 1237–1282.

Romano, J. P. and M. Wolf (2016). Efficient Computation of Adjusted p-Values for Resampling-Based Stepdown Multiple Testing. Statistics & Probability Letters 113, 38–40.

Roodman, D., M. Ø. Nielsen, J. G. MacKinnon, and M. D. Webb (2019). Fast and Wild: Bootstrap Inference in Stata Using Boottest. The Stata Journal 19(1), 4–60.

Rose-Ackerman, S. (2021). Corruption and COVID-19. EUNOMÍA. Revista en Cultura de la Legalidad (20), 16–36.

Saka, O., B. Eichengreen, and C. Aksoy (2022). The Political Scar of Epidemics. The Economic Journal.

Serra, D. (2012). Combining Top-down and Bottom-up Accountability: Evidence from a Bribery Experiment. The Journal of Law, Economics, & Organization 28(3), 569–587.

Serra, D. and L. Wantchekon (2012). Chapter 1 Experimental Research on Corruption: Introduction and Overview. In New Advances in Experimental Research on Corruption, pp. 1–11. Emerald Group Publishing Limited.

Settele, S. (2019). How Do Beliefs About the Gender Wage Gap Affect the Demand for Public Policy? Available at SSRN 3382325.

Shai, O. (2022). Out of Time? The Effect of an Infrequent Traumatic Event on Individuals' Time and Risk Preferences, Beliefs, and Insurance Purchasing. Journal of Health Economics 86, 102678.

Sharpe, M. J., H. M. Batchelor, L. E. Mueller, M. P. Gardner, and G. Schoenbaum (2021). Past Experience Shapes the Neural Circuits Recruited for Future Learning. Nature Neuroscience 24(3), 391–400.

Spunt, R. P. and R. Adolphs (2017). A New Look at Domain Specificity: Insights from Social Neuroscience. Nature Reviews Neuroscience 18(9), 559–567.

Transparency International India (2019). India Corruption Survey. `https://transparencyindia.org/wp-content/uploads/2019/11/India-Corruption-Survey-2019.pdf`. Online; accessed 25 January 2022.

Tsutsui, Y. and I. Tsutsui-Kimura (2022). How Does Risk Preference Change under the Stress of COVID-19? Evidence from Japan. Journal of Risk and Uncertainty, 1–22.

Vrushi, J. and R. Kukutschka (2021). Why Fighting Corruption Matters In Times Of COVID-19. In Corruption Perceptions Index 2020: Research Analysis. Transparency International.

World Health Organisation (2022). World Health Organisation. `https://www.who.int/news/item/05-05-2022-14.9-million-excess-deaths-were-associated-with-the-covid-19-pandemic-in-2020-and-2021`. Online; accessed 19 April 2022.

Xu, D. (2025). Only in my backyard: The effect of flood exposure on environmental behavior. Available at SSRN 4891207.

Zhang, P. (2023). Anti-corruption Campaign, Political Connections, and Court Bias: Evidence from Chinese Corporate Lawsuits. Journal of Public Economics 222, 104861.

Table 1: Descriptive Statistics and Balance Tests

	Pre-2nd Wave (1)	Post-2nd Wave (2)	Difference (3)=(1)-(2)	After Entropy Balancing (4)=(1)-(2)
Age 45+	0.149	0.144	0.005	-0.000
			[0.873]	[0.999]
Married	0.411	0.511	-0.100**	0.000
			[0.024]	[0.996]
Has Children	0.356	0.375	-0.019	0.000
			[0.636]	[0.998]
Lives with Parents	0.272	0.275	-0.003	0.000
			[0.934]	[1.000]
Reserved Caste	0.466	0.628	-0.162***	0.000
			[0.000]	[0.993]
Hindu	0.709	0.772	-0.064	0.000
			[0.219]	[0.994]
College Educated	0.819	0.779	0.039	0.000
			[0.200]	[0.992]
Monthly Income <INR 30K	0.434	0.469	-0.035	0.000
			[0.421]	[0.997]
Asset Index	6.197	5.997	0.201	0.003
			[0.305]	[0.990]
Frequent Survey Participants	0.738	0.781	-0.043	0.000
			[0.120]	[0.991]
Mobile Survey	0.680	0.642	0.038	0.000
			[0.359]	[0.994]
Lives with Elderly	0.592	0.576	0.017	0.000
			[0.712]	[0.996]
N	309	589		

Notes: "Pre-2nd wave" ("Post-2nd wave")indicates that the subject participated in the survey before (after) the COVID-19 peak in his state of residence. "Age 45+" is a dummy equal to 1 for subjects aged 45 and above, 0 otherwise; "Reserved Caste" is a dummy indicating SC (Schedule Caste), ST (Scheduled Tribe) and other backward classes (OBC) subjects, who are socio-economically deprived individuals in India, 0 otherwise. "Hindu" is a dummy indicating subjects who report belonging to the Hindu religion, 0 otherwise. "Income $<$ INR 30K" indicates subjects with monthly household income below INR 30K in the previous month; "Asset Index" indicates a count of assets owned by a subject from a list of ten household assets; "Frequent Survey Participant" is equal to 1 for individuals who state that they participate in Qualtrics surveys at least once a week, 0 otherwise; "Mobile Survey" is equal to 1 for subjects who participated in the survey using a mobile phone; "Lives with elderly" is equal to 1 if the subject lives with a household member who is older than 60, 0 otherwise; "Has children" is 1 if subject has children, 0 otherwise; "Lives with parents" is 1 if subject lives with parents, 0 otherwise. Column (3) reports the difference between the characteristic of the subjects surveyed pre- and post-state peak. Column (4) reports differences in individual characteristics after adjusting for entropy re-weighting (Hainmueller, 2012). Standard errors are clustered at state-month level. p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2: Impact of COVID-19 State-Level Exposure on Activism

	Willing to Protest		Willing to Act		Took Action	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Post	0.075***	0.075***	0.107**	0.116***	0.090**	0.098***
	(0.025)	(0.021)	(0.042)	(0.032)	(0.035)	(0.023)
Romano-Wolf p-value		[0.002]		[0.002]		[0.002]
Panel B						
Post	0.016	0.040	0.202***	0.240**	0.194***	0.157**
	(0.057)	(0.055)	(0.075)	(0.105)	(0.067)	(0.077)
Days x Post	0.000	0.000	0.009***	0.008***	0.007***	0.005***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Days	0.001	0.000	-0.006***	-0.007**	-0.006***	-0.004**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	898	898	898	898	898	898
Pre-peak Mean Y	0.832	0.832	0.372	0.372	0.233	0.233
State FE	no	yes	no	yes	no	yes
Controls	no	yes	no	yes	no	yes
Entropy Balancing	no	no	no	no	no	no

Notes: In both Panels A and B, "Post" is a dummy equal to 1 if the subject was surveyed after the peak in daily COVID-19 cases in his state of residence, and equal to 0 if he was surveyed before the peak. In Panel B, we also control for "Days", which is the difference between the date of the survey and the date of the state-level COVID-19 peak, and its interaction with the 'Post' indicator. The dependent variable in columns (1)-(2) is a 0-1 dummy which is equal to 1 if the respondent states that he is willing to participate in a protest against corruption in the provision of health services. The dependent variable in columns (3)-(4) is a 0-1 dummy, which is equal to 1 if the respondent is willing to either sign a petition, or donate, or watch a 5 minute video on how to fight fraud and corruption in the health sector. The dependent variable in columns (5)-(6) is a 0-1 dummy that is equal to 1 if the respondent actually signed a petition to the Health Ministry (with his name), or donated a positive amount to an NGO fighting fraud and demanding transparency in the health sector, or watched a 5 minute video on to help the fight against fraud and corruption in the health sector. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy variable for mode of survey participation (phone or computer), indicators for household composition. We report multiple hypothesis corrected p-values using the Romano-Wolf procedure (Romano and Wolf, 2016) in square brackets (across 3 outcomes reported in Table 2 and 6 outcomes reported in Table 4). Results unchanged after adjusting for entropy re-weighting (Hainmueller, 2012), as shown in Table A4 (columns (1) - (3)). Standard errors clustered at the state-month level reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: Impact of COVID-19 State-Level Exposure on Activism

Panel A: Extensive Margin of Action Taken				
	Willing to Sign	Willing to Donate	Willing to Watch Video	Willing to Choose Any
	(1)	(2)	(3)	(4)
Post	-0.041	0.180***	0.014	0.154**
	(0.062)	(0.056)	(0.056)	(0.068)
Romano-Wolf p-value	[0.792]	[0.028]	[0.816]	[0.156]
Observations	217	230	225	226
Pre-peak Mean Y	0.413	0.181	0.583	0.342
Panel B: Intensive Margin of Action Taken				
	Signed with Name	Donated Positive Amount	Watched Full Video	Actually Chose Any
	(1)	(2)	(3)	(4)
Post	-0.083	0.186***	0.042	0.157***
	(0.059)	(0.053)	(0.050)	(0.044)
Romano-Wolf p-value	[0.172]	[0.014]	[0.792]	[0.050]
Observations	217	230	225	226
Pre-peak Mean Y	0.373	0.145	0.292	0.139
State FE	yes	yes	yes	yes
Controls	yes	yes	yes	yes
Entropy Balancing	yes	yes	yes	yes

Notes: In Panels A and B, "Post" is a dummy equal to 1 if the subject was surveyed after the peak in daily COVID-19 cases in his state of residence, and equal to 0 if he was surveyed before the peak. In Panel A, the dependent variables respectively are, a 0-1 dummy equal to 1 if the respondent is willing to sign a petition (column (1)), willing to donate (column (2)), willing to watch a 5 minute video on how to fight fraud and corruption in the health sector (column (3)), and willing to choose any of these three actions, when given a choice (column (4)). In Panel B, the dependent variables respectively are, a 0-1 dummy equal to 1 if the respondent actually signed a petition to the Health Ministry (with his name) (column (1)), donated a positive amount to an NGO (column (2)), watched the full 5 minute video (column (3)), and actually decided to do any of these three actions, when given a choice (column (4)). Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy variable for mode of survey participation (phone or computer), indicators for household composition. We report multiple hypothesis corrected p-values using the Romano-Wolf procedure (Romano and Wolf, 2016) in square brackets (across 4 outcomes reported in Panel A and 4 outcomes reported in Panel B). In Panels A and B, we report multiple hypothesis corrected p-values using the Romano-Wolf procedure (Romano and Wolf, 2016) in square brackets across the 8 outcomes reported in these panels. "Entropy Balancing" indicates that the observations are weighted by the control variables so that the first and second moments of the distribution of co-variates among "Post" subjects mimic those of the "Pre" subjects (Hainmueller, 2012). Standard errors clustered at the state-month level reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Mechanisms: Impact of COVID-19 State-Level Exposure on Beliefs and Preferences

	Beliefs and Awareness			Preferences and Attitudes		
	Belief about Others	Information (Rights)	Corruption Perception	Risk Tolerance	Pro-sociality	Corruption Tolerance
	(1)	(2)	(3)	(4)	(5)	(6)
Post	5.947***	0.203***	0.222**	0.152**	-0.079	0.026
	(1.469)	(0.076)	(0.094)	(0.065)	(0.054)	(0.076)
Romano-Wolf p-value	[0.002]	[0.008]	[0.022]	[0.024]	[0.146]	[0.637]
Observations	898	898	898	898	898	898
Pre-peak Mean Y	57.961	0.000	0.000	0.000	0.000	0.000
State FE	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Entropy Balancing	no	no	no	no	no	no

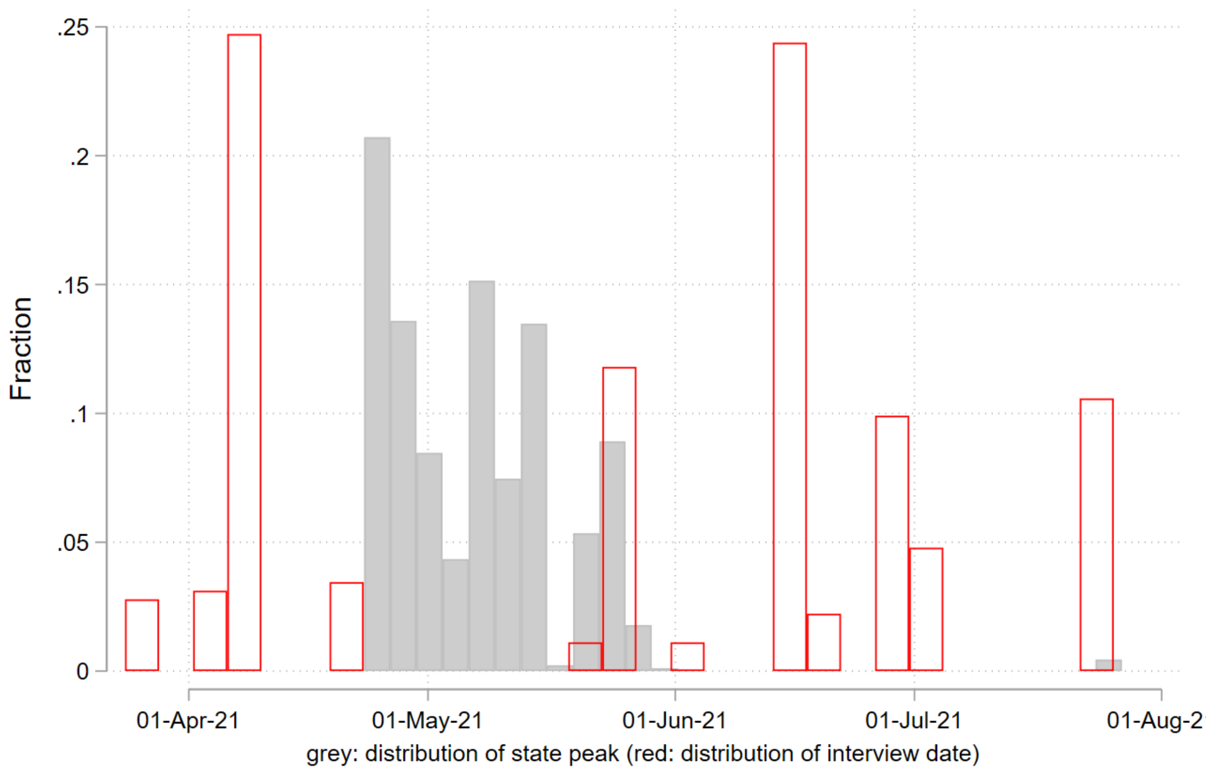
Notes: "Post" is a dummy equal to 1 if the subject was surveyed after the peak in daily COVID-19 cases in his state of residence, and equal to 0 if he was surveyed before the peak. In column (1), the dependent variable - "Belief about Others" - is the percentage of survey participants that the respondent believes had answered "yes" to the statement "I am willing to raise my voice and participate in a protest against corruption in the provision of health service". In column (2) the dependent variable is an index of the subject's degree of information about his own rights and entitlement regarding the provision of health services. In column (3), the dependent variable is an index of individual perceptions of corruption in the health sector. In column 4, the dependent variable - Risk Tolerance - indicates willingness to take risk on a scale from 0 to 10 (0 indicates completely unwilling, and 10 indicates very willing to take risks). In column (5), the dependent variable is a Pro-sociality index, which aggregates answers to questions eliciting trust, altruism and retaliatory preferences (i.e., tendency to punish people who treat you unfairly). The tolerance index - in column (6) - aggregates the respondents' general attitude towards corruption, which combined two questions- (1) the extent to which they think it's justified to pay bribe, or avoid fare or allow doctors to overcharge, and (2) how many people in their community would expect them to complain if they were overcharged or asked to pay a bribe by a doctor. Information on how the indices are constructed from survey questions is provided in the Online Appendix C. The dependent variables in columns (2) - (6) are standardized around the mean in the pre-peak period, therefore their estimated coefficients are expressed in standard deviations from this mean. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy variable for mode of survey participation (phone or computer), indicators for household composition. We report multiple hypothesis corrected p-values using the Romano-Wolf procedure (Romano and Wolf, 2016) in square brackets (across 3 outcomes reported in Table 2 and 6 outcomes reported in Table 4). Results unchanged after adjusting for entropy re-weighting (Hainmueller, 2012), as shown in Table A4 (columns (1) - (3)). Standard errors clustered at the state-month level reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Long Term Impact of COVID-19 on Willingness to Protest

	Long-term Sample		Full Sample	
	(1)	(2)	(3)	(4)
Post	0.136***	0.078***	0.111***	0.094***
	(0.024)	(0.027)	(0.025)	(0.019)
Observations	1158	1158	1747	1747
Pre-peak Mean Y	0.832	0.832	0.832	0.832
Controls	no	yes	no	yes
State FE	no	yes	no	yes
Entropy Balancing	no	yes	no	yes

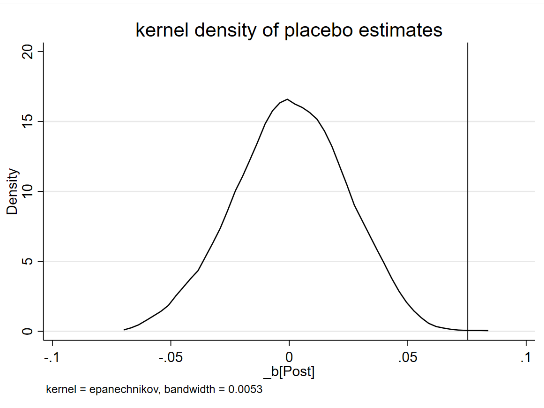
Notes: The dependent variable is equal to 1 if the survey participant stated his willingness to protest to fight corruption in the provision of health services. The *Long-term Sample* refers to subjects who participated in the survey more than a year after the initial study, i.e., in October and November 2022. The *Full Sample* refers to all survey participants, i.e., those surveyed between March and July 2021, and those surveyed in October and November 2022. In the *Long-term Sample*, in columns (1) - (2), "Post" is a 0-1 dummy that equals 1 if the subject participated in the survey in October or November 2022, over a year after the COVID-19 state-level peak; it is equal to 0, if the subject participated in the survey before the peak. In the *Full Sample*, in columns (3) - (4), "Post" is a 0-1 dummy that equals 1 if the subject participated in the survey after the state-level COVID-19 peak in either 2021 & 2022, and 0 if he participated before the peak. Controls include age, marital status, caste, religion, education, income, indicator for frequent repeated participation in Qualtrics surveys, dummy variable for mode of survey participation (phone or computer), an indicator for household composition. "Entropy Balancing" indicates that the observations are weighted by the control variables using entropy balancing; the weighting is such that the first and second moments of the distribution of covariates among "Post" subjects mimic those of the "Pre" subjects (Hainmueller, 2012). Standard errors clustered at the state-month level reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Figure 1: Survey Date and State COVID-19 Peaks

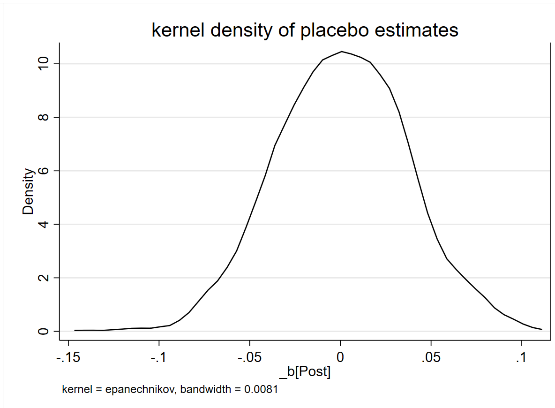


Notes: The red bins in the figure represent the distribution of survey dates. Individuals were surveyed only once, either before or after the COVID-19 peak in their state of residence, during the second wave of the pandemic in India. The grey bins depict the distribution of state-level COVID-19 case peaks.

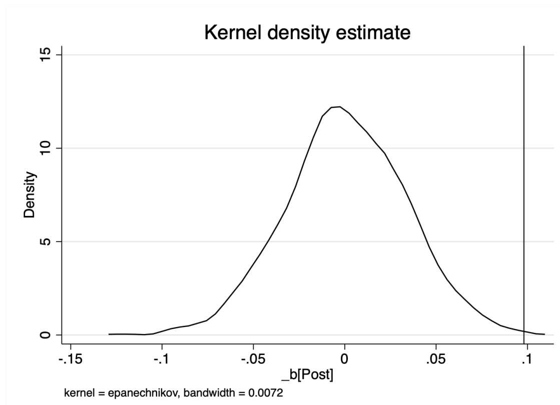
Figure 2: Randomization Inference Test



(a) Willingness to Protest



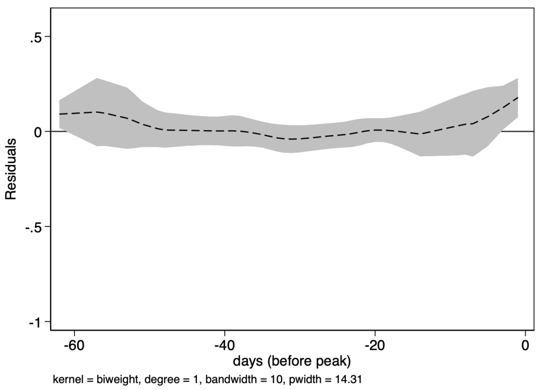
(b) Willingness to Act



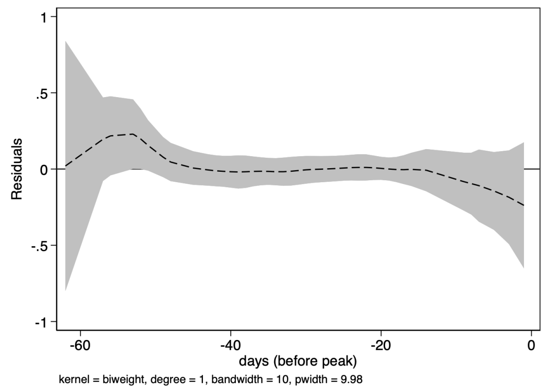
(c) Took Action

Notes: Figures (a) - (c) plot the estimates obtained from randomization inference test for false positive exposure effect created by chance for each outcome:(a) Willingness to Protest; (b) Willingness to Act and (c) Took Action. We create 'placebo peak dates' by assigning it, within state, to a random date within the time interval covered and reproduce the analysis of Panel A of Table 2 (columns (1), (2) and (3) for respective outcomes), repeating the process a 1000 times. Each figure plots the distribution of the 1000 placebo estimates for each of the three main outcomes. The vertical line in each figure is the estimate from Table 2 (Panel A) for that outcome, which are larger than almost all possible placebo effects confirming our results are not false positives or due to chance. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy for mode of survey participation, indicators of household composition, such as, a dummy indicating if the subject has children, another dummy if he lives with parents, and a third dummy if he lives with an elderly (older than 60 years). We include state fixed effects in all specifications.

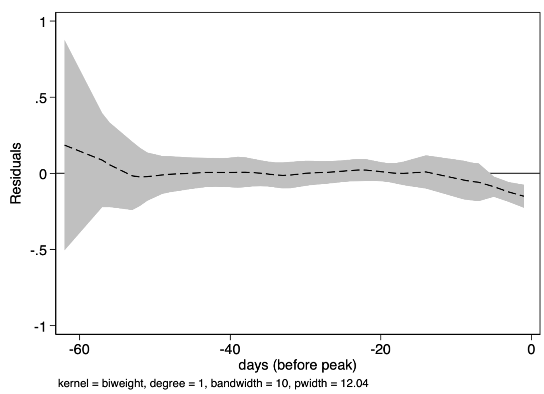
Figure 3: Activism by Day in Pre-event Period (0 = Day of Peak Infections)



(a) Willingness to Protest



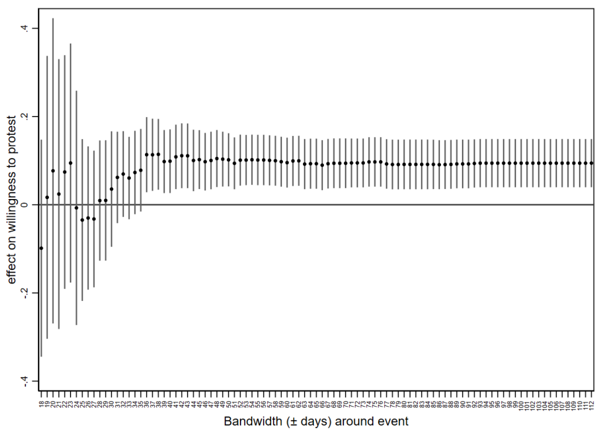
(b) Willingness to Act



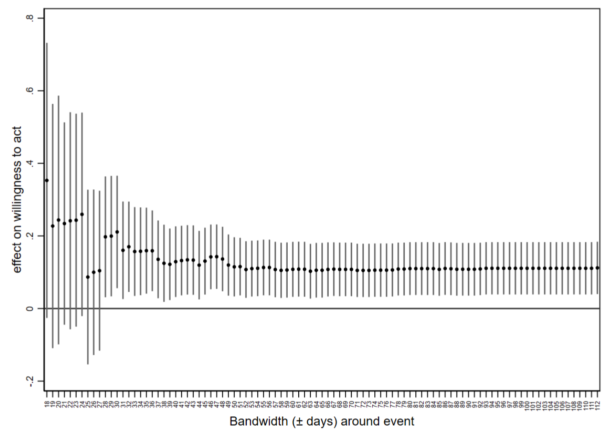
(c) Took Action

Notes: Figures (a) - (c) display smoothed values and 95% confidence band showing the relationship between residual variances of outcomes: (a) Willingness to Protest, (b) Willingness to Act, (c) Took Action, and the timing of interviews in the pre-peak period (up to 100 days prior). Residuals are obtained from a regression of each outcome on full set of controls for the sample of 307 subjects surveyed pre-peak. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy for mode of survey participation, indicators of household composition, such as, a dummy indicating if the subject has children, another dummy if he lives with parents, and a third dummy if he lives with an elderly (older than 60 years). We include state fixed effects in all specifications.

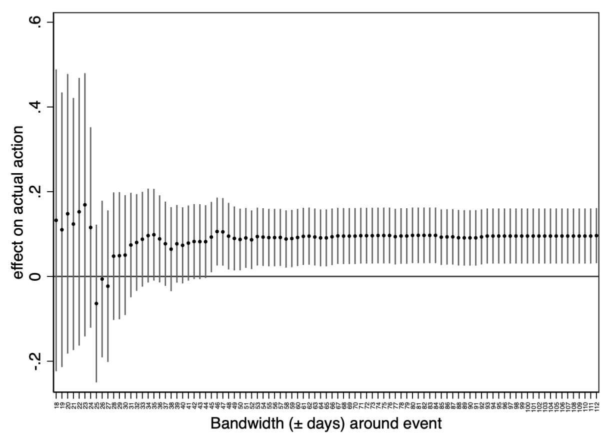
Figure 4: Effect of COVID-19 Exposure Over Multiple Bandwidths



(a) Effect on Willingness to Protest



(b) Effect on Willingness to Act



(c) Effect on Actual Action

Notes: The figure plots the coefficients of 'Post' from equation 1, including controls, state fixed effects and entropy balancing, for different time bandwidths. 'Post' is a dummy equal to 1 if the subject participated in the survey after the COVID-19 peak in the state of residence, 0 otherwise. The point estimates are denoted by black dots and the 95% confidence interval appears in gray. The initial bandwidth is ±18 days around the COVID-19 peak of each state, to ensure co-variate balancing. Starting from 18, the bandwidth is then increased progressively by 1 day, up to 112 days pre- and post-state peak. The small sample size makes it unfeasible to employ bandwidths lower than ±18 days. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy for mode of survey participation, indicators of household composition, such as, a dummy indicating if the subject has children, another dummy if he lives with parents, and a third dummy if he lives with an elderly (older than 60 years).

Appendix

A Additional Analysis

Table A1: COVID-19 Peak Dates and Sample Size by State

State	Peak date (1)	Pre-peak (N) (2)	Post-peak (N) (3)
Delhi	23-Apr-21	16	35
Maharashtra	24-Apr-21	51	83
Dadra Nagar Haveli Daman & Diu	26-Apr-21	1	0
Uttar Pradesh	27-Apr-21	33	37
Chhattisgarh	28-Apr-21	2	3
Jharkhand	28-Apr-21	5	13
Madhya Pradesh	29-Apr-21	8	21
Gujarat	30-Apr-21	14	30
Telangana	1-May-21	12	20
Bihar	6-May-21	9	30
Rajasthan	8-May-21	6	18
National Peak on 8-May-21			
Chandigarh	9-May-21	2	0
Haryana	9-May-21	6	12
Jammu And Kashmir	9-May-21	5	5
Karnataka	9-May-21	24	58
Goa	11-May-21	0	1
Uttarakhand	11-May-21	3	5
Kerala	12-May-21	10	27
Punjab	12-May-21	2	19
Himachal Pradesh	13-May-21	7	3
West Bengal	15-May-21	46	65
Nagaland	18-May-21	1	1
Andhra Pradesh	20-May-21	7	27
Assam	22-May-21	4	10
Lakshadweep	25-May-21	0	2
Meghalaya	25-May-21	3	2
Tamil Nadu	25-May-21	22	49
Tripura	25-May-21	1	1
Orissa	26-May-21	5	11
Sikkim	1-Jun-21	0	1
Manipur	27-Jul-21	4	0

Notes: The column 1 of this table reports the date at which each Indian state experienced the highest number (peak) of confirmed COVID-19 (in terms of 7 day MA) cases during the second wave of the pandemic (Data source: covid19india.org). The columns 2 and 3 report the number of subjects who participated in the survey in each state, before and after the state-level (7-day MA) COVID-19 peak.

Table A2: Survey Dates

Survey date	No. of subjects	Cumulative no. of subjects
24-Mar-21	17	17
25-Mar-21	8	25
2-Apr-21	28	53
7-Apr-21	222	275
21-Apr-21	20	295
22-Apr-21	11	306
National peak on 8-May-21		
19-May-21	10	316
26-May-21	106	422
1-Jun-21	9	431
3-Jun-21	1	432
15-Jun-21	132	564
16-Jun-21	82	646
17-Jun-21	5	651
18-Jun-21	20	671
30-Jun-21	89	760
1-Jul-21	43	803
26-Jul-21	95	898
Total	898	

Notes: We report the number of subjects who participated in the survey by date of the survey, before and after the national (7-day moving average) COVID-19 peak. The last column reports the cumulative number of survey respondents.

Table A3: Impact of Second-wave on Probability of Employment

	Employed	
	(1)	(2)
Post	0.002	-0.002
	(0.004)	(0.005)
Observations	227,200	227,200
Pre-peak Mean Y	0.657	0.657
State FE	yes	yes
Controls	no	yes

Notes: This regression analysis uses data from the nation-wide Consumer Pyramids Household Survey (CPHS) of the Centre for Monitoring Indian Economy (CMIE), in which each household is surveyed three times a year. We use data for the sample of adult male Indians interviewed between the months of March-July 2021. "Employed" is a 0-1 dummy variable equal to 1 if the subject worked on the day of the survey or the day prior, or was not working but returning to work in the near future. "Post" is a dummy equal to 1 if the subject was surveyed in a month after the month containing the peak in daily COVID-19 cases in his state of residence, and equal to 0 if he was surveyed before the month containing the peak. Controls include indicators for marital status, religion, caste category, literacy status, and age (in years). Standard errors clustered at the state-month level reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A4: Robustness: Impact of Second-wave on Activism (Entropy Balancing)

Panel A: Outcomes	Willing to Protest	Willing to Act	Took Action
	(1)	(2)	(3)
Post	0.094***	0.112***	0.096***
	(0.021)	(0.030)	(0.022)
Romano-Wolf p-value	[0.002]	[0.004]	[0.002]
Pre-peak Mean Y	0.832	0.372	0.233

Panel B: Mechanisms	Belief about Others	Information (Rights)	Corruption Perception	Risk Tolerance	Pro-sociality	Corruption Tolerance
	(1)	(2)	(3)	(4)	(5)	(6)
Post	6.503***	0.287***	0.238***	0.223***	-0.053	0.073
	(1.347)	(0.070)	(0.086)	(0.065)	(0.052)	(0.068)
Romano-Wolf p-value	[0.002]	[0.002]	[0.016]	[0.004]	[0.421]	[0.421]
Pre-peak Mean Y	57.961	0.000	-0.000	-0.000	0.000	-0.000
Observations	898	898	898	898	898	898
State FE	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Entropy Balancing	yes	yes	yes	yes	yes	yes

Notes: "Post" is a dummy equal to 1 if the subject was surveyed after the peak in daily COVID-19 cases in his state of residence, and equal to 0 if he was surveyed before the peak. In Panel A, the dependent variable in column (1) is a 0-1 dummy which is equal to 1 if the respondent states to be willing to participate in a protest against corruption in the provision of health services. The dependent variable in column (2) is a 0-1 dummy, which is equal to 1 if the respondent is willing to either sign a petition, or donate, or watch a 5 minute video on how to fight fraud and corruption in the health sector. The dependent variable in column (3) is a 0-1 dummy that is equal to 1 if the respondent actually signed a petition to the Health Ministry (with his name), or donated a positive amount to an NGO fighting fraud and demanding transparency in the health sector, or watched a 5 minute video on to help the fight against fraud and corruption in the health sector. In panel B, the dependent variable in column (1) - "Belief about Others" - is the percentage of survey participants that the respondent believes had answered "yes" to the statement "I am willing to raise my voice and participate in a protest against corruption in the provision of health service". In column (2) the dependent variable is an index of the subject's degree of information about his own rights and entitlement regarding the provision of health services. In column (3), the dependent variable is an index of individual perceptions of corruption in the health sector. In column (4), the dependent variable - Risk Tolerance - indicates willingness to take risk on a scale from 0 to 10 (0 indicates completely unwilling, and 10 indicates very willing to take risks). In column (5), the dependent variable is a Pro-sociality index, which aggregates answers to questions eliciting trust, altruism and retaliatory preferences (i.e., tendency to punish people who treat you unfairly). The tolerance index - in column (6) - aggregates the respondents' general attitude towards corruption, which combined two questions- firstly, the extent to which they think it's justified to pay bribe, or avoid fare or allow doctors to overcharge, and secondly how many people in their community would expect them to complain if they were overcharged or asked to pay a bribe by a doctor. Information on how the indices are constructed from survey questions is provided in the Online Appendix C. The dependent variables in columns (2) - (6) of panel B are standardized around the mean in the pre-peak period, therefore their estimated coefficients are expressed in standard deviations from this mean. Control variables include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, indicators of household composition, such as, a dummy variable for mode of survey participation (phone or computer), indicators for household composition. We report multiple hypothesis corrected p-values using the Romano-Wolf procedure (Romano and Wolf, 2016) in square brackets (across all outcomes reported in columns (1) - (3) of panel A and columns (1) - (6) of panel B)."Entropy Balancing" indicates that the observations are weighted by the control variables so that the first and second moments of the distribution of co-variates among "Post" subjects mimic those of the "Pre" subjects (Hainmueller, 2012). Standard errors clustered at the state-month level reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A5: Robustness: Clustering Standard Errors at the State Level

	Willing to Protest		Willing to Act		Took Action	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.075***	0.094***	0.116***	0.112***	0.098**	0.096**
	[0.003]	[0.002]	[0.003]	[0.004]	[0.033]	[0.030]
Observations	898	898	898	898	898	898
State FE	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Entropy Balancing	no	yes	no	yes	no	yes

Notes: "Post" is a dummy equal to 1 if the subject was surveyed after the peak in daily COVID-19 cases in his state of residence, and equal to 0 if he was surveyed before the peak. The dependent variable in columns (1)-(2) is a dummy which equals 1 if the respondent states to be willing to participate in a protest against corruption in the provision of health services. The dependent variable in columns (3)-(4) is a dummy which equals 1 if the respondent is willing to either sign a petition, or donate, or watch a 5 minute video on how to fight fraud and corruption in the health sector. The dependent variable in column (5)-(6) is a dummy that equals 1 if the respondent actually signed a petition to the Health Ministry (with his name), or donated a positive amount to our collaborator NGO fighting fraud and demanding transparency in the health sector, or watched a 5 minute video on to help the fight against fraud and corruption in the health sector. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy variable for mode of survey participation (phone or computer), indicators for household composition."Entropy Balancing" indicates that the observations are weighted by the control variables using entropy balancing; the weighting is such that the first and second moments of the distribution of covariates among "Post" subjects mimic those of the "Pre" subjects (Hainmueller, 2012). Standard errors are clustered at the state level, and wild-cluster bootstrapping is used to correct for the small number of clusters (N=31). p-values reported below coefficients in square brackets: * $p < .10$, ** $p < .05$, *** $p < .01$

Table A6: Heterogeneity by High Corruption Level, and by Hospital Density in Indian States

	Willing to Protest (1)	Willing to Act (2)	Took Action (3)
Panel A			
Post x *high corruption state*	0.039	0.137**	0.000
	(0.044)	(0.066)	(0.048)
Post	0.074**	0.058	0.101***
	(0.028)	(0.037)	(0.028)
Observations	848	848	848
Panel B			
Post x *hospital density*	0.003	0.012**	0.007*
	(0.005)	(0.006)	(0.004)
Post	0.079**	0.039	0.053
	(0.033)	(0.059)	(0.040)
Observations	898	898	898
State FE	yes	yes	yes
Controls	yes	yes	yes
Entropy Balancing	yes	yes	yes

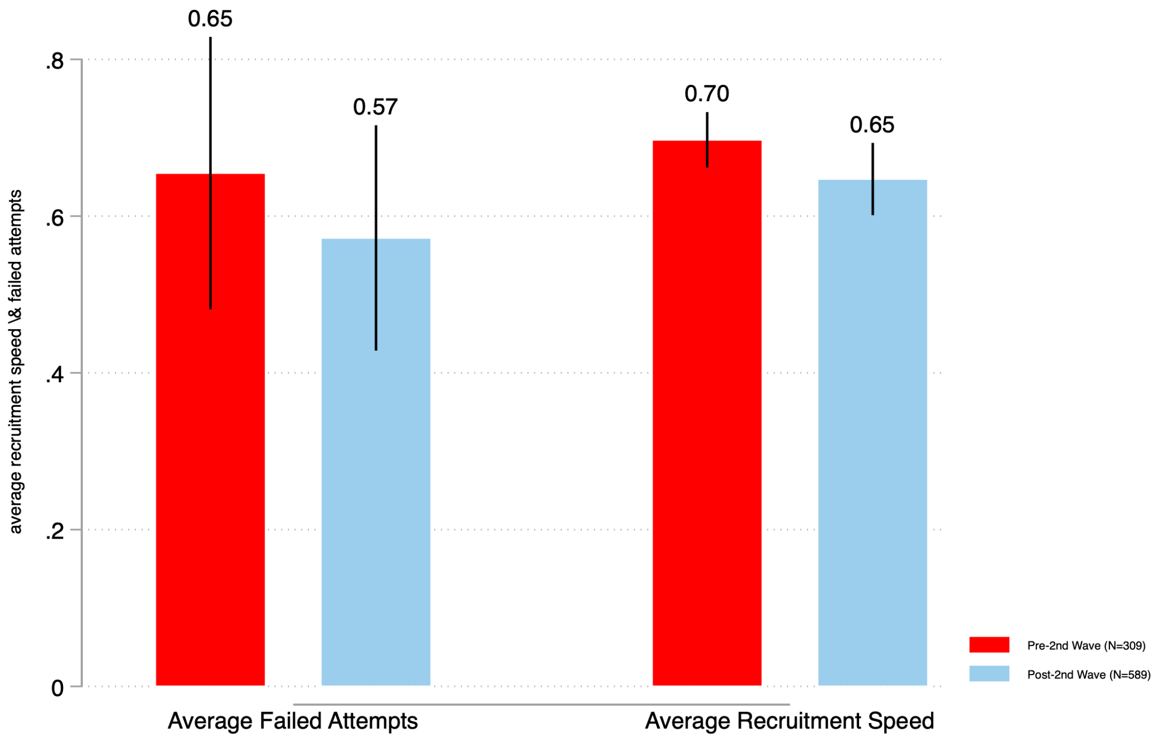
Notes: "Post" is a dummy equal to 1 if the subject was surveyed after the peak in daily COVID-19 cases in his state of residence, and equal to 0 if he was surveyed before the peak. *high corruption state* is a dummy equal to 1 for Indian state with high corruption levels, according to the India Corruption Survey Report by Transparency International India (2019), and 0 otherwise. Missing observations correspond to 9 states that were not included in the 2019 survey. In Panel B, *Hospital density* indicates the number of hospitals per 100,000 population in a state. Data on state level population is taken from Government of India (2019), whereas data on the number of hospitals (public and private) is taken from Kapoor et al. (2020). Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy variable for mode of survey participation (phone or computer), indicators for household composition. "Entropy Balancing" indicates that the observations are weighted by the control variables using entropy balancing; the weighting is such that the first and second moments of the distribution of covariates among "Post" subjects mimic those of the "Pre" subjects (Hainmueller, 2012). Standard errors clustered at the state-month level reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A7: Heterogeneities by Demographics

	Willing to Protest			Willing to Act			Took Action		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age 45+ x Post	-0.143*			-0.146			-0.065		
	(0.079)			(0.118)			(0.103)		
Co-residing Elderly x Post		-0.157**			-0.177***			-0.168***	
		(0.063)			(0.065)			(0.055)	
Hindu x Post			0.015			0.203**			0.141
			(0.052)			(0.081)			(0.092)
Age 45+	0.110	0.036	0.039	0.060	-0.016	-0.005	0.074	0.039	0.047
	(0.071)	(0.047)	(0.048)	(0.084)	(0.062)	(0.062)	(0.077)	(0.053)	(0.053)
Hindu	-0.031	-0.025	-0.037	-0.073	-0.065	-0.172***	-0.001	0.005	-0.071
	(0.025)	(0.024)	(0.038)	(0.047)	(0.047)	(0.064)	(0.048)	(0.048)	(0.076)
Co-residing Elderly	0.040	0.122**	0.040	0.035	0.126**	0.031	-0.006	0.081*	-0.009
	(0.034)	(0.054)	(0.034)	(0.037)	(0.055)	(0.037)	(0.035)	(0.041)	(0.035)
Post	0.115***	0.186***	0.083*	0.133***	0.214***	-0.045	0.105***	0.194***	-0.013
	(0.024)	(0.042)	(0.045)	(0.035)	(0.049)	(0.073)	(0.026)	(0.040)	(0.076)
Observations	898	898	898	898	898	898	898	898	898
State FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Entropy Balancing	yes	yes	yes	yes	yes	yes	yes	yes	yes

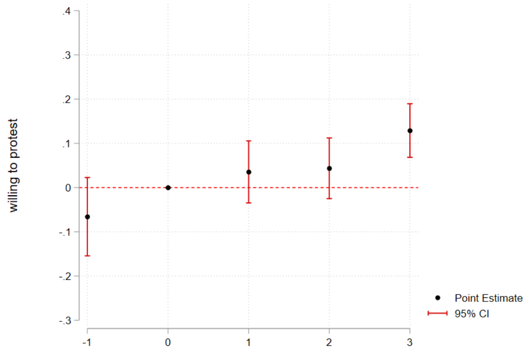
Notes: "Age 45+" is a dummy that takes value 1 the subject's age is more than 45 years, 0 otherwise. "Co-residing Elderly", which is a dummy indicating whether an elderly (above 60 years) lives with the subject. "Hindu" is a dummy indicating subjects who report belonging to the Hindu religion, 0 otherwise. "Post" is a dummy equal to 1 if the subject was surveyed after the peak in daily COVID-19 cases in his state of residence, and equal to 0 if he was surveyed before the peak. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy variable for mode of survey participation (phone or computer), indicators for household composition. "Entropy Balancing" indicates that the observations are weighted by the control variables using entropy balancing; the weighting is such that the first and second moments of the distribution of covariates among "Post" subjects mimic those of the "Pre" subjects (Hainmueller, 2012). Standard errors clustered at the state-month level reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Figure A1: Data Quality Checks Before & After COVID Case-peak

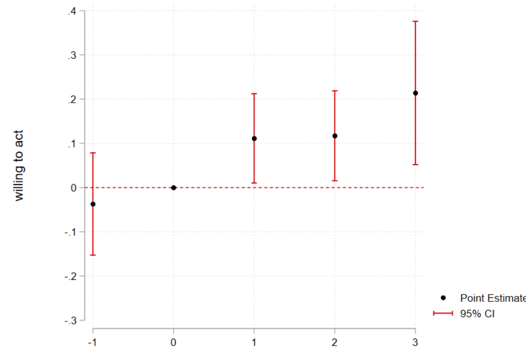


Notes: "Failed attempt" is a continuous variable indicating the number of times a subject attempted the attention manipulation check question embedded in the survey before answering it correctly. The recruitment speed is the number of surveys completed per minute to obtain the quota set by Qualtrics. Specifically, each time the Qualtrics team fielded the survey, they had a target quota that they needed to meet before temporarily closing the survey for data quality checks.

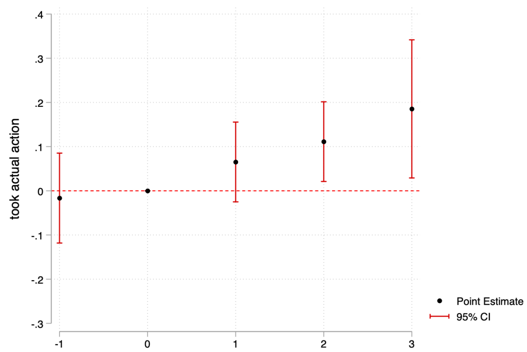
Figure A2: Activism by Month of Survey



(a) Willingness to Protest



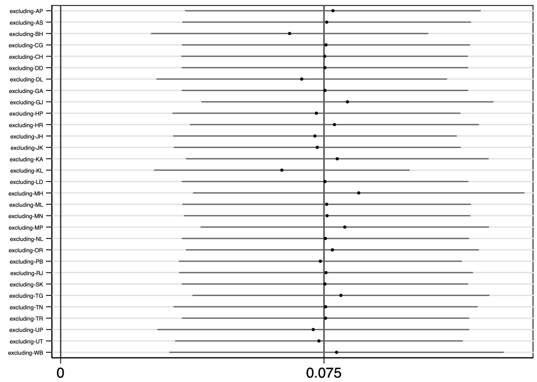
(b) Willingness to Act



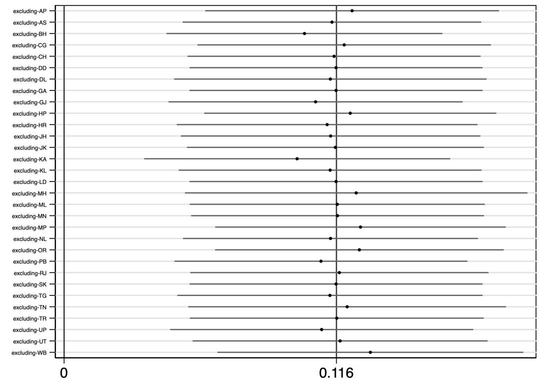
(c) Took Action

Notes: Figure (a), (b), and (c) show, respectively, time paths for subjects' willingness to protest, their willingness to engage in anti-corruption activism, and their likelihood of taking an actual anti-corruption action for the full sample over 5 months. The point estimates are denoted by black dots and 95% confidence interval are displayed in red. The numbers on the horizontal axis indicate the distance from the state level peak, in months. "0" on the horizontal axis indicates the month when the peak in daily cases was reached in a given state. Total count of subjects=898. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy for mode of survey participation, indicators of household composition, such as, a dummy indicating if the subject has children, another dummy if he lives with parents, and a third dummy if he lives with an elderly (older than 60 years). We include state fixed effects in all specifications.

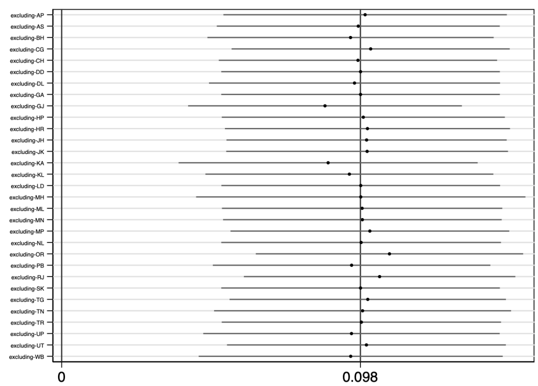
Figure A3: Sensitivity Analysis



(a) Willingness to Protest



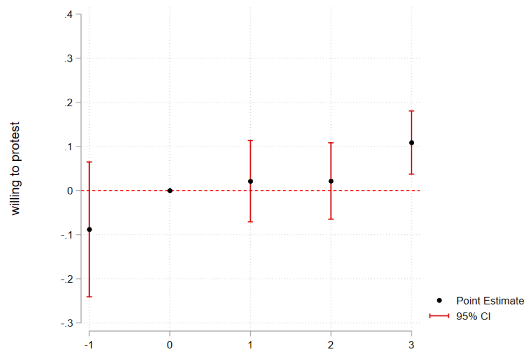
(b) Willingness to Act



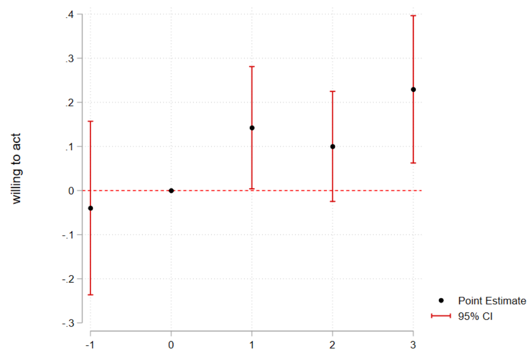
(c) Took Action

Notes: Figures (a) to (c) plot the effect of exposure to peak removing each of the 31 states one at a time for each outcome:(a) Willingness to Protest; (b) Willingness to Act and (c) Took Action. We then reproduce the analysis of Panel A of Table 2 (columns (1), (2) and (3) for respective outcomes). The point estimates are denoted by black dots with 95% confidence interval. The first vertical line indicates 0 while the second vertical line in each figure is the estimate from Table 2 (Panel A) for that outcome. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy for mode of survey participation, indicators of household composition, such as, a dummy indicating if the subject has children, another dummy if he lives with parents, and a third dummy if he lives with an elderly (older than 60 years). We include state fixed effects in all specifications.

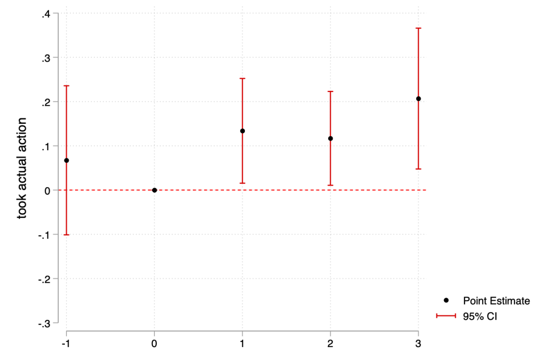
Figure A4: Activism by Month of Survey for Early Peak and Late Peak States



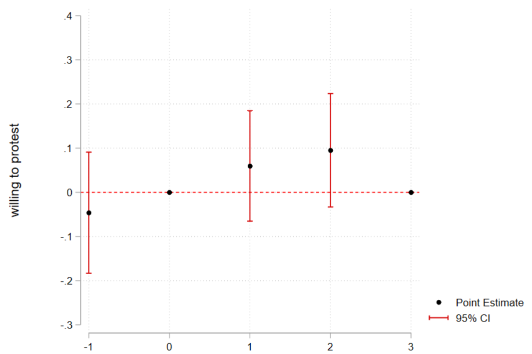
(a) Willingness to Protest (Early Peak)



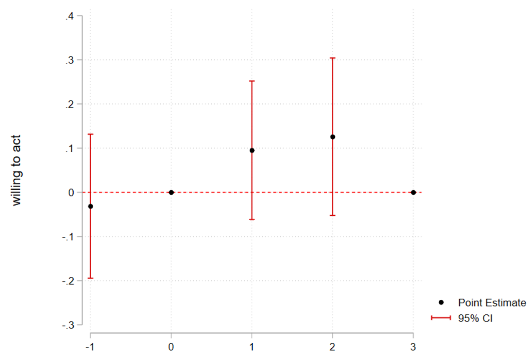
(b) Willingness to Act (Early Peak)



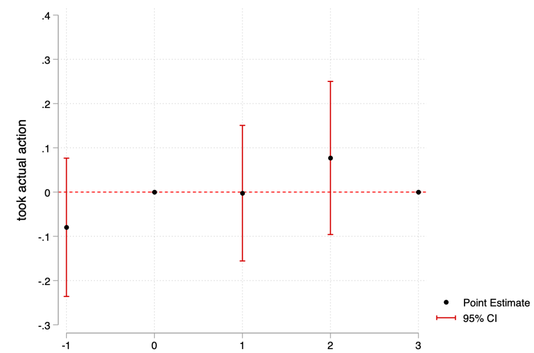
(c) Took Action (Early Peak)



(d) Willingness to Protest (Late Peak)



(e) Willingness to Act (Late Peak)



(f) Took Action (Late Peak)

Notes: We divide Indian states in two groups: those who peaked early, i.e., before the national peak of May 8th (7 day M.A.), and those who peaked late. Figures (a), (b) and (c) show time paths for subjects' willingness to protest against fraud and corruption in the health sector, willingness to engage in activism against such corruption, and actual activism for the early-peak sample, respectively, over 5 months. Figures (c), (d) and (e) show the time paths for the same outcome variables when restricting the sample to the late-peak Indian states. The point estimates are denoted by black dots and 95% confidence interval are displayed in red. The numbers on the horizontal axis indicate the distance from the state level peak, in months. "0" on the horizontal axis indicates the month when the peak in daily cases was reached in a given state. Controls include age, marital status, caste, religion, education, income, asset, indicator for frequent repeated participation in Qualtrics surveys, dummy for mode of survey participation, indicators of household composition, such as, a dummy indicating if the subject has children, another dummy if he lives with parents, and a third dummy if he lives with an elderly (older than 60 years). We include state fixed effects in all specifications. The black dots without confidence interval in figures (d), (e) and (f) are due to no observations on the third month post-peak for late peak states.

B Activism Decision Screens

Petition Decision Screen

Before you exit the survey, we would like you to think of the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic. The **"All India Drug Action Network" (A.I.D.A.N)** is a non-profit organization that has been pressuring local and central governments to better regulate health care in India, fostering transparency in hospitals and assisting patients who have been illegally overcharged.

Would you like to support the A.I.D.A.N.'s activities? If so, you could sign **a petition** to the Health Ministry asking for more regulation and transparency in health care charges. If you prefer to **exit the survey**, please click the "EXIT THE SURVEY" button below.

PETITION EXIT THE SURVEY

Donation Decision Screen

Before you exit the survey, we would like you to think of the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic. The **"All India Drug Action Network" (A.I.D.A.N)** is a non-profit organization that has been pressuring local and central governments to better regulate health care in India, fostering transparency in hospitals and assisting patients who have been illegally overcharged.

Would you like to support the A.I.D.A.N.'s activities? If so, you could make **a donation** to A.I.D.A.N. If you prefer to **exit the survey**, please click the "EXIT THE SURVEY" button below.

DONATION	EXIT THE SURVEY
○	○

Video Decision Screen

Before you exit the survey, we would like you to think of the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic. The **"All India Drug Action Network" (A.I.D.A.N)** is a non-profit organization that has been pressuring local and central governments to better regulate health care in India, fostering transparency in hospitals and assisting patients who have been illegally overcharged.

Would you like to support the A.I.D.A.N.'s activities? If so, you could watch **a 6 minute video** that explains AIDAN activities and how you could help. If you prefer to **exit the survey**, please click the "EXIT THE SURVEY" button below.

VIDEO	EXIT THE SURVEY
O	O

Choice Decision Screen

Before you exit the survey, we would like you to think of the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic. The **"All India Drug Action Network" (A.I.D.A.N)** is a non-profit organization that has been pressuring local and central governments to better regulate health care in India, fostering transparency in hospitals and assisting patients who have been illegally overcharged.

Would you like to support the A.I.D.A.N.'s activities?

If so, you could sign **a petition** to the Health Ministry asking for more regulation and transparency in health care charges. Please click PETITION below, and you will be redirected to the page containing necessary instructions.

OR make **a donation** to A.I.D.A.N. Please click DONATION below, and you will be redirected to the page containing necessary instructions.

OR watch **a 6 minute video** that explains AIDAN activities and how you could help. Please click VIDEO, and you will be redirected to the page containing necessary instructions.

If you prefer **to exit the survey**, please click the "EXIT THE SURVEY" button below.

EXIT THE SURVEY	PETITION	DONATION	THE VIDEO
○	○	○	○

Petition Signing Page

Now is the time to put pressure on our leaders to safeguard our health! The healthcare sector has enjoyed unbridled growth because of government subsidies and the lack of implementation of regulatory laws.

Overcharging and unethical practices are frequent concerns in health care, & all of this is propagated due to the COVID-19 pandemic, which has wreaked havoc on our healthcare system.
With no public health law in place, India is fighting COVID-19 Pandemic using a 123-year-old Epidemic Diseases Act, an even older Indian Penal Code of 1860, and a recent Disaster Management Act of 2005. The violation of patients' rights has shot up to an astronomical level in absence of any regulation.

Sign our petition to the Health Minister of India to show support for the following demands:
1. Adoption of regulatory laws like the Clinical Establishment Act, 2010
2. Clear display of treatment protocol and prescription audit
3. District level grievance redressal system for patients

The right to affordable and accessible care will only be achieved if people start demanding that government health services be strengthened, expanded and improved; and the government introduces and implements strict regulations for hospitals.

This petition is addressed to:
1. Union health minister: Dr. Harsh Vardhan (hfm[at]gov[dot]in)
2. health ministers of the states:

Click here to download a pdf copy of the petition.
If you would like to sign this petition, please write your full name below:

Donation Page

You can support A.I.D.A.N. by donating part or all of your bonus earnings from Section D of the survey. You can donate any amount between 0 and 100% of your bonus earnings.

How much would you like to donate to A.I.D.A.N out of your bonus earnings from Section D?

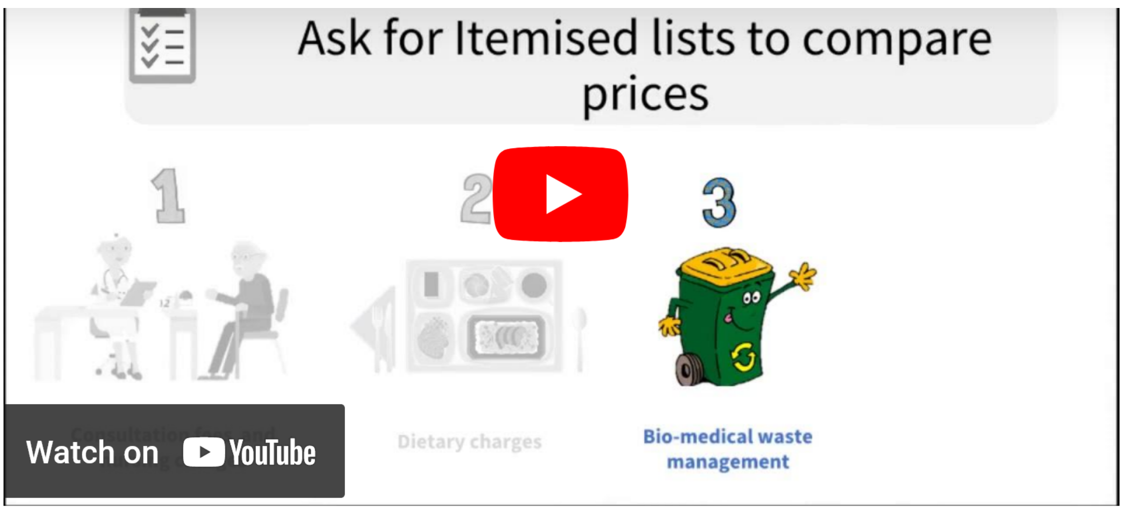
0% of bonus	60% of bonus
10% of bonus	70% of bonus
20% of bonus	80% of bonus
30% of bonus	90% of bonus
40% of bonus	100% of bonus
50% of bonus	

Video Pages

We are now going to show you the video.

Please make sure that you can listen to the video by putting headphones on or raising the volume of your device. If you are on mobile, you want to consider switching to landscape mode for better viewing experience. Once you have done that, please click the arrow on bottom right to proceed.

Once you have finished watching the video in the next page, please click the arrow on bottom right to end the survey.



C Data Generation Procedures

C.1 Sampling

In order to measure whether the subjects are paying attention to the survey and understand the instructions of the questionnaire, we employ a variety of checks and screener questions within the survey.

- The first screener question is a simple one to catch subjects who paid the least attention. Following the suggestions of Oppenheimer et al. (2009), we include the following question: "People are very busy these days and many do not have time to follow what goes on in the government. Some do pay attention to politics but do not read questions carefully. To show that you have read this much, please ignore the question below and just select the option C from the four choices below. That's right, just select the option C from the four choices below.

  How interested are you in information about what's going on in government and politics? (answer choices: option A/ option B/ option C/ option D)"

  Subjects who failed to pick option C are considered as 'inattentive'. We don't outright disqualify these subjects from continuing the survey, but they are not included in the final analysis sample.

- We then place three training questions prior to the belief questions that were real-effort, to capture the subjects' comprehension of how much they're going to earn from the real-effort questions. Using the set of training questions, we measure the number of failed attempts for each subject to grasp their prospective earnings.

- Finally, we include a descriptive question; "Some people who are asked to pay bribes do not complain about it. Why do you think this is the case? Please type your response in the text box below." We consider as inattentive the subjects who enter nonsensical text when answering this question.

Overall, we find that these three indicators of attention are highly correlated. Inattentive subjects are also more likely to have a much higher number of failed attempts in the training questions, and are more likely to leave a gibberish answer in the descriptive question. We do not find the proportion of inattentive subjects to vary significantly between treatment groups. Hence, from the main analysis sample, we decide to exclude them. This brings our subject pool to 898.

C.2 Procedure for Standardization and Index Construction

We constructed indices for corruption experience and individual preferences. These are the average of the relevant standardized variables, as listed in below. The procedure is as follows-

- Individual variables are coded such that the positive direction always corresponded with "higher" outcome for all sub-components of the aggregate index, 0 otherwise.
- Each variable is normalized by subtracting the overall control (pre-2nd wave) mean and dividing by the control group standard deviation. The index is then generated by averaging over relevant components.
- The final index is then re-scaled such that the control mean is 0 and the standard deviation is 1.

C.2.1 Corruption Perception

The corruption perception index aggregates the following survey questions.

- "Please consider all the contact you or members of your household had with health workers in clinics or hospitals since April 2020 till date. How many times did you have to pay extra money to obtain a medical service? (never/1/2/.../10/more than 10 times)."[40]
- "In your opinion, has the level of corruption in the health sector during the COVID-19 pandemic - (increased a lot/ increased somewhat/ stayed the same/ decreased somewhat/ decreased a lot)"[41]?
- "According to your experience, the current level of corruption in the health sector is - (not a problem at all/ a small problem/ a moderate problem/ a major problem)"[42].

C.2.2 Information (Rights)

Subjects' information on rights and entitlements are captured through this index, which aggregates the following survey questions.

- "Do you know what is the rate you have to pay per day for an ICU bed at your local hospital?"[43]

[40]response coded into a continuous variable.
[41]response coded into a continuous variable with higher value indicating increase in corruption.
[42]response coded into a continuous variable with higher value indicating bigger problem.
[43]response coded into a dummy=0 if subject answered with 'don't know', 1 otherwise.

- "Do you think you or a member of your household were illegally overcharged by the healthcare professionals for the hospital stay? - (does not apply / don't know or can't say/ no/ yes)"[44]

C.2.3 Corruption Tolerance

The corruption tolerance index aggregates the following survey questions.

- "Please tell us for each of the following actions whether you think it can never be justified, always be justified or something in between using a scale of 1 to 10 below (1 denotes never justifiable, and 10 denotes always justifiable)."[45]
  - avoiding fare on a public transport
  - doctors overcharging for a hospital bed during COVID-19 pandemic
  - someone accepting a bribe in course of their duties.
- "How many people in your community do you think expects you to complain if you are overcharged or asked to pay a bribe by a doctor? (nobody/ a few people/ many people/ most people/ everybody)."[46]

C.2.4 Preferences

'Risk' is a self-assessed measure of risk preference. Similarly, the pro-sociality index is generated by combining self-assessment indices of trust, retaliation and altruism. These variables are measured following Falk et al. (2018):

- The *risk index* is computed using response to "Please tell us, in general, how willing or unwilling are you to take risks, using a scale of 0 to 10 below (0 indicates completely unwilling, and 10 indicates very willing to take risks.) (answer choices: completely unwilling 0/ 1/ ..../very willing 10)"
- *Trust* is computed using response to "Please tell us whether the following statement describes you as a person: you assume that people only have the best intentions, using a scale of 0 to 10 below (0 indicates that the statement does not describe you at all, and 10 indicates that the statement describes you perfectly). (doesn't describe you at all 0/1/ .../ describes you perfectly 10)."

[44] response coded into a dummy=1 if subject answered with a 'yes.

[45] responses coded into a continuous variable.

[46] response coded into a dummy=1 if subject answered with 'nobody'.

- *Retaliatory behavior* is based on response to
  - "Please tell us whether, if you are treated very unjustly, you will take revenge at the first opportunity, even if there is a cost to do so, using a scale of 0 to 10 below (0 indicates you are completely unwilling to take revenge, 10 indicates you are very willing to take revenge)."
  - "Please tell us how willing you are to punish someone who treats you unfairly, even if there may be costs for you, using a scale of 0 to 10 below (0 indicates you are completely unwilling to do so, 10 indicates you are very willing to do so)."
  - "Please tell us how willing you are to punish someone who treats others unfairly, even if there may be costs for you, using a scale of 0 to 10 below (0 indicates you are completely unwilling to do so, 10 indicates you are very willing to do so)."
- *Altruism* is measured by response to "Please tell us how willing you are to give to good causes without expecting anything in return, using a scale of 0 to 10 below (0 indicates you are completely unwilling to give, 10 indicates you are very willing to give) (answer choices: completely unwilling to give 0/ 1/ ..../ very willing to give 10)."

The trust, altruism and reverse-coded retaliation measures are combined to create the prosociality index using the same process described above.