Do Crises Affect Citizen Activism? Evidence from a Pandemic*

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PRELIMINARY DRAFT - NOT FOR CIRCULATION

Abstract

Do critical junctures drive citizens' motivation to fight corruption? We elicit perceptions about corruption in the health sector and the willingness to act against it in an online survey, conducted with nearly 900 men during the height of the second wave of the COVID-19 pandemic in India between March and July 2021. We assess how these measures changed with the severity of the pandemic during this period, using both hypothetical and real-effort measures of citizen activism. We find a significant surge in the proportion of respondents agreeing to participate in protests after the COVID-19 peak, as well as in the willingness to take anti-corruption actions. Furthermore, we observe a substantial increase in subjects' perception of corruption and their level of information on citizen rights and entitlements during the same period. The evidence, therefore, suggests that the second wave of the pandemic not only acted as a focal point leading to greater willingness to act, but it also increased the probability of citizens taking an anti-corruption action.

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1 Introduction

Existing research suggests that direct lived experiences, or 'personal effects' are often powerful motivators for belief formation and actions - they can induce long and short-term change in both beliefs and behavior of individuals (Malmendier and Nagel, 2011; Malmendier, 2021). Crises caused by economic or natural shocks can affect consumer behavior in financial markets, healthcare, social attitude and civic engagement.[1] While this literature has studied citizens' self-reported beliefs, there is less rigorous evidence available on the effect of crises on citizen activism to improve accountability.

The ongoing pandemic gives us an opportunity to test the short-term effects of crises on citizen anti-corruption activism, which has been on the rise during the time (Withnall, 2020; AP, 2020; BBC, 2021). We add to the literature on the impact of crises on individuals' beliefs and behavior by examining how pandemic experience (private/collective) affects beliefs, and citizens' own anti-corruption efforts during the crisis. Specifically, we investigate whether the COVID-19 pandemic impacted individuals' willingness to fight against the extant and wide-spread corruption in the healthcare sector in India. The number of people who died in the second wave of the pandemic in India, which reached its peak in May 2021, was unprecedented in history, either by official or unofficial estimates (Jha et al., 2022). The grief and pain that the citizens have experienced due to the loss of loved ones touched nearly every family. The health sector was so burdened by the catastrophic pandemic that its collapse affected the socio-economically better-off as well, who are typically not invested in improving the (public) health system in India.

From a sample of 900 Indian men, we elicited perceptions about corruption in the health sector and the willingness to act against it in an online survey between March and July 2021. We then analyzed how these responses changed with the intensity of the pandemic during this period.[2] Data on total daily cases between March 1st and July 31st show that the

[1] Evidence, on this front, comes not only from Economics but also from Psychology and Neuroscience literature (LaBar and Cabeza, 2006; Sharpe et al., 2021; Spunt and Adolphs, 2017; Isen et al., 1978).

[2] Subjects in our study represent more educated and higher than the average income for India. 79% have

second wave of the pandemic peaked just after May 1st 2021 in terms of daily cases, whereas the peak for daily deceased occurred roughly two weeks after that, in India. We classify our sample of 898 respondents across the country into those surveyed before the second wave peak (309 subjects) and after the peak (589 subjects) in their respective states.[3] We then compare the experiences, beliefs and willingness to act to fight corruption in the health sector for these two groups.[4]

Following the survey questions, we randomly assigned respondents to four possible real-effort actions they could take to address corruption – sign a petition addressed to the Ministry of Health to improve accountability in health sector, donate to a non-profit organization that works to improve health sector accountability, gather information on what actions individuals can take by watching a video on health sector regulations of prices and practices, and choose from any of these three actions. In addition, we asked subjects whether they were willing to participate in a (hypothetical) protest against corruption in the health sector. Our findings indicate a consistent increase in the subjects' willingness to take actions after being exposed to the second wave of COVID in India; we document a 29% increase in willingness to take any anti-corruption action, relative to pre-peak. Our estimate accounts for state-level unobservables, individual characteristics and any unobservable differences in characteristics of subjects surveyed before and after peaks through sample re-weighting.[5] We attribute subjects' increased willingness to take action to a corresponding rise in subjects' perception of corruption and their baseline level of information about their rights and entitlements,

a college degree, 54% have monthly household income above INR 30 thousand. For comparison, 1 U.S. dollar was roughly equal to INR 74 as of 2nd October, 2021. Subjects remained anonymous throughout.

[3]Since both samples are random draws in terms of timing of survey, the pre and post sample are comparable – urban males, 85% below 45 years of age, 79% with a college degree, 48% married and 75% had visited a health clinic for some ailment (own or family member, which may or may not be COVID related) over the previous 12 months.

[4]Such a study design is also known as 'Unexpected Event during Study Design'. (e.g., see Muñoz et al., 2020, for a review). We expect citizens to be more willing to take action against corruption in the health sector when they are personally exposed to the health shock versus when they hear or read about it in the news. Thus, a higher likelihood of *personal* exposure should affect anti-corruption activism.

[5]The 'peak' refers to the state-level peak in new confirmed COVID cases. In section 2, we describe that health is a state subject in India. Existing evidence shows that the quality of infrastructure and service varies substantially from state to state (Choutagunta et al., 2021). Therefore, the condition of healthcare in subjects' own state of residence bears more importance for their personal experience of the crisis.

which likely occurred due to the heightened experience with the health system during this crisis. We also find that citizens are more willing to take risks (self-reported), and have higher beliefs about fellow citizen's willingness to protest. This suggests that in the context of anti-corruption activism, where one's actions are contingent on the behavior of others, beliefs about other's willingness to act are important.

Our paper is amongst the first to test citizen activism in the context of the current pandemic, in one of the world's hardest-hit countries, India.[6] We utilize survey data collected in real-time as the crisis unfolded, which allows us to provide credible estimates of the effects of unexpected occurrence of the second wave of pandemic on citizen activism for anti-corruption efforts.

Existing empirical evidence shows that there is substantial resetting of individual behavior through personal experiences. Here, the bulk of evidence comes from the finance literature. For example, using the U.S. Survey of Consumer Finances data, Malmendier and Nagel (2011) find that individuals' experiences of macro-economic shocks, such as a depression, have long-term effects on their risk attitudes from consumer finance data, with more recent return experiences having a stronger effect. Further, Giuliano and Spilimbergo (2014) show that historical macroeconomic events like a recession also impact political and economic preferences for those who lived through it when young. Using data from seismic events in Italy for a period of three decades, Gualtieri et al. (2018) find that natural disasters, such as earthquakes, can affect individual opinions – collected a few months later – on income inequalities in favor of redistribution. Voors et al. (2012) find that in rural Burundi, large adverse shocks like violent conflict can alter pro-social preferences, savings and investments decisions, and potentially have long-run consequences—even if the shocks themselves are temporary. Malmendier (2021) points out that such experience effects are long lasting, highly domain specific and affected by recency bias, where more recent experiences weigh in the belief formation of individuals. On domain specificity, Malmendier and Nagel (2011)

[6] According to the World Health Organization dashboard, India has a cumulative 43,142,192 total cases, second only to the United States and the third highest death count (`https://covid19.who.int/table`).

show that stock market experiences affect stock-market investment, bond-market experiences affect bond investment, but there is no significant cross-over experience-based learning. Further, investors' equity allocation is driven by the stock market's weighted past performance, with more recent experiences receiving higher weights than those from early in their lives.

More recently, several papers examine the effect of exposure to epidemics on beliefs and attitudes towards institutions and governments. Using data from 138 countries since 1970, Eichengreen et al. (2021) show that exposure to an epidemic over an individual's formative years significantly reduces confidence in scientists and the benefits of their research. Further, using worldwide individual-level survey data from the Gallup polls, Aksoy et al. (2020) found that epidemic exposure in formative years leaves a negative effect on trust in political leaders, governments and institutions. These findings are increasingly relevant in the context of the ongoing COVID-19 pandemic. Based on a survey of 2500 US adults, Klemm and Mauro (2022) show that serious illness or job losses caused by the COVID-19 pandemic increased support for temporary progressive levies or structural progressive tax reform. Using Spanish data, Amat et al. (2020) illustrate the shift in public preference towards more technocratic and authoritarian government due to COVID-19 crisis. On the other hand, Bol et al. (2021) survey citizens of 15 western European countries and find that COVID-19-related lock-downs were associated with a 2% increase in trust in government in the short term, with no effect on self-reported ideology.

We contribute to this literature by directly examining changes in bottom-up anti-corruption efforts undertaken by citizens during a time of crisis. A unique feature of our study is that the design facilitated the collection of real-effort as well as hypothetical measures of citizen activism. Use of real-effort measures, which allow for revelation of true preferences, in a similar context have not been examined in-depth to the best of our knowledge.[7] Overall, our study is consistent with the previous literature which documents that economic or political

[7]Using incentivized outcomes in the context of survey experiment is still nascent, the exception being research in context of political donations (Grigorieff et al., 2020; Roth and Wohlfart, 2020). Incentivized elicitation about beliefs, on the other hand, has been used in experiments, especially in the political context (see Haaland et al. (2020) for a review).

shocks shape individuals' behavior. Particularly, it helps to further our understanding of the pandemic's impact on citizen's anti-corruption activism and collective action.

In the next section we discuss India's health sector and the timing of the COVID-19 waves in the country. Section 3 outlines our data and sampling, along with the empirical methodology. The results are presented in Section 4. Section 5 discusses the findings and we conclude in Section 6.

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).[8] Existing research has also documented that at the state level, there are significant variation in healthcare spending as a proportion of budget, capacity of hospital (especially Intensive Care Unit) beds, doctors and nurses, and availability of testing centers (Choutagunta et al., 2021).[9] Along with the overall picture of capacity constraint, the domestic private health expenditure in India is 66% of current health expenditure, one of world's highest, whereas the share for low and middle countries over the world is at 46%.[10]

Private healthcare business has been steadily on the rise in India, with a strong presence

[8] According to the World Bank (`https://data.worldbank.org/indicator/SH.XPD.CHEX.PC.CD`), 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%.

[9] The same research points out that poorer states have fewer hospital beds across public, private, and charitable hospitals. A rich state like Maharashtra has six times the capacity as Bihar. There is also a lot of intra-state variation, since larger urban and metropolitan areas have more and larger hospital facilities. This leads to substantial variation in intra-state healthcare capacity. Intensive Care Unit (ICU) beds at a meager 5% of total beds in India. A similar picture emerges for hospital personnel, especially doctors and nurses, with states like Bihar, Jharkhand, and Uttar Pradesh being the least supplied. These facilities are the hardest to scale up, and indeed were not scaled up between the two COVID waves (The Hindu, 2021).

[10] See `https://data.worldbank.org/indicator/SH.XPD.PVTD.CH.ZS?end=2019&start=2019&view=map` for more details.

in virtually all medical sub-markets, even though they face minimal de-facto regulation and poorer training than public sector personnel.[11] Over the years, the private sector has become a dominant player in various markets within the medical field, such as hospital constructions, diagnostic services, technology, training and pharmaceuticals. A large chunk of private providers are situated in urban areas and are relatively more expensive.[12] As a result, patients are often compelled to seek treatment in urban areas (Selvaraj and Karan, 2009). In particular, the treatment for COVID-19 requires intensive care units, frequent testing facilities and provision of oxygen supplies all of which are lacking in rural areas. Hence, by focusing on urban residents of India, we hope to capture more accurately the corruption experience of the masses even though infection was relatively more evenly spread in rural and urban areas during the second wave as compared to the first wave (Panneer et al., 2022; Hindustan Times, 2021a).[13] [14]

It is well-acknowledged that healthcare frequently ranks as one of the most corrupt service sectors in India, as gauged by people's actual experiences (Kumar, 2003). India's unsatisfactory health system has been a cause of alarm long before COVID-19 wreaked havoc. A Lancet report from 2011 (Reddy et al., 2011) notes that-

> "The country's health system ranks as one of the most heavily dependent on out-of-pocket expenditure and private health care in the world....The increasing dependence on the private sector, in addition to very weak regulation and

[11] Das et al. (2016) discusses that the proliferation of private sector not only reflects a dearth of public options, especially in rural areas, but it also indicates a preference of patients in favor of private providers. They argue that this tendency is due to private providers exert significantly higher effort than in their public practice.

[12] It has been documented that the quality of both in-patient and out-patient care in rural private healthcare is inferior to urban private healthcare (Selvaraj and Karan, 2009).

[13] For example, from a study in Karnataka, Mohanan et al. (2021) finds that adjusted seroprevalence in the state was 46.7%, including 44.1% in rural and 53.8% in urban areas by the end of August 2020. This implied already high level of disease spread in rural areas, consistent with a rapidly growing pandemic.

[14] Additionally, we restrict our sample to only adult men, to avoid differential responses arising from extant gender disparities in access to computer/mobile devices that would be required for participation in the study, healthcare access and intra-household decision-making on health expenditures in India (Moore and Sabherwal, 2017; Saikia and Bora, 2016). National Family Health Survey (NFHS- 5th round) also confirms that that only 54% of women (15-49 years) have a mobile phone that they themselves use, and about 80-81% of them makes decisions regarding their own health care (NFHS 2019-21; `https://dhsprogram.com/pubs/pdf/FR375/FR375.pdf`).

> corruption, has led to a huge increase in health-care costs with the result that out-of-pocket payments are now one of the leading causes of direct debt and poverty in India."

Another report (Patel et al., 2015) highlights several key issues of Indian health system. Important among these are- low levels of public expenditure, poor regulatory framework, increasing commercialization and corruption, and the inadequate convergence between various state and federal departments of health care. The issue of regulation of private hospitals and practice, in particular, is one that is becoming increasingly more important for citizens.

Conversations with the All India Drug Action Network (A.I.D.A.N), a collective of medical and legal professionals that has been at the forefront of advocating better regulation of health care, revealed that in context of an emergency situation in particular, the lack of government regulations allows corrupt actors to go free. The landmark Clinical Establishments Act (2010) which provides for the registration and regulation of clinical establishments and prescribes minimum standards of facilities, has not been adopted in all states as yet.[15] Moreover, the standards for registration of hospitals have not been notified by the federal government, suggesting that the act is not implementable even in states where it has been adopted. Lack of regulatory framework is a serious impediment to states attempting to hold hospitals and corrupt actors accountable. With no public health law in place, India has been fighting the pandemic using a 125-year-old Epidemic Diseases Act, an even older Indian Penal Code of 1860, and a recent Disaster Management Act of 2005. As a direct consequence, the violation of patients' rights has shot up to an astronomical level in absence of any regulation.

All of these constraints require a large amount of time and resources to address, but in emergencies like the COVID-19 pandemic, there is a need for swift action from the government.

[15]See `http://www.clinicalestablishments.gov.in/cms/Home.aspx` for more detail about the act. For more press coverage of the limited implementation of this act, see: `https://theprint.in/talk-point/fortis-regulate-charges-corporate-hospitals/17730/`, `https://www.tribuneindia.com/news/punjab/7-yrs-on-clinical-act-hangs-fire-1100`.

2.2 Pandemic Timeline

The outbreak of COVID-19 in India has evolved through distinct stages, prompting a policy response to combat the disease transmission as a first order effect, and subsequent measures to contain numerous ripple effects spreading throughout the economy. The first wave of 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 gradually peaking around September 2020. The strict lockdown measures imposed by the federal government served as a barrier preventing a severe large scale outbreak in India's large population, although it came at a significant economic cost (Beyer et al., 2021; Dhingra and Machin, 2020; Afridi et al., 2022).[16]

In contrast, the second wave in India was marked by several factors which underscored the general unpreparedness. Numerous reports showed that mass gatherings in religious places, public examinations, festivals that encourage mass participation, political rallies and even protests were going on in an uncontrolled manner (Reuters, 2021a; Economic Times, 2021; Times of India, 2021a). These factors were indications that there was a clear lack of coordinated effort to keep the upsurge of COVID-19 cases in control. Reports also indicate that in contrast to the first wave, the control of disease spread and vaccination in the second wave was mostly shifted from the federal to the state governments (often resulting in even public altercations) (Press Information Bureau, 2021).[17] However, there is significant variation in healthcare provision among Indian states, particularly in their ability to scale it up during an emergency (Garg and Karan, 2009; Choutagunta et al., 2021).[18] On top of these, the second wave became more deadly as double-mutant and triple-mutant strains of SARS-CoV-2 began spreading which are more pathogenic than the initial strains (Asrani et al.,

[16]In the cross-country context, Chiplunkar and Das (2021) provide an overview of how different political institutions responded to the COVID crisis, in terms of containment and health policies.

[17]Health is a state subject in India.

[18]Our own interviews with representatives from the A.I.D.A.N. portray the same experience that reflects an overall picture of a severely compromised regulatory health framework, coupled with inadequacy of laws that are rendered ineffectual due to technical gaps, a persistent shortage of hospital beds, insufficient enforcement of standard treatment guidelines, and deliberate obfuscation of the treatment costs.

2021). As a result, India sleepwalked into a disaster, within a fortnight of mid-April 2021. The confirmed daily case-load surged from the 80,000-mark on April 1 to over 400,000 by April 30, 2021 (see Figure A1, (World Health Organisation, 2022)). The meteoric increase in fresh cases is the primary reason behind the shortage of crucial drugs and ventilators, which couldn't be scaled up at a short notice. According to news reports, most states issued a complete or partial lockdown (Indian Express, 2021) this time in the absence of a nation-wide lockdown. However, despite the localized lock-downs, we find that almost every state showed a similar rapid rise in daily confirmed cases, mirroring the national experience (see Figure A2). The decline has been just as quick with India taking the same amount of time to fall back to similar numbers. Additionally, there was significant variation in the state wise distribution of fresh COVID cases; nearly three-fourth of new cases were traced to six states of the country. Analyzing data on confirmed cases in 2021 (Figure A3), we find that the second wave was primarily driven by case-loads from Maharashtra, Kerala, Karnataka, Tamil Nadu, Andhra Pradesh and Uttar Pradesh. This is also supported by press reports from that time (Hindustan Times, 2021b).

While in the first wave, India's cases per million was far lower than the rest of the world, the infection was initially contracted from international travelers and mostly concentrated in urban areas. This already hit the city healthcare systems hard. Under the avalanche of cases in the second wave, even the better equipped systems collapsed (Reuters, 2021b). Taken together, these reports underline that historically, Indian states vary significantly in terms of their healthcare capacity and resource constraints. These factors, coupled with difference in incidences of COVID-19 and the growth of infection rates indicate that citizens' experience and struggle wavered quite widely depending on the part of the country they found themselves in, even though the surge of second wave caught the entire nation unawares.

3 Data and Methodology

3.1 Data

Our data come from the web and phone based Qualtrics survey for adult Indian men conducted over March-July 2021.[19] The study was framed as a general survey focused on understanding people's behavior and attitude during the pandemic, thereby minimizing mentions of the word 'corruption' in order to avoid priming the subjects. We opened and closed the survey every month between this period. Specifically, we operated the survey on the following dates in 2021- March 24-25, April 2, April 7, April 21-22, May 19, May 26, June 1, June 3, June 15-18, June 30, July 1 and July 26. The reason behind this is how survey firms work. In our case, Qualtrics maintains a large pool of subjects who are representative of relatively younger, economically better-off and urban Indian population. The survey firm then sends a link to the potential subjects and wait 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, in our data collection process, it took between 1-4 days to collect information. In Figure A4, we show the distribution of subjects according to the date of case peak experienced in their respective states of residence (in grey). In the same figure, the distribution based on their timing of interview is shown in red. Depending on the date of survey for a particular subject, we compute a dummy variable that indicates if the subject took the survey on or before his respective peak-date of daily COVID cases at the state level.[20]

There are plenty of media coverage explaining how the deadly second COVID-wave took India by surprise, with hospitals pleading for oxygen supplies and doctors watching helplessly

[19] We recruited only men to avoid gender disparities arising from access to computer/mobile devices, healthcare access and intra-household decision-making. Participation was conditional on having a monthly household income of INR 60,000 or less.

[20] The state-wise peak in daily cases is given in Table A1. The national peak in daily cases was on May 8 2021. In Table A2, we show the number of subjects interviewed on successive survey dates with respective to the national level peak. This table also demonstrates the cumulative count of subjects, showing that about 34 percent of our sample was interviewed at about six interview dates before the shock whereas the rest were interviewed after, at about eleven interview dates till 26 July 2021.

as patients perished from preventable deaths (India Today, 2021a,b; Times of India, 2021b). The dramatic increase in daily cases from around mid-April also lends support to this fact. To identify the peak in state-level daily cases, we rely on the publicly available data gathered by the website covid19india.org. Using this data on daily case-load at the national level in Figure A1, we demonstrate how the COVID situation in virtually every state showed a dramatically sharp rise, thus evolving from poor to catastrophic within just a fortnight.

Following a battery of initial questions on demographics and experience with healthcare, we elicited subjects' (hypothetical) agreement/disagreement with a statement related to their personal willingness to take part in a protest towards malfeasance/irregularities in the health sector during the pandemic. This constitutes our (hypothetical) outcome measure called 'willingness to protest'.[21]

Next, once subjects reached the end of the survey, we thanked them for their participation. They were then directed to a new page where we invited them to "think about the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic." In the next paragraph we then briefly described a local non-profit organization, the All India Drug Action Network (A.I.D.A.N), 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 A.I.D.A.N.'s activities. We experimentally manipulated the type of action that participants could engage in to support A.I.D.A.N. Specifically, they could either sign a petition, or make a monetary donation, or watch an informational video on A.I.D.A.N. activities and ways to get involved in the fight against corruption.[22] A fourth action treatment presented subjects with all three actions and allowed them to choose among them, or to exit the survey. Here, we capture respondent's willingness to take action through a dummy. Then we pool subjects' responses

[21]Subjects remained anonymous to researchers throughout the survey, since anti-corruption activism may be a sensitive issue to some.

[22]We developed each of these actions in partnership with A.I.D.A.N.

from all four action treatment groups.

Subjects were informed that if they decide to sign, they would then be taken to the petition page, which contained a petition against corruption in the health sector, directed toward the Union Health Minister of India, and promoted by the non-profit organization.[23] Similarly, if they decide to make a donation, they would be given the chance to donate any portion of the money they earned in the incentivized survey tasks to the same non-profit organization. Finally, if the subject decide to gather information online, they are redirected to a page containing a 5-minute video showing ways for the public to be involved in the fight against corruption in India, with special focus on the activities of the organization, their suggestions in instances of malpractice and ways to get in touch with them.[24] Note that we focus on individuals' decision to act, rather than actual behavioral outcomes associated with each action (for example - time spent in watching the video, or the actual amount of donated). This allows us to combine all the four action groups into one, thereby giving us more power to estimate impact on probability of taking <u>any</u> real-effort action.

We focus on two key outcome variables related to anti-corruption actions. These are – (1) real-effort willingness to take action against health corruption through a non-profit organization. This variable is a dummy that equals 1 if the subject indicated that they were willing to take any real-effort action, i.e., sign a petition (and reveal their name) to support A.I.D.A.N., or make a monetary donation to A.I.D.A.N., or watch an informational video on A.I.D.A.N.'s activities and ways to get involved in the fight against corruption, or select any one of the three when offered all together. The variable equals 0 if the subjects instead, preferred to exit the survey rather than take a real-effort action.[25] (2) a measure of hypothetical willingness to protest. This variable is another dummy to indicate subjects who were personally willing to participate in a protest again corruption in health. It indicates the

[23]The petition was also copied to all the state health ministries. It asks the government to fast-track the adoption of regulatory laws of health establishments, clearly communicate treatment protocol and carry out prescription audits, and implement district level grievance redressal system for patients.

[24]link to the video: `https://youtu.be/xxG37wWmAv8`

[25]These questions were placed at the very end of the survey, in order to minimize experimenter demand effects.

group of subjects who'd stated that they personally agree with the statement "I am willing to raise my voice and participate in a protest against corruption in the provision of health service."

We classify the first outcome (willingness to act) as a 'real-effort' behavioral measure since subjects have to make incur a cost when they choose to take any of these real actions versus exiting the survey without taking any action and incurring costs. Identity revelation when signing a petition carried the threat of backlash or punishment by the government. In making a donation, the subject would incur pecuniary costs, while watching the video providing information on identifying and recognizing corruption in the health sector time costs were at stake.[26] We, thus, expect that the real-effort measure carries lower experimenter demand effects and is likely to reveal the true preferences of subjects.[27] The second outcome (willingness to protest), on the other hand, is hypothetical and self-reported, not entailing any cost to the subjects. However, while less reliable, the willingness to protest outcome is contextually important because the protest action is not explicitly covered in the three real-effort actions, but is relevant in the context of the tidal wave of COVID deaths in India during this period. Overall, we believe that our outcomes provide a well-rounded measure of 'citizen activism'.

A brief summary of the major characteristics of the respondent pool is presented in Table 1. The majority of our subjects (over 80%) are younger than 45 years of age, married (48%) and with a college degree (79%). Around 46% of the subjects' monthly household income is below INR 30K. More than half (58%) of the subjects reside with an elderly and 37% report having children with them. About 65% of subjects participated in the study through a mobile device.[28]

From Figure 1, we find that roughly 37% of our subjects were willing to take an anti-

[26]On an average, subjects donated 12% of their survey earnings, or about INR 7 per subject. On an average, subjects spent about 2 minutes of their time watching the 5-minute video.

[27]For example, Roth and Wohlfart (2020) use real-effort outcomes in context of political donations.

[28]Therefore, our average respondent is younger, more educated and belongs to wealthier households than the average Indian urban man.

corruption action (real-effort question) before the peak of the second wave of pandemic. This figure increased by 11 percentage points to 48% in the post-peak period. Similarly, the hypothetical willingness to participate in a protest saw a jump of 8 percentage points during the same period.[29]

To assess whether exposure to crises affects individuals' beliefs and preferences, we use a series of measures constructed from our survey.[30] These measures include: standardized indices for corruption perception, information (rights and entitlements), tolerance, a self-reported measure of risk, an index capturing pro-sociality (standardized) and a bias dummy to indicate if the subject underestimated the true willingness of protest of other subjects.[31]

3.2 Empirical Methodology

3.2.1 Estimation Equation

We use an Ordinary Least Squares (OLS) regression to compare outcomes before and after the occurrence of the state-level peak in confirmed COVID cases. This specification allows

[29]We also explore the impact by the 4 different types of action (petition/ donation/ video/ choice) in Figure A5. The estimates remain in the same direction as the main result, but with larger confidence intervals. For subsequent analysis, we continue with the pooled sample.

[30]The index of corruption perception was created by combining- a measure of prevalence of bribery from subjects' experience in health sector since the beginning of the pandemic; a measure of their opinion on the acuteness of health corruption present in current system, and whether the level of corruption has gone up/down since April 2020. The information (rights) index was constructed using an indicator of subjects' knowledge of ongoing rate for intensive care beds in hospitals, and if they were illegally overcharged by the healthcare professionals for the hospital stay. The tolerance index was created to measure 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. All indices were standardized with respect to the control (pre-2nd wave) group mean and standard deviation. The risk index and the pro-sociality index which is a combination of trust, retaliation (reverse-coded) and altruism measures, are calculated following (Falk et al., 2018). For more details on index construction, please refer to subsection B.1.

[31]Subjects were first asked to state their own willingness to participate in a protest for corruption in health, and subsequently asked to guess what percentage of other participants were willing to do the same. They were paid INR 50 for a correct guess. We compute the bias variable based on this data. The bias dummy equals one for subjects who strictly underestimated the actual share of others willing to protest, and is 0 otherwise. Hence for example, if the true share is between 70-80%, then the bias dummy indicates subjects who'd stated that they believe only less than 70% of others will be willing to protest; it is 0 for subjects who guessed correctly and those who over-estimated others' willingness. The average payoff per subject was INR 59 on while the maximum possible earnings per subject was INR 198 for the entire survey, which had two more incentivized questions and an incentivized measure of risk preference.

us to measure the increase in outcomes for subjects who were exposed to the peak of COVID cases, versus those who were not. In other words, this setup lets us investigate if is there a significant relationship between the timing of the second wave of pandemic and willingness to participate in anti-corruption actions, corruption perception and information about citizens' rights and entitlements.

Our main estimating equation is the following[32]

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

where $\mathrm{Y_{ist}}$ is the relevant outcome variable. Recall that we have two main outcomes of interest, i.e., indicators of whether a subject is willing to take anti-corruption action to support the non-profit organization (real-effort) and whether he is willing to participate in a protest (hypothetical). $\mathrm{Post_{ist}}$ is a dummy variable equal to 1 if the subject i was interviewed on date t after the peak in daily COVID cases for the subject's state s of residence, 0 otherwise.[33] 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 (1 - 45 years and above; 0 - 18-45 years), education (1- went to college; 0- otherwise), marital status (1-currently married; 0- otherwise), religion (1- Hindu; 0- otherwise), income (1- household income is below INR 30K in previous month; 0- otherwise), asset (count of assets owned by a subject from a list of common household asset), co-residing elderly (1- elderly aged above 60 living with subject; 0- otherwise), mode (1- participated through mobile; 0- otherwise) and frequency (1- subjects who usually participate in Qualtrics surveys one or more times a day or week; 0- otherwise) of participation in online surveys. We also introduce α_s to denote state fixed effects and an idiosyncratic error term $\varepsilon_{\mathrm{ist}}$.[34] Standard errors are

[32]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).

[33]To illustrate the main results graphically, we extend this model by replacing the $\mathrm{Post_{ist}}$ dummy with a set of dummies indicating multiple time periods (in our case, months), with the month before the state-peak being the base month.

[34]Note that in absence of centralized lock-downs, we can consider the stringency of localized lock-downs as a factor that varied at the state-level. Hence, the state fixed effects, among other things, would also

clustered at the state-month level to account for unobserved heterogeneity over time and space.

3.2.2 Identification

Since the experience of the pandemic or its timing is not randomized, we utilize data staggered over time that allow us to compare the impact before and after the onset of the COVID-19 peak across states of residence that experienced the peak of the second wave at different times. Note that given our data-set, we cannot measure the change in willingness to act for a *given* individual, but rather aim to make a comparison *across* observed pre and post group. For causal estimation, we require that conditional on observables, assignment to pre or post period is independent of the outcomes. Hence, so long as there are no systematic changes over time except for treatment, the difference can be interpreted as causal.[35]

Note that in surveying respondents before and after the peak caseload of their state, we do not assume that the subject interviewed before the peak did not expect the same to occur. Once news broke out about the consequences of COVID infection, it is possible that subjects that took the survey before the occurrence of the case-peak in their state, expected the same to occur soon. The difference between the pre and post group subjects, therefore, is whether they were interviewed past the peak of their own state of residence, which is a finer indicator of whether they personally experienced the height of the pandemic. Note that the subjects could not select into either pre or post group because the survey was opened and closed for several brief spans, which was unpredictable from respondents' point of view and outside their ability to choose.[36] Hence, the occurrence of the peak assigns subjects into a pre and post group, as good as randomly. Therefore, the independence of being assigned in either pre or post group and willingness to act is plausible.

absorb the impact of such stringency of lock-downs.

[35]We believe that such changes are unlikely to occur, given our survey period is fairly short, i.e., ranging from March 24 to July 26th, 2021. We also provide several additional robustness checks to address this concern.

[36]From the back-end, we also ensured that a subject can't retake the same survey.

This does not necessarily mitigate concerns about unobserved differences and therefore needs further elaboration. To that end, we first show that indeed, a comparison of the pre and the post samples reveals (see Table A3) that the respondent pool is quite similar in terms of observable characteristics.[37] Additionally, as a robustness check, we repeat the main analysis by using weights derived from entropy balancing (Hainmueller, 2012).[38] Next, as a second robustness check, we introduce a running variable that measures the difference of interview date from peak date to our main specification. Given that subjects are interviewed at random times when the survey opened up, they also are subject to varying state level shocks, our data-set can be used to capture the propagation of the shock, rather than only the impact of the shock. Therefore, we interact this running variable with our main regressor to separate the immediate effect of exposure to the shock, versus whether that effect strengthens or weakens over time. We further supplement this analysis by looking at the effect of equation 1 at successive bandwidths around the moment of the shock, capturing the impact dissemination over time. Finally, we use equation 1 to provide some suggestive evidence about whether the exposure to crises also shifted individual's beliefs and preferences and attitudes.

[37]In Qualtrics, potential respondents can still decide to not take the survey after receiving the link. Therefore, we consider a number of data quality checks in pre and post period in order to ensure the quality of response remains consistent. These checks are in terms of response speed, level of comprehension, i.e., degree to which the individuals can understand the instructions of a test question, and their attentiveness, i.e. if they mindful enough to pass attention check questions. The response speed is measured as the average speed i.e. surveys completed per minute, at which the desired sample size was obtained. Failed attempts capture subjects' level of comprehension with respect to the instructions explaining their bonus earnings, in pre & post group. This was operationalized through a set of test questions where we measure their total number of attempts required to get the correct answer. Hence, number of failed attempt is measured by the total attempt minus 1. Figure A6 shows that these two measures are not statistically different in the pre and post group. Attentiveness or the extent to which subjects devote attention to answering questions is also maintained at a uniform level throughout different interview dates, by only including subjects who select the correct response to the attention check question. The precise screener question is given in Appendix B.

[38]Entropy balancing 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. An advantage of this method is that unlike the traditional coarsened exact matching, entropy balancing does not require enormous data sets or drop large portions of the sample. Column 4 of Table A3 confirms that after re-weighting, balance is achieved.

4 Results

We first report the results from equation 1 in Table 2. We begin with a basic specification with no controls in columns 1 and 4, and then successively introduce controls and fixed effects in columns 2 and 5 for each of our outcomes. In columns 3 and 6, we reproduce our main estimates by applying weights derived from entropy balancing (Hainmueller, 2012). We match the moments of the distribution of co-variates of treatment and control observations, with the advantage of not requiring large data-sets. Hence, this process reduces imbalance in co-variates between the pre and post group of subjects. We find that even after introducing controls and balancing, the magnitude and significance are very similar to our initial estimates.

The regression results show that the willingness to take action against corruption increases by 10.7 percentage points (pp) after the peak exposure to COVID in the state, as shown in column 1. This translates into 29% increase over the pre-peak mean. Adding a set of controls and state fixed effects slightly raises the coefficient to 0.116 from 0.107. Finally in column 3, we introduce the weights generated from entropy balancing; the point estimate shows an increase in willingness to act by 11.2 pp. From column 4 and 5, The willingness to protest increases by 7.5 pp, which implies a 9% increase in willing to protest over the pre-peak mean.[39] In the balanced sample, the coefficient is 0.094. These increases are all significant at 1 percent level.[40]

These results are also supported by time paths plotted in Figure 3. To graphically illustrate our results, we dis-aggregate the pre and post time periods as distance (in months)

[39]This indicates the high baseline level of the hypothetical measure vis-a-vis the real-effort measure. While incentives reveal the true preferences of respondents, it is also likely that general willingness to protest at the time of the survey was quite high due to the salience of the second wave and the subsequent breakdown of the health system.

[40]The standard deviation (SD) of the real-effort willingness to act for the pre group is 0.484. The effect size from column 3 of Table 2 is 0.112 translates to an increase of 0.231 SD. Figure A7a shows that in order to detect this effect size, we need a minimum of about $\pm$ 50 days bandwidth to ensure sufficient observations. Similarly, for willingness to protest variable, the minimum bandwidth requirement is about $\pm$ 35 days to detect an effect size of 0.25 SD (Figure A7b). This indicates that our study is adequately powered and the estimated effects are meaningful.

from the month containing the state peak. Figure 2a reveals that the real-effort measure of willingness to act indeed shows an increase on the subsequent three months after the peak. Similarly, Figure 2b shows that the hypothetical measure of willingness to protest also increases steadily in those months.

4.1 Robustness

We begin by estimating if the increase in citizens' anti-corruption activism happened immediately after the peak.[41] For this reason, we define a model with a running variable 'Days', ranging from -112 to 93, with 1 corresponding to the first day after the peak, and 0 for the day of the peak.[42] Simply put, this variable measures the difference between the interview days before and after the peak for each subject. In other words, we estimate

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

where D_{ist} (i.e., the 'Days' variable) denotes the difference in days, between interview date t and peak date for subject i belonging to state s. In this model, the interaction term $D_{ist} \times Post_{ist}$ indicates if the impact of the peak weakened or strengthened over time, whereas the term $Post_{ist}$ indicates the immediate impact of exposure to the peak.

Columns 1 and 2 of Table 3 captures the estimates of equation 2 for the entire sample. From the full sample, we find that the immediate impact of exposure to peak on the real-effort willingness to act was substantial; In column 1 (without co-variate balancing), the estimate shows a 24.8 pp increase, whereas in column 2 (with co-variate balancing), the increase is 22.7 pp.[43] The interactive term 'Days x Post' indicates that in the full sample,

[41] Throughout the paper, 'peak' refers to the peak in daily new confirmed cases of COVID. Our main results go through if we use the peak in daily deceased instead.

[42] 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 will take the value 1.

[43] Additionally, one can argue that the timing of the pandemic peak varied at the state level, and hence treatment occurred by state of residence. Therefore, as another robustness check, we rerun equation 1 by changing the level of clustering from state-month to state level. Since there are only 35 states in our sample, we have a small number of clusters, hence making it necessary to use the wild cluster-bootstrap

this coefficient is statistically significant, but the magnitude of the coefficient is small (0.8 and 0.7 pp respectively in columns 1 and 2), indicating that the effect of the exposure did not meaningfully change thereafter. For the hypothetical measure of willingness to protest, however, neither the estimate of immediate effect nor exposure over time, is statistically significant (columns 3 and 4), even though the average impact of exposure (column 4-6 of Table 2) is. While we can't pinpoint the exact reason, one possibility behind this result is that decisions to act or protest are costly, hence the presence of incentives may be important to disentangle dynamics of immediate and over-time effects.

Next, we summarize the results of the exposure by increasing the bandwidth around the peak day by ±1 day(s) till the last interview dates are covered. By limiting the time window around the peak at successively decreasing intervals, we aim to limit the effect of any time-varying changes other than the event of interest. Recall that our initial time window was March 24 to July 26, 2021, i.e., 125 days. We begin with ± 18 days around peak in order to ensure there are sufficient observations for ensuring a balance of co-variates between pre and post groups for every bandwidth, while recognizing that the bandwidth could not be lowered than ± 18 days with the current data at hand.[44] The results are presented in Figure 4 shows that the estimated impact of exposure to peak is consistently positive and stable over time, for both willingness to act (Figure 4a) and willingness to protest (Figure 4b). The observed stability also indicates that time trends or other events are not likely driving the estimated effects.[45]

method (Roodman et al., 2019). This translates into a 61% increase over the control mean immediately after exposure. Table A4 shows that our main results are robust to clustering by state.

[44] As the number of observations is very small for narrow bandwidths, we calculate standard errors without any adjustment for clustering at state-month level. In other words, we are estimating equation 1 for each of the bandwidths.

[45] The Table A5 tests for a linear and quadratic relationship between the timing of the interview and the outcomes in the pre-peak period. The result shows a statistically significant but practically trivial decline over the pre-peak period. Additionally, we graphically illustrate the same relationship and corresponding confidence intervals using a kernel-weighted local polynomial regression in Figure A8 (Figure A8a for willingness to act and for Figure A8b for willingness to protest), which lends support to our claim.

4.2 Heterogeneity

To complement our main findings, we turn to a number of heterogeneity analysis by comparing various sub-samples. In the first heterogeneity exercise, we split the sample into two groups of states for early and late peak sub-samples and consider the baseline specification (equation 1) for each group. Early peak sub-sample indicates the states where the peak in daily confirmed cases occurred earlier than the median peak date of all states.[46] The late peak sub-sample corresponds to the opposite. To graphically illustrate our findings, we plot the month-by-month time paths of our outcomes for the early and late peak sub-samples in Figure 3.

In Figure 3a, we find that real-effort willingness to act increases in the months after being exposed to the peak. Similarly, Figure 3b shows the same result for the hypothetical measure of willingness to protest, but the magnitude is somewhat smaller than Figure 3a. In contrast, the time paths for late-peak sub-sample show a less obvious pattern; Figure 3d shows some increase in hypothetical willingness to protest in the third month after peak, whereas the values of the real-effort willingness to act (Figure 3c) is not statistically significant for the same sub-sample. Overall, it seems that the willingness to act (both real-effort and hypothetical) increases earlier in the early-peak states than in the late peak states. We do not claim any causality for these results, but we undertake this exercise to see if any suggestive evidence can be presented regarding the timing of state level case-peak and willingness to act.[47]

Finally, by interacting the Post_{ist} variable with certain state level characteristics, we check if pre-existing level of corruption in Indian states or quality of health services had any differential impact on willingness to protest or act as a result of being exposed to the peak of second wave of COVID. To capture the pre-existing level of corruption, we refer to the Transparency International India (2019) report, that covers 20 Indian states. Based

[46] Table A1 provides a list of state level peaks of confirmed cases.

[47] It is also possible that with prolonged personal exposure to the pandemic, subjects were better able to anticipate or adjust to the crisis.

on this information, we created a dummy ('*high corruption states*') indicating the states with high corruption level as 1; 0 otherwise.[48] By interacting this dummy with 'Post' in Table A6, we find that the coefficient is positive and significant at 5 percent level for the real-effort measure of willingness to act, indicating that in states with relatively high level of baseline corruption, the exposure to second wave peak significantly increased the willingness to act.[49] We further conduct a check of whether the impact of exposure varies by the quality of health services, in particular, availability of hospital facilities at the state level. Data on the number of hospitals, including public establishments and estimates for private establishments at the state level are taken from Kapoor et al. (2020), whereas estimated measures of state level population for 2020 is obtained from Government of India (2019). Using these two measures, we compute the variable 'hospital density', which captures the density of total (public *and* private) hospitals per 100,000 population at the state level. We interact this variable with 'Post' and present the regression results in Table A7, which shows that an increase in hospital density is positively correlated with the real-effort measure of willingness to take action against corruption.

5 Discussion

To recap our main findings so far, the analysis shows consistent increase in willingness to take actions against corruption in health after being exposed to the second wave of COVID in India. This increase is reflected both in a hypothetical measure as well as a real-effort measure, but more consistently in the latter (more reliable) measure. What explains the observed increased willingness of citizens to act against corruption? In Table 4, we explore

[48]The high corruption states, as indicated in the report, are Punjab, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Karnataka, Telangana and Tamil Nadu. For more details, visit the website of Transparency International India `https://transparencyindia.org`. In this report, the above eight Indian states were classified as 'high' corruption, based on the state-wise percentage of citizens who resorted to paying bribes in order to have access to various government services. Since this report covers only 20 Indian states from our sample, the rest of the states were excluded from analysis for the purposes of this analysis, bringing down the sample size from 898 to 848.

[49]From column 2 of the same table, we find that the differential impact on the hypothetical measure is not statistically significant.

if the exposure had any influence on measures that are arguably tied to individuals' willingness to act, such as their perception of corruption, initial information about rights and entitlements, willingness to take risk and beliefs about other's willingness to act.

From column 1 of Table 4, we find that subjects' bias or mis-perception about others' willingness to take action decreases by 9.1 pp, i.e., the proportion of subjects strictly underestimating others' willingness to protest has seen a fall of 13% over control mean. From columns 2 and 3, initial information and perception of corruption, respectively, show an increase of 0.287 standard deviation (SD) and 0.238 SD, which are significant at 5 and 1 percent levels. Similarly from column 4, the willingness to take risk goes up by 0.223 SD.[50] [51]

The second wave of COVID in India was a highly salient event. A significant impact on these outcomes underscores the overall stress brought about by the COVID peak. While we are able to detect a significant increase in public's perception of others' behavior, corruption and information about rights and entitlements in the health sector, we do not find a significant change in their corruption tolerance or their innate pro-sociality (Table A8). One possibility is that corruption perceptions are more malleable than people's attitude and tolerance towards corruption. Finally, the result for risk preference is significant; note that risk was measured through a survey question via self-assessment. Dohmen et al. (2011) find that such generalized self-assessed survey measure of risk is the most stable and are more correlated with real world outcomes. Our result confirms that in a developing country context, the generalized measure of risk is indeed affected through salient events. In Bangladesh, Islam et al. (2020) have shown that exposure to natural disaster lead individuals from disaster-affected villages chose riskier bets. Further, Tsutsui and Tsutsui-Kimura (2022) have recently shown that in Japan, people became more tolerant of risk after being

[50] These effect sizes are similar to that of our main outcomes.

[51] Since we are estimating equation 1 for a total of 8 outcomes, we control for the family wise error rate (FWER), i.e., the probability of rejecting at least one true null hypothesis in the family of hypotheses under test (Romano and Wolf, 2016) in Table A9. The significance of all our main outcomes are preserved after the correction.

exposed to COVID-19.[52]

6 Conclusion

This study examines the impact of the devastating second wave of pandemic in India through the lens of survey conducted in real-time - between March-July 2021 - during the rapid spread of COVID-19 infections. Through public reports, we gather evidence that this unprecedented rise was characterized by a lack of medical resources, general unpreparedness and institutional capacity constraints, all of which severely handicapped India's pandemic response. From our survey data, we show that as a result of being exposed to this shock, the survey participants' willingness to act against corruption went up. Further, we validate this by plotting time paths meant to capture temporal movements in the outcomes, which also show a similar rise. We use several robustness checks in order to gain confidence in our results. Through heterogeneity analysis, we find that the increase is higher in certain sub-samples, such as the states with a case-peak earlier than average.They became better informed about their rights and entitlements, and the willingness to voice their protest and take meaningful action also increased substantially. We also find that the increased willingness to take action was accompanied with a corresponding rise in subjects' perception of corruption and their level of information about their rights and entitlements. This might indicate a correlation between personal experience of a crisis and subsequent increased willingness to take action.

In the context of citizen anti-corruption activism, these observed differences are indeed meaningful and significant. Further research is required to understand whether these changes sustain over time and have longer-term effects.

[52]For a review on occurrence of natural disasters and risk preference, see Chuang and Schechter (2015).

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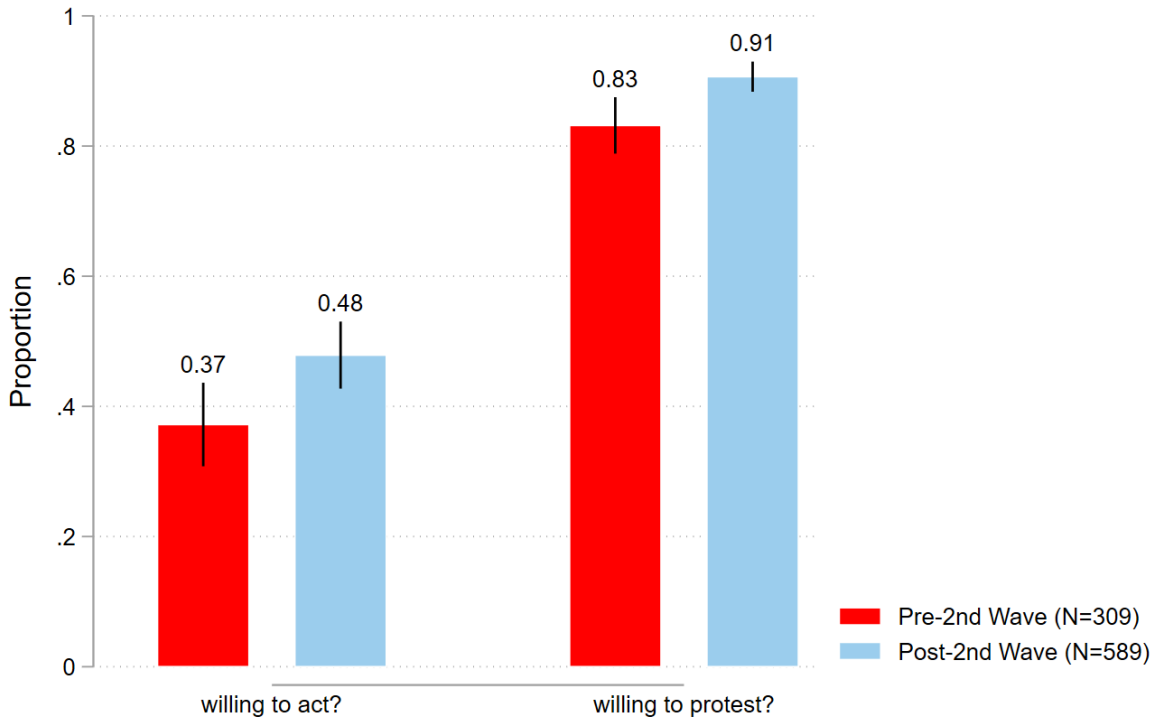
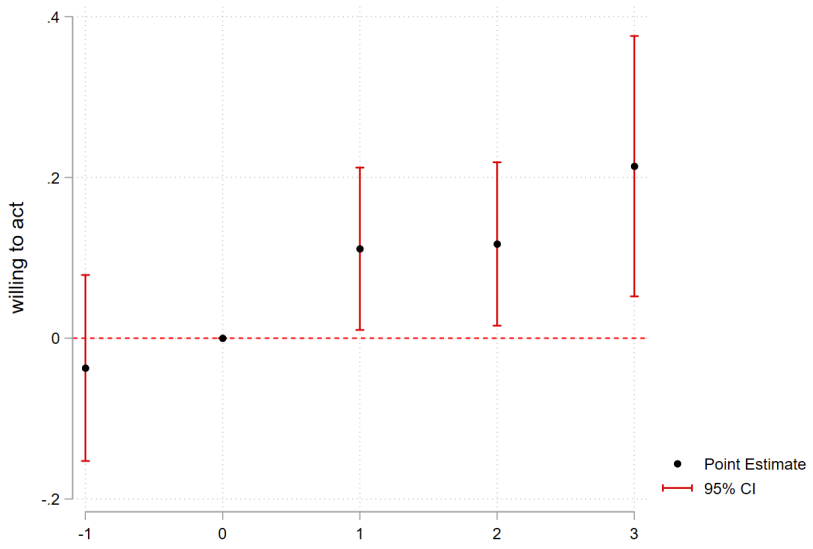
7 Tables and Figures

Figure 1: COVID-19 and Willingness to Act, Protest, Corruption Perception and Information

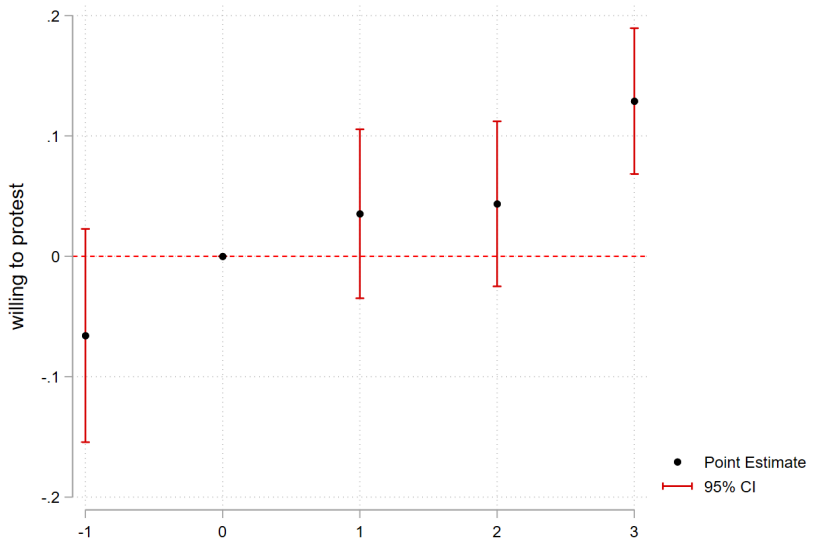


Notes: Figure shows, respectively, the percentages of subjects willing to take anti-corruption action ('willing to act?') and willing to participate in protest ('willing to protest?'), pre and post 2nd wave peak. Total count of subjects=898. The figure displays percentages and 95% confidence intervals. Standard errors are clustered at state-month level.

Figure 2: Willingness to Act and Protest, by Month of Survey



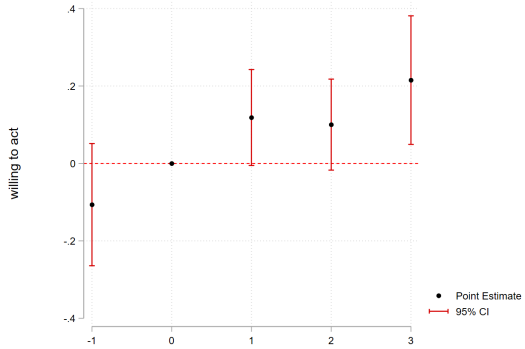
(a) Willingness to Act



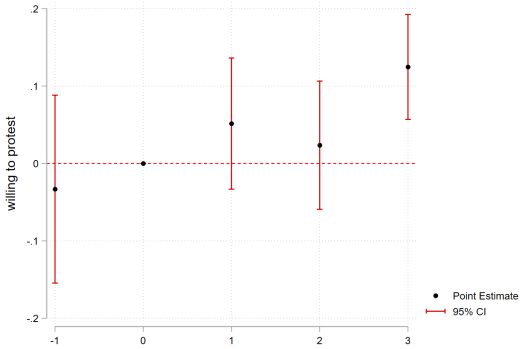
(b) Willingness to Protest

Notes: Figure a, b show, respectively, time paths for subjects' willingness to take anti-corruption action and their willingness to protest for the full sample over months. The horizontal axis measures the distance from the case-peak, in months. The point estimates are denoted by black dots and 95% confidence interval in red. Standard errors are robust. Total count of subjects=898. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence.

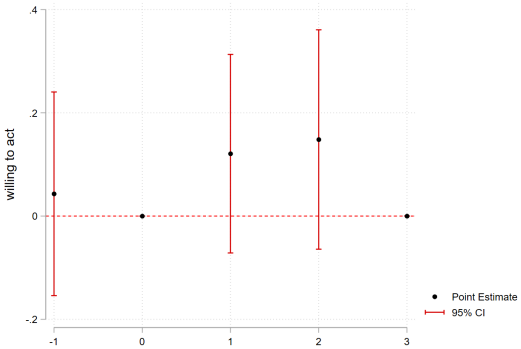
Figure 3: Willingness to Act and Protest, by Month of Survey



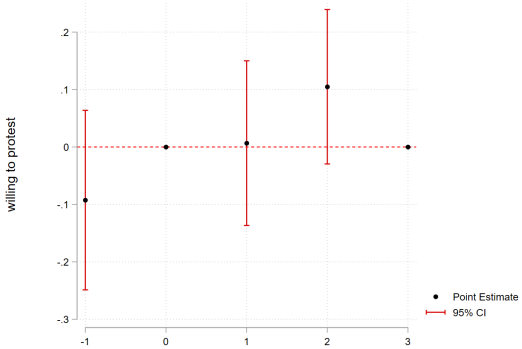
(a) Willingness to Act (Early Peak)



(b) Willingness to Protest (Early Peak)



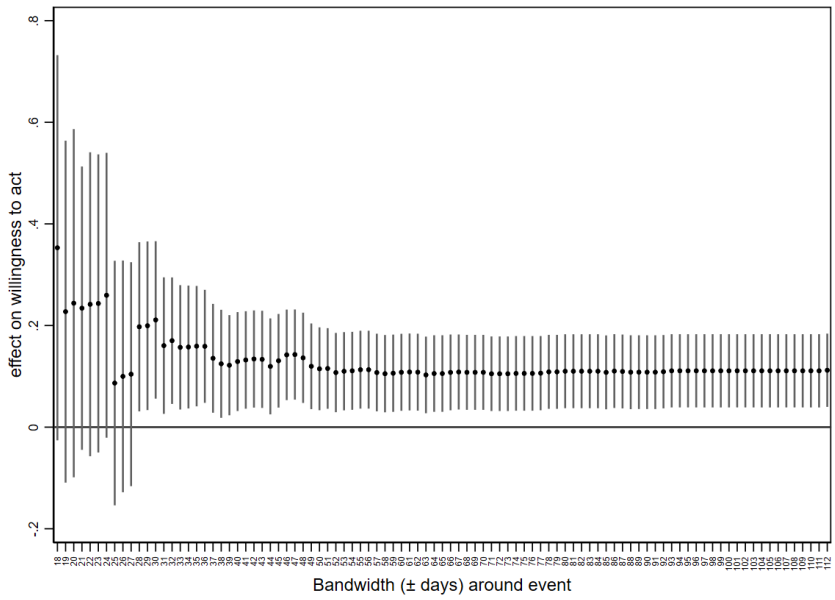
(c) Willingness to Act (Late Peak)



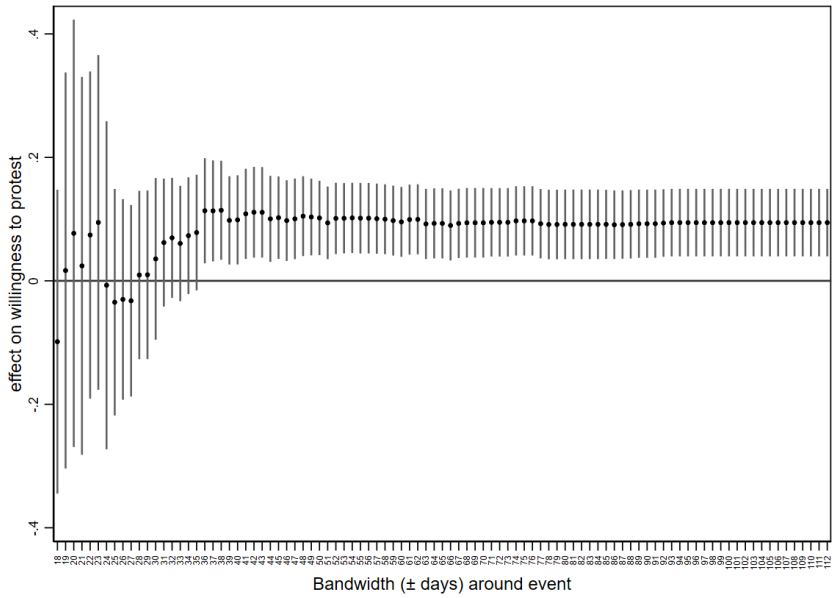
(d) Willingness to Protest (Late Peak)

Notes: Figure a, b show, respectively, time paths for subjects' willingness to take anti-corruption action and their willingness to protest for the early-peak sample over months. Figure c, d show, respectively, time paths for subjects' willingness to take anti-corruption action and their willingness to protest for the late-peak sample over months. The horizontal axis measures the distance from the case-peak, in months. The point estimates are denoted by black dots and 95% confidence interval in red. Standard errors are robust. Total count of subjects=898. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence.

Figure 4: Effect of Exposure Over Multiple Bandwidths



(a) On Willingness to Act



(b) On Willingness to Protest

Notes: Figure plots the coefficient of 'Post' from equation 1 with controls, fixed effects and entropy balancing for different bandwidth. 'Post' is a dummy to indicate if the subject was interviewed after the peak in daily COVID cases for his state s of residence, 0 otherwise. Initial bandwidth is ± 18 to ensure co-variate balancing. The point estimates are denoted by black dots and 95% confidence interval. Standard errors are robust. Total count of subjects=898. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence.

Table 1: Summary Statistics

	Mean	Std. Dev	N
Age 45+	0.15	0.35	898
Married	0.48	0.50	898
Has Children	0.37	0.48	898
Living with Parents	0.27	0.45	898
SC/ST	0.57	0.50	898
Hindu	0.75	0.43	898
College Education	0.79	0.41	898
Household Income	0.46	0.50	898
Asset Ownership	6.07	2.30	898
Co-residing Elderly	0.58	0.49	898
Survey Participation Frequency	0.77	0.42	898
Survey on Mobile	0.65	0.48	898

Notes: 'Age 45+' is a dummy equal to 1 for subjects aged 45 and above, 0 otherwise; 'Reserved' is a dummy indicating SC (Schedule Caste), ST (Scheduled Tribe) and other back classes (OBC) subjects, who are socio-economically deprived individuals in India; 'income' indicates subjects with monthly household income below INR 30 thousand in the previous month; 'asset' indicates a count of assets owned by a subject from a list of common household assets; 'Co-residing Elderly' indicates subjects who say 'yes' to the question "In your household, do you have elderly (above 60) living with you?"; 'Participation Frequency' is a dummy indicating subjects who usually participate in Qualtrics surveys one or more times a day or week; 'Mobile' indicates subjects participating using a mobile phone.

Table 2: Impact of Second-wave of COVID Cases on Willingness to Act and Willingness to Protest

	Willing to act			Willing to protest		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.107**	0.116***	0.112***	0.075***	0.075***	0.094***
	(0.042)	(0.032)	(0.030)	(0.025)	(0.021)	(0.021)
Observations	898	898	898	898	898	898
Control Mean		0.372			0.832	
Controls?	no	yes	yes	no	yes	yes
Balanced?	no	no	yes	no	no	yes
R^2	0.010	0.097	0.110	0.012	0.062	0.091

Notes: 'Post' is a dummy to indicate if the subject was interviewed after the peak in daily COVID cases for his state s of residence, 0 otherwise. The dependent variable in column 1-3 is a dummy that equals 1 if the respondent is willing to either sign a petition, or donate, or gather information online for fighting corruption in health. The dependent variable in column 4-6 is another dummy equal to 1 if the respondent is willing to participate in a protest against corruption in health. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted by using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of co-variates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. Standard errors clustered at the state-month level and given in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: Impact of Second-wave of COVID Cases on Willingness to Act and Willingness to Protest over Days

	Willing to act		Willing to protest	
	(1)	(2)	(3)	(4)
Post	0.248**	0.227**	0.040	0.008
	(0.107)	(0.091)	(0.056)	(0.058)
Days x Post	0.008***	0.007***	0.000	-0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Observations	898	898	898	898
Control Mean	0.372	0.372	0.832	0.832
Balanced?	no	yes	no	yes
Controls?	yes	yes	yes	yes
R^2	0.108	0.118	0.063	0.092

Notes: 'Post' is a dummy to indicate if the subject was interviewed after the peak in daily COVID cases for his state s of residence, 0 otherwise. 'Days' measures the difference between the subjects' interview date and the date of COVID peak in his state of residence. The dependent variable in column 1-2 is a dummy that equals 1 if the respondent is willing to either sign a petition, or donate, or gather information online for fighting corruption in health. The dependent variable in column 3-4 is another dummy equal to 1 if the respondent is willing to participate in a protest against corruption in health. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted by using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of co-variates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. Standard errors clustered at the state-month level and given in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Impact of Second-wave of COVID Cases on Beliefs, Information about Rights and Entitlements, Corruption Perception and Risk

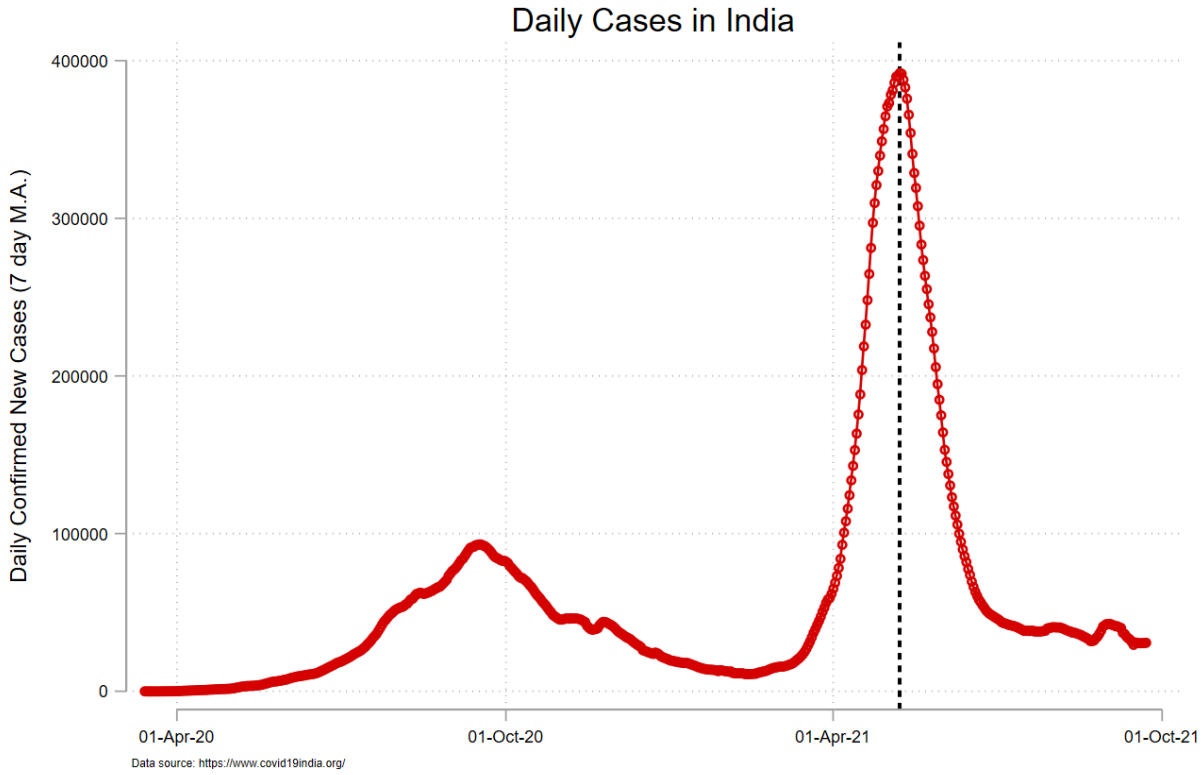
	Bias in Belief	Information (Rights)	Corruption Perception	Risk
	(1)	(2)	(3)	(4)
Post	-0.091***	0.287***	0.238***	0.223***
	(0.028)	(0.070)	(0.086)	(0.065)
Observations	898	898	898	898
Control Mean	0.702	0.000	-0.000	-0.000
Controls?	yes	yes	yes	yes
Balanced?	yes	yes	yes	yes
R^2	0.092	0.172	0.122	0.103

Notes: 'Post' is a dummy to indicate if the subject was interviewed after the peak in daily COVID cases for his state s of residence, 0 otherwise. Corruption perception, information (rights) and risk are standardized measures computed from relevant questions, as described in subsection B.1. 'Bias' is a dummy to indicate subjects who underestimated the true willingness of protest of other subjects. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted by using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of co-variates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. Standard errors clustered at the state-month level and given in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendices

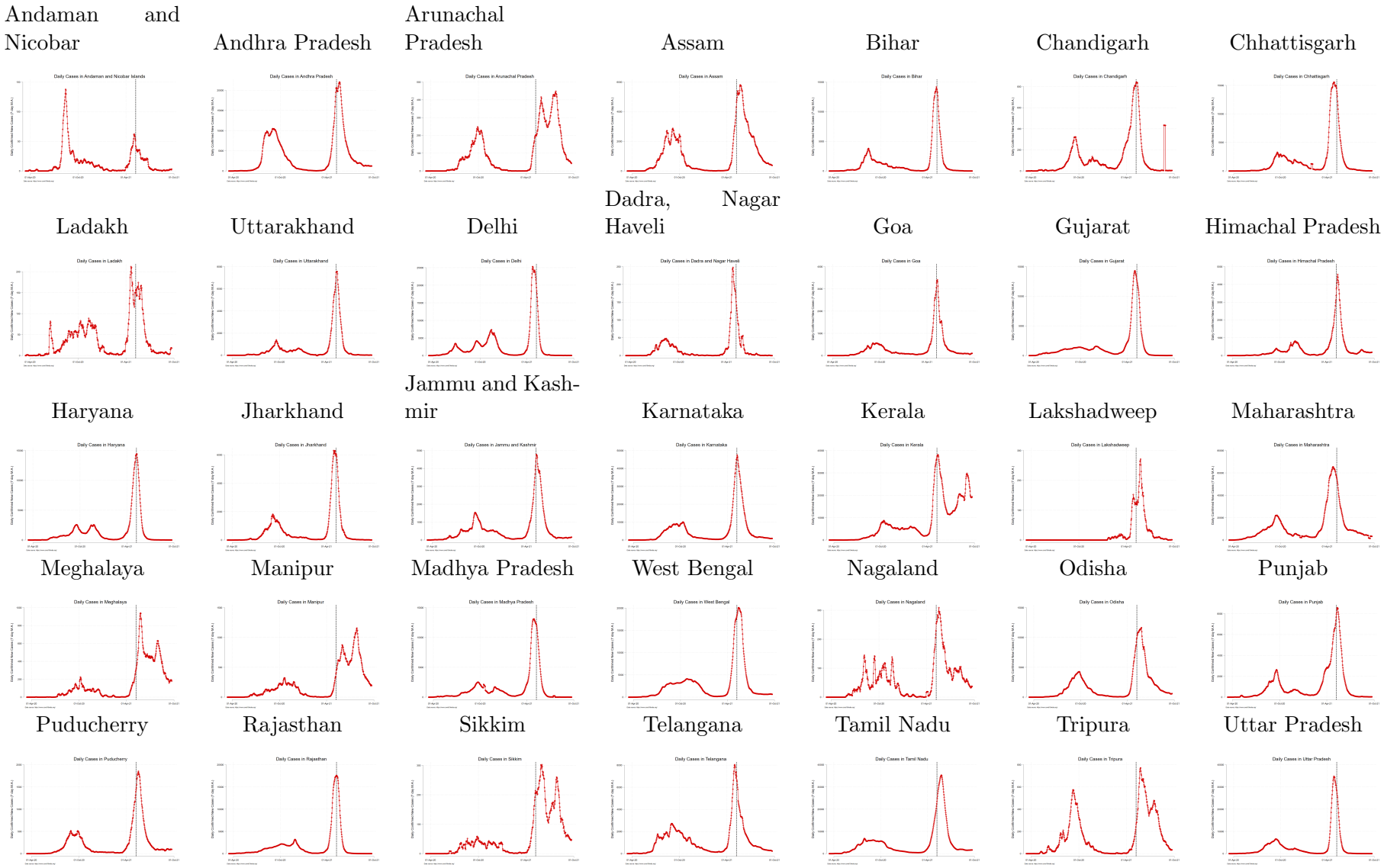
A Additional Analysis

Figure A1: Daily COVID Cases



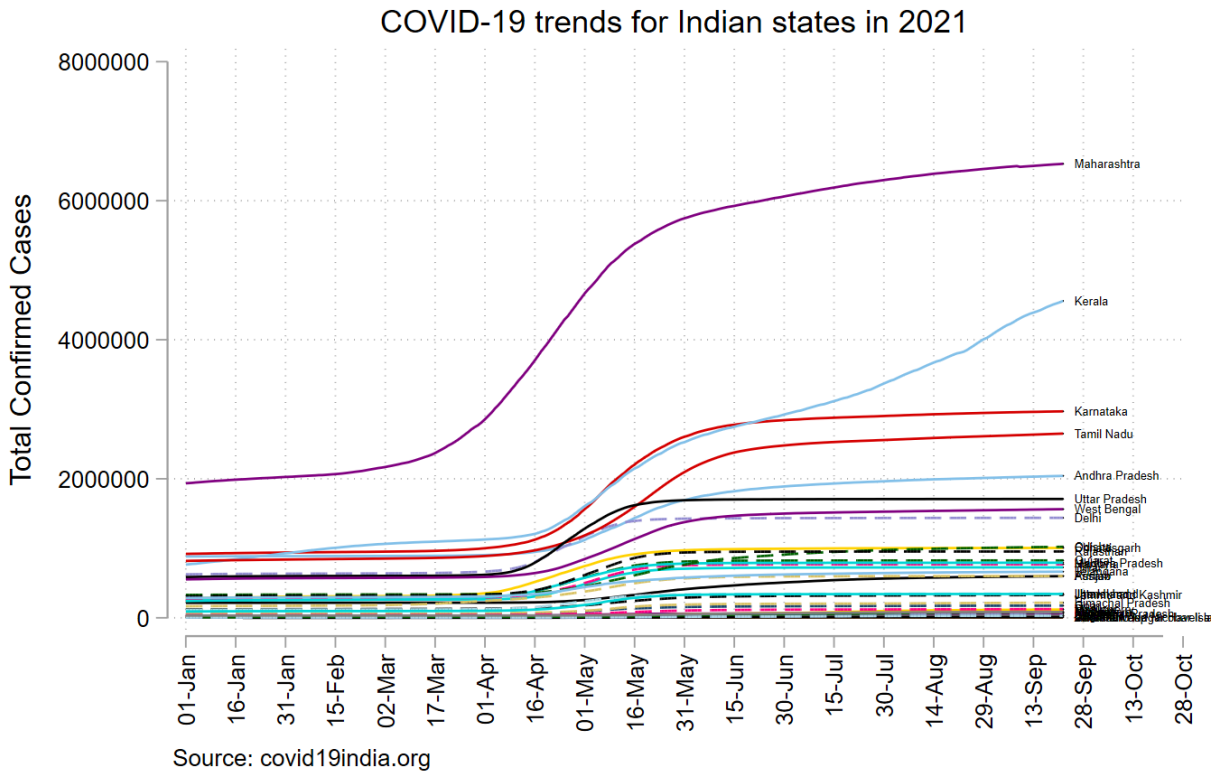
Notes: Figure shows the peak in daily confirmed cases (7 day moving average) for April 2020 to October 2021. The black line corresponds to the national peak. Data taken from covid19india.org.

Figure A2: Daily COVID Cases - Indian States



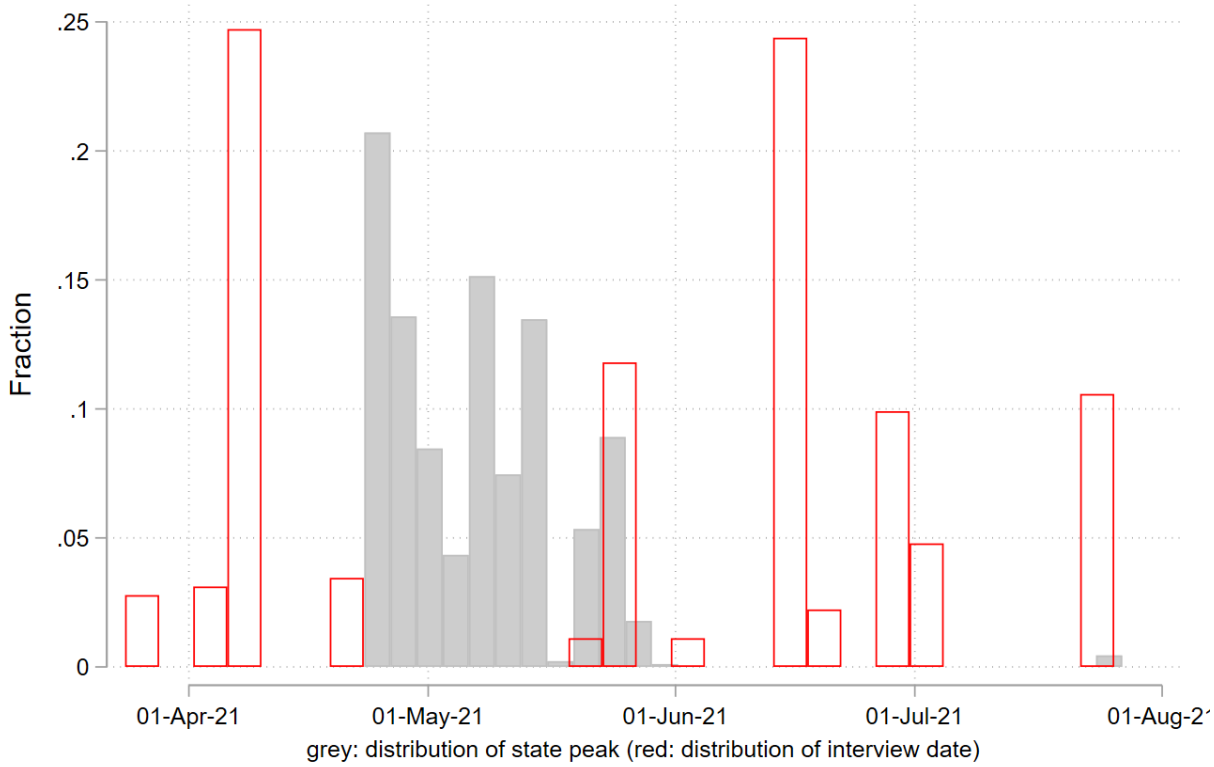
Notes: Figure shows the state-wise trend in daily confirmed cases (7 day moving average) for April 2020 to October 2021. The black line corresponds to the national peak. Data taken from covid19india.org.

Figure A3: Total COVID Cases - Indian States



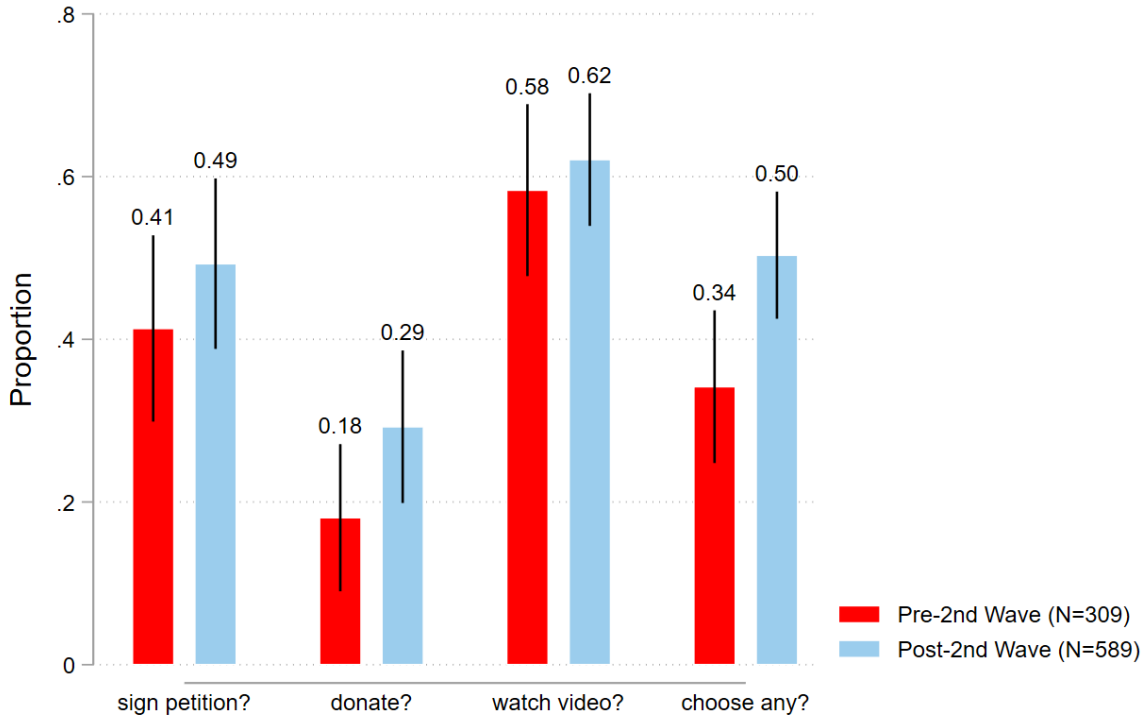
Notes: Figure shows the total confirmed cases for Indian states, from January to October 2021. Data taken from covid19india.org.

Figure A4: Distribution of Subjects According to Interview Dates and Case-peak in State of Residence



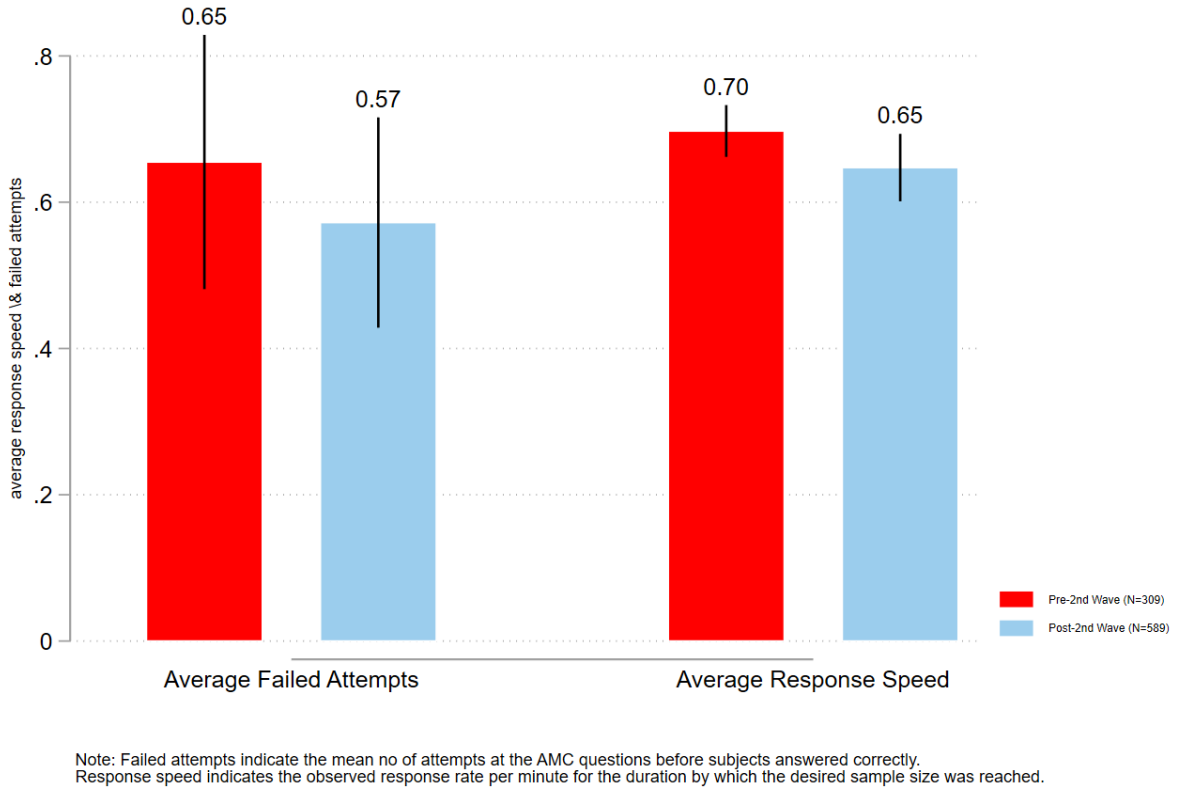
Notes: The distribution of subjects according to date of case peak is captured in grey, while the distribution of interview dates of subjects is in red. N=898.

Figure A5: Impact of Second-wave on Willingness to Sign Petition, Donate, Watch Video or Choose Any Action When Offered All Three



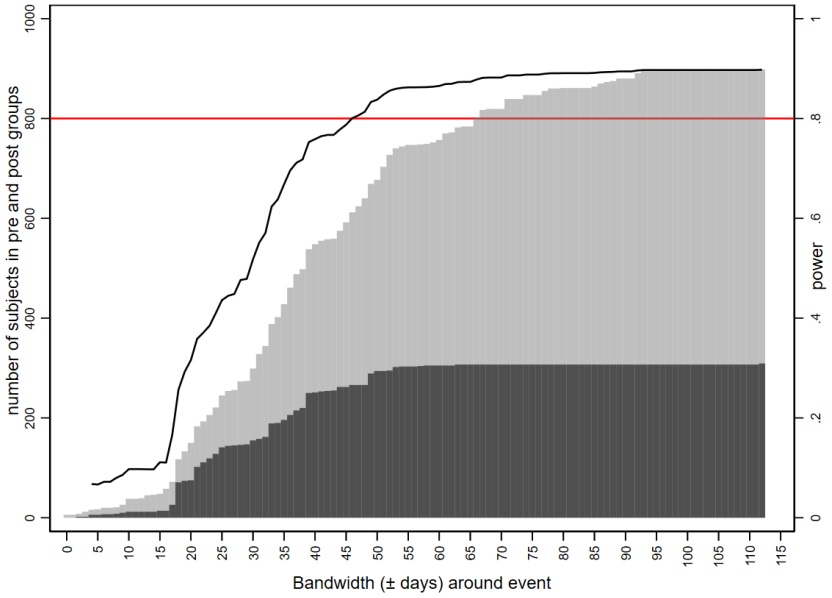
Notes: Figure shows, respectively, the percentages of subjects willing to sign a petition to the Ministry of Health, donate a portion of their earnings to the non-profit organization, gather information online by watching a 5-minute video on how to fight corruption in health or choose any when offered all three, pre and post 2nd wave peak. Total count of subjects=898. The figure displays percentages and 95% confidence intervals. Standard errors are clustered at state-month level.

Figure A6: Data Quality Checks Before & After COVID Case-peak

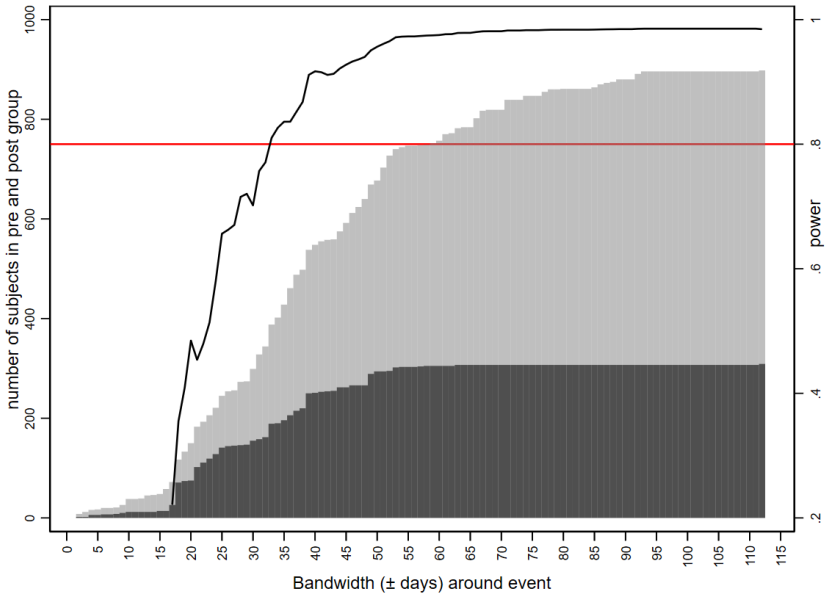


Notes: Failed attempts capture the comprehension level of subjects, in pre & post group. The response speed captures the average speed (surveys completed per minute) at which the desired sample size was obtained, in pre & post group. N=898.

Figure A7: Statistical Power



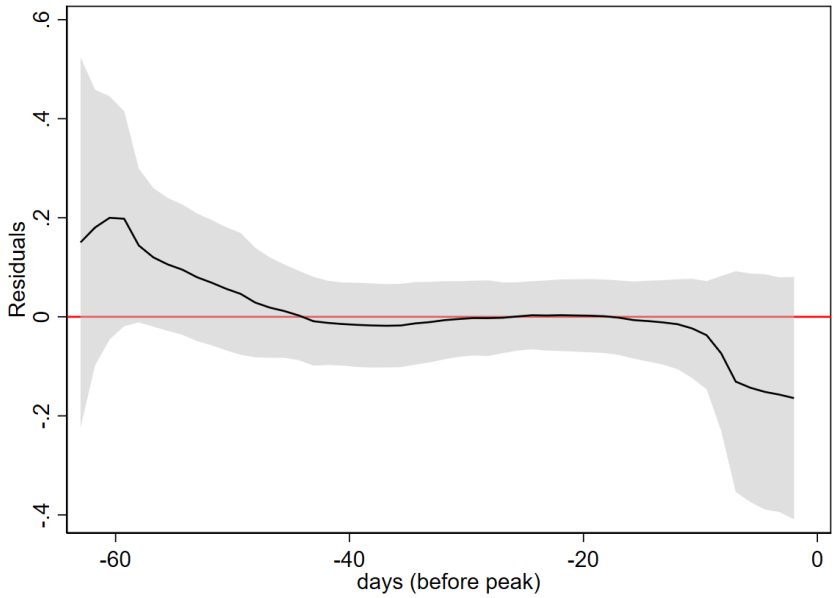
(a) On Willingness to Act



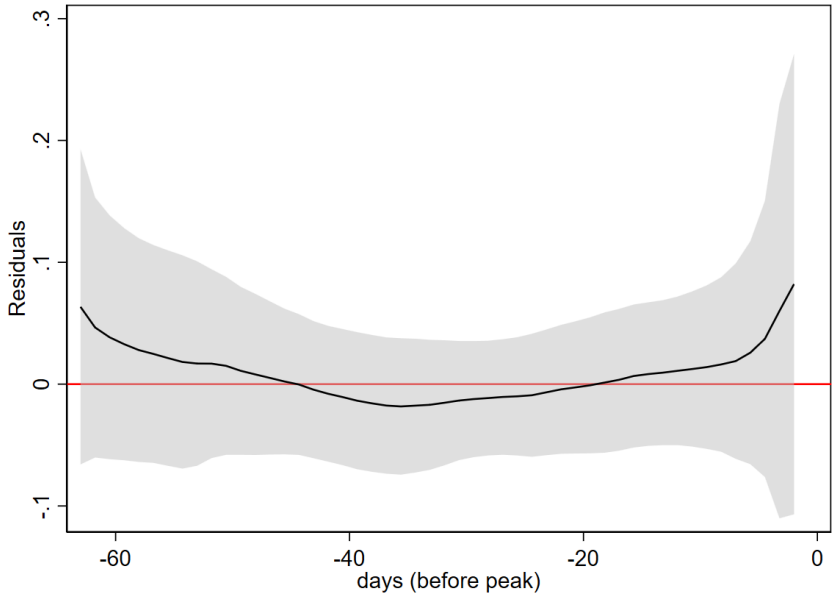
(b) On Willingness to Protest

Notes: Figure shows the power calculations for a 0.05 significance level, based on the SD of the pre group. Relevant effect sizes for panel a (b) is 0.23 (0.25) SD. The histogram shows the the total number of subjects in each bandwidth (indicated by the total height of the stacked bars). The black and grey bars refer to the number of subjects in the pre and post groups, respectively. The red line indicates power = 0.8.

Figure A8: Average Willingness to Act and Protest by Day in Pre-event period (0 = Day of Peak Infections)



(a) On Willingness to Act



(b) On Willingness to Protest

Notes: Figure a(b) displays smoothed values and 95% confidence band showing the relationship between residual variances of willingness to act (protest) and the timing of interviews in the pre-event period. Residuals are obtained from a regression of outcome on full set of controls. Total count of subjects=309. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence.

Table A1: State-wise Peaks in Daily COVID Cases (7 day Moving Average)

State	state-peak
NCT Of Delhi	23-Apr-21
Maharashtra	24-Apr-21
Dadra Nagar Haveli Daman & Diu	26-Apr-21
Uttar Pradesh	27-Apr-21
Chhattisgarh	28-Apr-21
Jharkhand	28-Apr-21
Madhya Pradesh	29-Apr-21
Gujarat	30-Apr-21
Telangana	1-May-21
Bihar	6-May-21
Rajasthan	8-May-21
Chandigarh	9-May-21
Haryana	9-May-21
Jammu And Kashmir	9-May-21
Karnataka	9-May-21
Goa	11-May-21
Uttarakhand	11-May-21
Kerala	12-May-21
Punjab	12-May-21
Himachal Pradesh	13-May-21
West Bengal	15-May-21
Nagaland	18-May-21
Andhra Pradesh	20-May-21
Assam	22-May-21
Lakshadweep	25-May-21
Meghalaya	25-May-21
Tamil Nadu	25-May-21
Tripura	25-May-21
Orissa	26-May-21
Sikkim	1-Jun-21
Manipur	27-Jul-21
Total Obs In Survey Sample	898

Notes: Table shows the peak in confirmed cases for Indian states, from April 2020 to October 2021. Data taken from covid19india.org.

Table A2: Count of Subjects at Different Interview Dates with Respect to National Case-peak

interview dates	count of subjects	cumulative count
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: Table shows the count and cumulative count of subjects interviewed at successive dates when the survey was opened, with respect to the national level peak in COVID cases.

Table A3: Comparison of Observable Characteristics

Variable	Pre-2nd Wave (1)	Post-2nd Wave (2)	before balancing Difference (3)=(1)-(2)	after balancing Difference (4)
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]
Living with Parents	0.272	0.275	-0.003	0.000
			[0.934]	[1.000]
Reserved	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	0.819	0.779	0.039	0.000
			[0.200]	[0.992]
Income	0.434	0.469	-0.035	0.000
			[0.421]	[0.997]
Asset	6.197	5.997	0.201	0.003
			[0.305]	[0.990]
Participation Frequency	0.738	0.781	-0.043	0.000
			[0.120]	[0.991]
Mobile	0.680	0.642	0.038	0.000
			[0.359]	[0.994]
Co-residing Elderly	0.592	0.576	0.017	0.000
			[0.712]	[0.996]
N	309	589		

Notes: 'Post-2nd wave' indicates that the subject was interviewed after the peak in daily COVID cases for his state s of residence, 'Pre-2nd wave' indicates the opposite. 'Age 45+' is a dummy equal to 1 for subjects aged 45 and above, 0 otherwise; 'Reserved' is a dummy indicating SC (Schedule Caste), ST (Scheduled Tribe) and other back classes (OBC) subjects, who are socio-economically deprived individuals in India; 'income' indicates subjects with monthly household income below INR 30 thousand in the previous month; 'asset' indicates a count of assets owned by a subject from a list of common household assets; 'elderly' indicates subjects who say 'yes' to the question "In your household, do you have elderly (above 60) living with you?"; 'Participation Frequency' is a dummy indicating subjects who usually participate in Qualtrics surveys one or more times a day or week; 'Mobile' indicates subjects participating using a mobile phone. Column 4 summarizes potential difference after adjusting for re-weighting (Hainmueller, 2012). Standard errors are clustered at state-month level. The values displayed for t-tests in square brackets are p-values. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A4: Clustering at State Level

	Willing to act			Willing to protest		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.107***	0.116***	0.112***	0.075***	0.075***	0.094***
	[0.009]	[0.003]	[0.004]	[0.002]	[0.003]	[0.002]
Observations	898	898	898	898	898	898
Controls?	no	yes	yes	no	yes	yes
Balanced?	no	no	yes	no	no	yes
R^2	0.010	0.097	0.110	0.012	0.062	0.091

Notes: 'Post' is a dummy to indicate if the subject was interviewed after the peak in daily COVID cases for his state s of residence, 0 otherwise. The dependent variable in column 1-3 is a dummy that equals 1 if the respondent is willing to either sign a petition, or donate, or gather information online for fighting corruption in health. The dependent variable in column 4-6 is another dummy equal to 1 if the respondent is willing to participate in a protest against corruption in health. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted for using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of co-variates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. Standard errors clustered at the state level, using wild-cluster bootstrapping. p values are reported below coefficients in square brackets: * $p < .10$, ** $p < .05$, *** $p < .01$

Table A5: Pre-existing Time Trend in Pre-peak Period

	Willing to act		Willing to protest	
	(1)	(2)	(3)	(4)
Days	-0.009**	-0.010	0.001	0.004
	[0.025]	[0.106]	[0.783]	[0.237]
Days x Days		-0.000		0.000
		[0.723]		[0.125]
Observations	309	309	309	309
Controls?	yes	yes	yes	yes
R^2	0.187	0.187	0.153	0.154

Notes: Sample consists of subjects interviewed before the COVID case-peak of their respective states. 'Days' measures the difference between the subjects' interview date and the date of COVID peak in his state of residence. The dependent variable in column 1-2 is a dummy that equals 1 if the respondent is willing to either sign a petition, or donate, or gather information online for fighting corruption in health. The dependent variable in column 3-4 is another dummy equal to 1 if the respondent is willing to participate in a protest against corruption in health. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted for using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of co-variates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. Standard errors clustered at the state level, using wild-cluster bootstrapping because of small number of state-month clusters in the pre-peak period. p values are reported below coefficients in square brackets: * $p < .10$, ** $p < .05$, *** $p < .01$

Table A6: Heterogeneity by High Corruption Level in Indian States

	Willing to act (1)	Willing to protest (2)
Post x *high corruption states*	0.137**	0.039
	(0.066)	(0.044)
Post	0.058	0.074**
	(0.037)	(0.028)
Observations	848	848
Balanced?	yes	yes
Controls?	yes	yes
R^2	0.099	0.074

Notes: 'Post' is a dummy to indicate if the subject was interviewed after the peak in daily COVID cases for his state s of residence, 0 otherwise. *high corruption states* is a dummy indicating states with high corruption level, as specified in the India Corruption Survey Report by Transparency International India (2019). Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted by using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of co-variates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. Standard errors clustered at the state-month level and given in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A7: Heterogeneity by Hospital Density in Indian States

	Willing to act (1)	Willing to protest (2)
Post x *hospital density*	0.012**	0.003
	(0.006)	(0.005)
Post	0.039	0.079**
	(0.059)	(0.033)
Observations	898	898
Balanced?	yes	yes
Controls?	yes	yes
R^2	0.112	0.091

Notes: 'Post' is a dummy to indicate if the subject was interviewed after the peak in daily COVID cases for his state s of residence, 0 otherwise. *hospital density* indicates number of hospitals per 100,000 population in a state. Data on state level population is taken from Government of India (2019), whereas the number of hospitals (public and private) is taken from Kapoor et al. (2020). Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted by using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of covariates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. Standard errors clustered at the state-month level and given in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A8: Impact of Second-wave of COVID Cases on Pro-sociality and Tolerance of Corruption

	Pro-sociality (1)	Tolerance (2)
Post	-0.053	0.073
	(0.052)	(0.068)
Observations	898	898
Control Mean	0.000	-0.000
Controls?	yes	yes
Balanced?	yes	yes
R^2	0.090	0.159

Notes: 'Post' is a dummy to indicate if the subject was interviewed after the peak in daily COVID cases for his state s of residence, 0 otherwise. Pro-sociality and tolerance are standardized measures computed from relevant questions, as described in subsection B.1. Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted by using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of co-variates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. Standard errors clustered at the state-month level and given in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A9: Multiple Hypothesis Testing: Impact of Second-wave of COVID Cases on Outcomes

Outcome	Coefficient (1)	Model p-value (2)	Romano-Wolf p-value (3)
Willing to Act	0.112	0.000	0.006
Willing to Protest	0.094	0.000	0.002
Corruption Perception	0.238	0.007	0.014
Information (Rights)	0.287	0.000	0.004
Risk	0.223	0.001	0.006
Bias	-0.091	0.001	0.006
Pro-sociality	-0.053	0.304	0.493
Corruption Tolerance	0.073	0.280	0.493

Notes: Controls include age, education, marital status, religion, income, asset, household composition, mode and frequency of participation, state of residence. 'Balanced' implies that observations are weighted by using these controls. The weights, generated using entropy balancing, mimics the first and second moments of the distribution of co-variates among 'Post' subjects to the equivalent distribution among 'Pre' subjects. * $p < .10$, ** $p < .05$, *** $p < .01$. Romano-wolf p-values, computed following Romano and Wolf (2016) are reported in column 3.

B Sampling

In order to measure whether the subjects are paying attention to the survey and understand the instructions of the quuestionnaire, 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've 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."

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.

B.1 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.

B.1.1 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)."[53]
- "In your opinion, has the level of corruption in the health sector during the COVID-19

[53] response coded into a continuous variable.

pandemic - (increased a lot/ increased somewhat/ stayed the same/ decreased somewhat/ decreased a lot)"[54]?

- "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)"[55].

B.1.2 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?"[56]

- "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)"[57]

B.1.3 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)."[58]

  - 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.

[54]response coded into a continuous variable with higher value indicating increase in corruption.
[55]response coded into a continuous variable with higher value indicating bigger problem.
[56]response coded into a dummy=0 if subject answered with 'don't know', 1 otherwise.
[57]response coded into a dummy=1 if subject answered with a 'yes.
[58]responses coded into a continuous variable.

- "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)."[59]

B.1.4 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)."

- *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)."

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

  - "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.