Essays on Corruption: The Role of Information, Beliefs and Incentives

Ahana Basistha

A thesis submitted in partial fulfillment for the degree of Doctor of Philosophy (Economics)

in the

Economic and Planning Unit
Indian Statistical Institute, Delhi

Supervisor: Prof. Farzana Afridi

Delhi, India 2023

Contents

List of Figures

List of Tables

Abstract

It is well acknowledged that corruption is rampant in low-income countries. However, there is a less than ideal propensity to take action against it. Lack of information is one important factor that might explain why citizens don't take an initiative to fight against it. Another important issue is citizens' ability to co-ordinate with each other to reduce corruption. This implies that when individuals decide to take an action, they need to have some knowledge about whether and how others are going to act, since the success or failure of many anti-corruption efforts depend on individual actors being able to co-ordinate. The first essay addresses the importance of these two channels in context of anti-corruption actions. Building on the same context, the second essay posits that the drive to take actions against corruption might be strong when major crisis or disaster is fresh in the memory, thereby making it more personal. A period of crisis heightens public attention- a fact that is not lost on politicians / public officials. The third essay explores the delivery of a public good in the context of a period when there is heightened public attention during the electoral term of an incumbent politician. Anticipating such behavior from the public, politicians might time their actions in a way that would be more rewarding or to their advantage. Through the third essay, we empirically test if such a manipulation can be detected in the provision of an important public good, both in terms of its quantity and quality.

In the first essay, we conduct an online experiment to test whether increasing awareness of corrupt practices and/or updating beliefs about others willingness to take action against corruption affects individuals' own anti-corruption efforts in the health sector during the ongoing COVID-19 pandemic. Subjects from India are randomized into three treatment groups. In the first treatment, subjects are exposed to increased awareness about corruption. In the second,

we correct their misaligned beliefs about others' willingness to stand up against corruption and in the third treatment, subjects are exposed to both increased awareness and belief correction. Within each treatment group we randomly assign subjects to different anti-corruption actions that vary in their private costs and expected benefits. Our results indicate that our treatments' impact on subjects' personal decision to act depends on the relative costs and benefits of anti-corruption actions.

In the second essay, we exploit the unexpected occurrence of a health crisis to answer if 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 real-effort and hypothetical 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.

In the final essay, we analyze the incentive of politicians to engage in corrupt behavior-specifically through their predisposition to adjust policies in systematic ways - around elections in India. We leverage a nationwide road program covering 150,000 roads from 18 large Indian states to demonstrate the presence of election cycle progressively through different stages of program implementation over two decades. Through heterogeneity analysis, we document that politicians are more likely to increase project sanctions in areas with low literacy, but not subsequently improve project award and completion. Additionally, re-election chances are positively correlated with increase in project awards, but tighter electoral competition is unlikely to explain the continuance of electoral cycle in this program; rather, it acts as a force of scrutiny, likely increasing the efficiency of road delivery around elections.

Acknowledgment

I am indebted to my thesis advisor, Prof. Farzana Afridi for her continuous support and invaluable guidance throughout my entire time here in the Indian Statistical Institute. She is a real source of inspiration for me. I'm grateful for all the detailed comments and helpful suggestions that I received throughout my entire thesis work. In my mind, she will forever be an ideal for a researcher, a mentor, and a role model who forges through the challenging life of academia while still maintaining a balance between personal and professional life.

I'm extremely fortunate to have worked with my co-authors, without whom I cannot imagine creating this body of work. I'd like to thank Prof. Amrita Dhillon for her support and sharp insights that helped me see the big picture in research work. I've absorbed a great deal of knowledge in experiment design and execution from Dr. Danila Serra, who has been tremendously encouraging of my ideas. Finally, Dr. Arka Roy Chaudhuri has been a source of constant support and enthusiasm; he is someone I can always call up to talk, even when I faced those inevitable roadblocks in research.

I would like to thank all the faculty members of the Indian Statistical Institute for their teaching, support and care for the PhD students. I am grateful for the funding support I received from DFID-Accountability Initiative and PPRU, ISI. I am also grateful to PhD-DSc committee in ISI for supporting my work through a research scholarship and for facilitating the thesis submission process. I'm immensely thankful for the help I received from the PPRU staff (especially Mr. Ramesh Saini and Athisii) and the research assistants (especially Nitesh Yadav and Rakesh Kumar). I'd also extend my thanks to all the non-teaching staff of ISI who'd always greet me with a smile & made my stay in the hostel comfortable. I'm thankful to my batch-mates, juniors and seniors from ISI who have become an inseparable part of my life, going beyond the confines of academia. Lastly, I can't thank my family members and parents enough. They've always had faith in me and had my back, even at times when I couldn't do that myself.

Chapter 1

Introduction

1.1 Motivation

This thesis consists of three essays that utilize both original survey data as well as publicly available administrative data to discuss the role of information, beliefs and incentive in the Indian context, where corruption is a common occurrence in the day to day lives of ordinary citizens. For example, a 2011 survey done by Transparency International, the global civil society organization leading the fight against corruption, states that about 54% of respondents in India reported paying a bribe to have access to basic services in the past twelve months (Hardoon, 2011). Yet, the loss of funds through bribery or embezzlement is only one aspect to consider. In developing countries like India, corruption can be potentially very costly, because it can also cause distortions in economic and political institutions. For example, elected politicians may become dependent on bribes to sustain their election campaigns, thus attracting even more corrupt actors to public office positions (Vaishnav, 2017). Or, corrupt public officials can purposefully put off enforcing regulations that are introduced to serve public interests, in order to line their own pockets.[1] In

[1]For example, the erstwhile health minister of India, Dr. Harsh Vardhan, went so far as to call the Indian drug regulator, Central Drugs Standard Control Organization (CDSCO) as a "snake pit of vested interest" and the Medical Council of India (MCI), the top regulatory medical body, a corrupt organization (Pulla, 2014). We will revisit the context of Indian health sector shortly, but this issue is pervasive in other public spaces as well. See for example, the Adarsh Housing Scam from 2010 (`https://en.wikipedia.org/wiki/Adarsh_Housing_Society_scam`, the *Vyapam* scam related to admission examinations to government jobs from 2013 (`https://en.wikipedia.org/wiki/Vyapam_scam`), the Indian coal allocation scam from 2012

many instances, the general public may be aware of corruption, which in turn leads to the erosion of trust between the public and the government (Chang and Chu, 2006). However, people's perception may not be an accurate reflection of the true extent of it, because by nature, corruption is hidden and difficult to measure.[2]

Despite its damaging effects, corruption can persist due to a number of reasons. One such reason is a lack of information about the actions of the government representatives or regulations. Residents in many parts of the world often don't keep up on current events, whether by choice or because they are simply not able to do so. In such a case, providing better information may have some positive effect on reducing corruption. For example, (Ferraz and Finan, 2008) find that release of audit reports about corruption practices helps voters evaluate their politician's performances, thereby impacting their chances of getting re-elected. However, as the literature has shown, information may not be the be-all and end-all of corruption. In a study done in Mexico, (Chong et al., 2015) has shown that providing more information to voters about incumbents' corruption discourages them to show up to vote for incumbents and challengers alike. Hence, the role of information in curbing corruption is far from settled, and other factors that have a simultaneous effect of corruption also need to be examined.

If we view corruption as a collective action problem, a single individual cannot do much to bring her society to a better equilibrium, even if she is given information about the occurrence of corruption. This is also important in a context where bribes or kickbacks exist as a norm, thus making it easier to avoid the enforcement of penalties imposed from the top down. In such a case, it might be necessary to launch bottom-up anti-corruption efforts to initiate successful public policy reforms. However, such bottom-up efforts depend heavily on everybody successfully coordinating their actions. Information about corruption may become salient to a single individual if she knows that others have also received the same information or that they are also willing to do something about it (Adida et al. (2020); George et al. (2018) study a context where information about legislative performance is provided in private versus in public, whereas Cantoni et al. (2019) directly update citizen's beliefs about others' decision to participate in anti-corruption

(`https://en.wikipedia.org/wiki/Indian_coal_allocation_scam`) to name a few.

[2]For example, in another developing country context, Olken (2009) shows that reported perception of corruption in a road project from Indonesian villagers, in fact, relate closely to the real extent of corruption involved in the delivery of the specific public good. However, their reported perception of corruption may only contain a limited amount of information, because public officials are capable of hiding corruption in places where it is hardest for the villagers to detect. In this thesis, we too, will look at the delivery of a large nationwide village road program in India. While we do not explicitly measure perceived corruption, we will still capture how the different aspects of this delivery are tied to the timing of elections, a critical event in India's democratic system of governance.

actions). These examples underscore that in order to reduce corruption, coordination and common knowledge about others' intention to act are also important. Therefore, in addition to the role of information, we also discuss the role of updating individual's prior beliefs on real actions in the first essay.

It is no surprise that people have a tendency to ignore events physically removed from them, that would fail to motivate them to do something about corruption in their own community. Historically, it has been shown that direct lived experiences, such as job loss from a financial crisis or loss of loved ones due to an epidemic, or being exposed to economy-wide shocks like the Great Depression in youth, can induce long and short term changes in individuals' behavior, even after the event or crisis initiating the change is long over (Malmendier, 2021; Giuliano and Spilimbergo, 2014). Such historical macroeconomic events often leave an 'emotional tagging' effect on us, potentially increasing our desire to initiate changes that would prevent an onslaught of a similar crisis in future. In this thesis, we also explore if proximity to such a crisis has any substantial impact in changing people's decision to join any anti-corruption effort. Such events can also bring about a change in individuals' existing knowledge of corruption and more specifically, their knowledge about fellow citizens' willingness to act against it.[3] Therefore, it is important to ask if any change in willingness to act is also accompanied by changes in existing behavior and perception of corruption. The sweeping effect of the COVID-19 crisis has brought these findings to the forefront. In the next essay, our context is the health crisis that ensued following the second wave of the COVID-19 pandemic in India, forcing almost every Indian to suddenly scrabble for medical help in various degrees. We rely on real-time survey data collected during the height of the pandemic to study any potential changes in their attitude, perception of corruption and desire to take action. By exploiting the proximity of our subjects' exposure to this crisis, we track a substantial increase in willingness to participate in anti-corruption efforts, that was not present before the health crisis broke out in India.

When talking about corruption, it is also important to note the role of public officials or more generally, powerful actors who may have an incentive to perpetuate corruption for personal benefits even when it is detrimental to larger public interest. In the third essay, we turn our focus to a setting where we study how incumbent politicians provide an important public good as elections get closer.[4] We center our attention to a nationwide rural road building program, which

[3] For example, multiple studies talk about the exposure to epidemics leading to a decline in trust on government, elections and leaders, and a corresponding move towards authoritarianism (Aksoy et al., 2020; Amat et al., 2020; Bol et al., 2021).

[4] This phenomenon, widely known as electoral cycle, indicates opportunistic behavior that is often tied to

not only provides a crucial public service, but also serves an important political agenda for our elected leaders (Lehne et al., 2018). Using publicly available administrative data from eighteen Indian states, we first construct a comprehensive data-set that maps rural road construction at the village level to relevant political districts, using Geographic Information Systems (GIS). Detailed information was collected to assess different stages of the road construction program, starting from project design and approval, award of road contracts and final delivery. To analyze whether the quality of roads was compromised in presence of an increase in quantity, we also include data on multiple quality parameters such as an internal quality measure of roads, as well as other measures such as time and cost overruns. We then supplement these data with election information for those leaders, taken from multiple sources such as the Election Commission of India and other publicly available data-sets (Bhogale et al., 2019). Through this exercise, we were able to aggregate information from road, village and constituency level to inspect changes in incumbent politician's behavior prior to an election.

Taken together, this thesis attempts to take a rounded view of corruption through its three essays, because political, bureaucratic and economic corruption often co-exist in a developing country like India. It is divided into five chapters: the first chapter is an introductory one, providing a synopsis of the thesis. The second chapter uses original survey data collected through online panels from Indian adult men to study the role of information and belief in context of bottom-up anti-corruption actions. Chapter 3 uses the same setting, but examines if exposure and proximity to a health crisis affects citizen's willingness to participate in activism. These two chapters use the context of corruption in health during March-July 2021, when the COVID-19 pandemic was at its peak. Chapter 4, on the other hand, shifts focus to politicians, where we examine their incentives to deliver an important public good from a nationwide program in India, vis-a-vis their proximity to elections. Below, we provide a brief overview of the analysis conducted for each chapter.

1.2 Information, Beliefs and Anti-Corruption Activism: Experimental Evidence from India

Fighting corruption is especially challenging in environments where rent-seeking and bribe or gift exchanges are the norm (Abbink et al., 2018; Barr and Serra, 2010; Cameron et al., 2009). In these

re-election incentives (Lindbeck, 1976; Rogoff, 1990; Rogoff and Sibert, 1988).

settings, bottom-up anti-corruption efforts may be necessary to pressure higher-level officials to initiate reforms. This is especially true in a context where scarcity in the supply of goods or services is coupled with overwhelmingly high demand and by urgent needs, opportunities for corruption are abound (See for e.g., Maffioli, 2021; Nikolova and Marinov, 2017; Leeson and Sobel, 2008, for catastrophic events other than the COVID-19 pandemic.). However, successful anti-corruption initiatives require collective action, yet individual participation comes at a private cost. Information on the illegal behavior of service providers as well as beliefs about others' willingness to act against corruption may be important for anti-corruption activism.

We conduct an online survey experiment in India with almost 1800 men to test how information about corrupt practices in the health sector and beliefs about others' willingness to fight corruption affect individuals' anti-corruption efforts during the COVID-19 pandemic. In one treatment, we expose subjects to information aimed at increasing awareness on how corruption and fraud take place in hospitals. In another treatment, we correct individuals' misaligned beliefs about others' willingness to stand up against health sector corruption. In a third treatment, we combine the information and the belief correction interventions. We assess individuals' willingness to engage in anti-corruption actions that differ in their private costs. In particular, we experimentally manipulate whether subjects are given the chance to: (1) make a monetary donation to a local non-profit organization that is fighting corruption in the health sector, (2) sign a petition to help the cause brought forward by the same organization, (3) watch a longer informational video on how to concretely fight corruption in health with the help of the same non-profit organization, or (4) choose among the three anti-corruption actions.

Our results suggest that, absent any treatment, subjects are more willing to watch the informational video (62%), as opposed to make a donation (27%) and sign the petition (39%). Our information and belief correction treatments, and their combination, significantly increase individuals' willingness to sign the petition but have no impact on the other two actions. Moreover, we find that giving subjects a choice of possible actions decreases their likelihood of engaging in any of the actions.

1.3 Do Crises Affect Citizen Activism? Evidence from a Pandemic

Direct lived experiences, or ‘personal effects’ are often powerful motivators for belief formation and action. Existing research (Malmendier and Nagel, 2011; Malmendier, 2021) suggests that such an effect can induce long and short-term change in both beliefs and behavior. This insight is generally admissible in a wide variety of contexts, such as consumer behavior in financial markets, race and gender, healthcare, social attitude and civic engagement. The ongoing COVID-19 pandemic gives us an opportunity to test this hypothesis in the context of citizen activism, which has been on the rise during the pandemic (Withnall, 2020; AP, 2020; BBC, 2021). Do critical junctures drive citizens’ motivation to fight corruption? In a study we conducted with nearly 900 Indian men between March and July 2021, residing across the country, we elicited perceptions about corruption in the health sector and the willingness to act against it in an online survey. We then analyzed how these changed with the severity of the intensity of the pandemic during this period. 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. Subjects in our study represent this demographic group - they are more educated (79% have a college degree) and have higher income (54% have monthly household income above Rs 30K) than the average for India. The crisis amplified corruption in the health sector. Nearly 75% of our respondents personally visited or had a household member visit a hospital since the beginning of the pandemic in March - April 2020. A majority of them report having paid a bribe (61%) to a health provider to obtain a medical service. Moreover, nearly 50% thought that they have been overcharged for a medical service. These findings are supported by media reported incidents of cheating and fraud in COVID treatments as well (Mishra, 2021; Singhal, 2021). Next, we asked their willingness to address corrupt behavior. The respondents had to either ‘agree’ or ‘disagree’ with the statement: “I am willing to raise my voice and participate in a protest against corruption in the provision of health services”. After measuring whether a subject personally agrees with the statement, we further ask them to guess the percentage of other respondents who’d agree with the statement.

We then analyzed change in their responses to these questions as the severity of the pandemic - and thus the timing of the crisis - changed. Subjects' responses were incentivized to ensure truthful reporting.

Data on total daily cases between March 1st and July 31st shows that the second wave peaked just after May 1st 2021 in terms of daily cases, whereas the peak for daily deceased occurred roughly two weeks after that. We classify the sample of respondents across the country into those surveyed before the second wave peak (N=309) and after the peak (N=589). Since both samples are random draws in terms of timing of survey, the pre and post sample are comparable – young urban males who are college educated, 47% 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. We then compare the experiences, beliefs and willingness to act to fight corruption in the health sector for these two groups. 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 an NGO 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.

We find that there is an 8-percentage point (pp) increase in the probability of a subject's willingness to participate in protest after the COVID-19 peak in June and July 2021, while the willingness to take any one of the real-effort anti-corruption actions offered in the survey increases by 12 pp after the peak of the second wave. Overall, the month-to-month impact between March to July 2021 reveals that both the willingness to take an anti-corruption action and the willingness to participate in a protest increased post the peak of infections. We also split the sample based on the timing of peak in daily cases at state-level, which shows us that the willingness to act seems to increase earlier in the states that peaked earlier than average. This might indicate a correlation between personal experience of a crisis and subsequent increased willingness to take action. A similar pattern is also found for the willingness to protest variable. Additionally, the beliefs about willingness to respond to corruption in health coalesce after the peak, with the proportion of subjects underestimating others' true willingness to protest falling significantly, by 8 pp. This suggests that there is greater commonality of opinions regarding fighting fraud in the health sector when a crisis loom- supporting the "critical junctures" hypothesis that individual's own willingness to act depends on what they believe about others' willingness to act. The evidence suggests, therefore, 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 taking an anti-corruption action.

1.4 Electoral Cycles in Road Building: Evidence from India

There is an influential theoretical literature starting from Nordhaus (1975) which argues that economic outcomes will follow the electoral calendar due to fiscal manipulation by opportunistic politicians in order to boost their re-election prospects thus generating electoral cycles in economic outcomes (Lindbeck (1976), Rogoff (1990),Rogoff and Sibert (1988), Persson and Tabellini (1990)). There is now a large body of empirical evidence[5] which shows that such electoral cycles are a common occurrence and are seen for a wide range of economic outcomes in both developed and developing countries. In the Indian context, there is a growing literature on the presence of electoral cycles. (Khemani, 2004) studies state budgets and documents no strong impact on aggregate fiscal variables but on individual budget components. (Cole, 2009) observes electoral cycle in public sector loans, and finds that election year credit booms induced substantially higher default rates. More recently, the focus has moved beyond credits, state budget etc. to provision of important public services; (Baskaran et al., 2015) examines if provision of electricity is affected before special elections. We add to this literature by looking at the delivery of another essential public good- village road provision- both quantitatively and qualitatively. Using a novel data set generated by matching assembly constituencies and roads built over a decade (2000-01 to 2012-13), we demonstrate a clear presence of electoral cycle in PMGSY provision for a number of outcomes.

The staggered nature of election timing provides the necessary variation to estimate electoral cycles. Elections to state legislative assemblies are scheduled to occur after every five years. In this program, the federal and state government have shared a role in the provision, with a part of project money being sanctioned from federal government. This sets us apart from previous studies that focus on agricultural credit, electricity supply or state budget, which are in more direct control of the state government ((Cole, 2009), (Khemani, 2004), (Baskaran et al., 2015)).

A distinctive feature of the program is the record of detailed information about various stages of project planning and execution at the road level, which allows us to trace the existence of

[5]See Alesina et al. (1997), De Haan and Klomp (2013), Dubois (2016) for reviews of the literature

electoral cycle step by step. To the best of our knowledge, no other study in this literature shows a progressive occurrence of election cycle through time. Further, using the same detailed data set, we are able to assess not just quantitative changes in road delivery, but also the impact on the quality of the roads built. A presence of electoral cycle is detected through all three phases of road construction such as sanctioning, award of projects and completion of projects. On the fourth year of an incumbent's term, 2 extra roads are sanctioned (40% increase over mean). We find similar effects for total sanctioned road length (7km more length). On the fifth year of incumbent's term, we observe that award and completion outcomes spike significantly. Consistent with previous literature, we find suggestive evidence of increase in re-election probability correlated with the more visible aspects of the program. Further, we document the magnitude of the cycle to be stronger in areas with a higher proportion of uninformed voters.

Chapter 2

Information, Beliefs and Anti-Corruption Activism: Experimental Evidence from India[1]

2.1 Introduction

The past decade has seen a substantial increase in social movements and activism across the world, often facilitated by the fund-raising, advocacy and coordinating efforts of non-governmental organizations. Between 2010 and 2020 nearly 7000 protests have been recorded across the world (Clark and Regan, 2016)[2] Advocacy through petition signing also increased rapidly in the past 10 years. In the US, nearly 800,000 petitions were created in 2021 on the Change.org site, reaching over 400 million signatures, and leading to some notable successes, including the installation of

[1]This chapter is joint work with Farzana Afridi (ISI-Delhi), Amrita Dhillon (King's College London) and Danila Serra (Texas A&M University). The study is registered at AsPredicted.org. #60725. Ethics approval was obtained from the Institutional Review Board of King's College, London, U.K.; registration number MRA-19/20-20739 dated 10th August, 2020. Financial support was provided by DFID-Accountability Initiative.

[2]The Mass Mobilization Protest Data records protests against the government in 162 countries between 1990 and 2020. See `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HTTWYL` According to the Armed Conflict Location and Event Data (ACLED) Project, nearly 7 percent of worldwide demonstrations in 2020 led to law enforcement intervention. See: `https://reliefweb.int/sites/reliefweb.int/files/resources/ACLED_Annual-Report-2020_Web_March2021.pdf`

Juneteenth as a national holiday.[3]

What are the drivers of social activism? Activism requires widespread information about the *cause*, i.e., the social problem that calls for mobilization, and it is successful only for high levels of participation.[4] The fundamental constraint to effective activism is that it requires collective action, yet it comes at a private cost.[5] Beliefs about others' willingness to sustain such cost are likely important. Incorrect beliefs, in particular, may act as a barrier to individual efforts and lead to an "inactivity equilibrium" even when the percentage of people willing to "act" is above the critical mass that would lead to a successful outcome.

In this paper, we investigate the role that information about the cause and beliefs about others play in one's decision to "act." We focus on India and on the social problem of fraud in the provision of health services during the COVID-19 pandemic. This was a time where scarcity in the supply of health services coupled with overwhelmingly high demand and urgent needs, allowed corruption to flourish.[6] Through an online experiment embedded in a survey involving nearly 2000 individuals, we examine whether and to what extent activism can be increased by providing information about the occurrence of provider misbehavior in hospitals, and/or by correcting individuals' misaligned beliefs about others' willingness to act. We partner with a local non-governmental organization and study the impact of our treatments on three different forms of activism, which are commonly used to mobilize the public: (i) signing of a petition to the Ministry of Health, (ii) making a donation to the non-profit organization, and (iii) obtaining practical information on different ways to help the cause by watching a how-to video. These actions differ markedly in their expected costs and benefits, and in the extent to which they are subject to collective action problems, hence they may respond differently to the information and belief correction manipulations. Through our experiment, we are able to examine which form of activism is more likely to be taken up by the public, and which action is more responsive to information and belief correction. Moreover, we test whether it is preferable to ask individuals to engage in a given form of activism – say, signing a petition – or to provide them with a choice

[3]For examples of other successful petition efforts, see: https://www.change.org/l/us/change-org-releases-top-ten-petitions-that-changed-2021

[4]For instance, in the US, a petition directed to the White House needs to gather 100,000 signatures within 30 days to be reviewed by government officials.

[5]Such cost may be as small as the cost of time devoted to searching for ways to protest, and as large as the cost of being arrested when participating in a street protest.

[6]In India, numerous news outlet reported on the occurrence of corruption in the form of overcharging for COVID-related services, favoritism in service provision, and administration of fake vaccines for a fee. See for instance https://www.indiatoday.in/india/story/corruption-second-covid-pandemic-black-marketing-medicines-tiii-1799395-2021-05-06

between different ways to support the cause.

Our paper contributes to theoretical and empirical studies of activism and bottom-up accountability. Our focus on beliefs about others builds on recent theoretical work that models social activism, e.g., the decision to join a protest, as a coordination game, or a game of strategic complements, where individual beliefs about others' willingness to participate play a crucial role (e.g., Barbera et al., 2020; Passarelli and Tabellini, 2017).[7] Consistent with the theory, there is empirical evidence that protest turnout increases with the diffusion of social networks (Enikolopov et al., 2020) and mobile phones (Manacorda and Tesei, 2020), and with the activism of peers (Bursztyn et al., 2021; González, 2020).[8]We add to these studies by *directly* asking whether beliefs about others' willingness to act for a cause may be misaligned, and whether correcting such beliefs may positively impact one's decision to act. The only other direct investigation of the impact of belief correction on activism[9] was conducted by Cantoni et al. (2019) with university students in the context of protest participation in Hong Kong. Crucially, Cantoni et al. (2019) finds evidence of strategic substitutability, rather than complementarity, in protesting, which is in contrast with much of the theoretical and empirical work on social activism. The authors suggest that this may be due to the specific nature of protests in Hong Kong - a semi-democratic regime with long-standing anti-authoritarian movements. No other study has directly tested the strategic complementarity (versus substitutability) hypothesis in the context of social activism in other settings, and/or focusing on different forms of activism and/or a different cause. We contribute to this literature by conducting such investigation in relation to anti-corruption activism in India.

Our focus on information relates to a number of studies that have highlighted the importance of informing the public of officials' malfeasance in the context of political corruption and voting (see, e.g., Aker et al., 2017; Ferraz and Finan, 2008). The evidence on the effectiveness of informing citizens on bureaucratic corruption, i.e., illegal behavior by public sector providers, in the context of the delivery of public services is, however, limited.[10] We are not aware of other

[7]Strategic considerations can be important when an individual's participation decision is shaped by their beliefs about participation of others. Strategic complementarity implies that an individual is more likely to participate in activism if they believe that others are also willing to do so.

[8]Relatedly, in the context of voting, Adida et al. (2020) shows that informing voters about politicians' criminal behavior reduces political support for them only when voters know that others are getting the same information.

[9]See Bursztyn and Yang (2021) for a review of studies experimentally manipulating beliefs about others in other contexts.

[10]Reinikka and Svensson (2005) show that, in Uganda, leakage of education funds was reduced by a newspaper campaign aimed at informing parents about funds that were directed to schools. Other studies have assessed the impact of providing service recipients with information on the existence of participatory mechanisms or institutions (e.g., Banerjee et al., 2010; Pandey et al., 2009), or on the relative performance of local health facilities/providers

studies testing whether providing citizens with information on the occurrence of corruption in the public sector, and in particular the health sector, impacts their decision to engage in some form of activism.

We employ an online experiment involving nearly 2000 Indian men between May and July 2021.[11] A number of studies have recently used similar experiments to examine a variety of topics, ranging from xenophobic views (Bursztyn et al., 2020) and racial discrimination (Haaland and Roth, 2021), to opinions about monetary compensation for kidney donations (Elias et al., 2019), to support for immigration (Haaland and Roth, 2020).[12]

In our pre-registered online experiment, subjects answer questions measuring demographic characteristics, individual preferences, and personal experiences with both the COVID-19 pandemic and corruption in the health sector. Toward the end of the survey, we elicit (incentivized) beliefs about the percentage of previous survey participants who expressed their willingness to protest against corruption in the provision of health services, using the methodology first introduced by Bursztyn et al. (2020).

Participants are then randomly assigned to a control group (C) or one of three activism treatment arms. In our Information (I) treatment, we show subjects a 3-minute video providing information on the occurrence of fraud in the health sector in India during COVID-19, e.g., news stories documenting overcharging for hospital beds. In our Belief Correction (BC) treatment, we follow Bursztyn et al. (2020) and correct subjects misaligned beliefs about other's willingness to act by providing them with the true percentage of previous participants who expressed their willingness to protest against corruption in the health sector. Finally, in our Combined (COM) treatment, we show participants both the video and the true percentage of previous participants who stated their willingness to act.

Our primary outcome of interest is individuals' willingness to engage in activism. A challenge in online surveys is the generation and measurement of outcome variables. Our approach is as follows. At the completion of the survey, we inform participants that they have reached the end of the survey. On that last page, where we thank them for their participation (as is customary in online surveys) we give them the chance to engage in a form of activism just before exiting

(e.g., Björkman and Svensson, 2009) or of schools/teachers (e.g., Andrabi et al., 2017; Afridi et al., 2020; Di Maro et al., 2021).

[11]he data collection was implemented by Qualtrics through local survey firms that manage large panels of potential study participants.

[12]Previous studies have successfully used both a petition (Bursztyn et al., 2020; Facchini et al., 2016; Settele, 2019) and a monetary donation (Alesina et al., 2018; Bursztyn et al., 2020; Settele, 2019) to measure individual preferences and support for a given cause.

the survey. Crucially, within each activism treatment arm (C, I, BC and COM), we further randomize participants in one of four Action treatments, where we vary the form of activism that is offered to them. In particular, we chose three actions that are often used by activists, including non-governmental organizations, to increase public involvement with a cause, and that vary substantially in their (expected) costs and benefits. Specifically, participants randomized into the *Petition* treatment are offered to sign a petition against corruption in the health sector, directed toward the Union Health Minister of India. Subjects randomly assigned to the *Donation* treatment are given the chance to donate any portion of the money they earned in the incentivized survey tasks to a non-profit organization, which specializes in anti-corruption in the health sector. Participants randomized into *Video* action treatment are given the chance to watch a 5-minute video showing ways for the public to help the cause, with special focus on the activities of the same local non-profit organization.[13] We assume these actions to be differently affected by strategic complementarities in (expected) costs and/or benefits, with the petition and the video being, respectively, the most and the least affected. We also implement a fourth action treatment - the *Choice* treatment - where subjects are shown all three anti-corruption actions and given the chance to engage in one of them (of their choice) or to exit the survey.

In each action group, subjects are given the choice to engage in the assigned action (or one of the actions in the *Choice* treatment) or exiting the survey. If they choose to engage in the action, they are then given the chance to act, by either signing their name on a letter to the Ministry of Health (*Petition*), or choosing the percentage of their earnings (still unknown to them) they want to donate (*Donation*) or starting the video presented to them (*Video*). They can still decide to exit the survey without acting, i.e., without signing/donating/watching the video. We record both the first decision, i.e., their willingness to act, and than their actual decision to act.

Overall, our 4 x 4 experimental design allows us to answer five pre-registered research questions.[14] First, does providing information about the cause increase individuals' willingness to act? Second, does correcting misaligned beliefs about others' willingness to fight corruption increase activism? Third, do information and belief correction have an additive effect on activism, or are they effective only when combined? Fourth, what action is more likely to be taken up and to be affected by our treatments? And finally, is it better to present individuals with a set of

[13]The petition presented to the subjects in the Petition treatment is promoted by the same organization. In each treatment, subjects are first presented with a brief statement introducing the organization, and then presented with the action they could engage in.

[14]We pre-registered the experiment on AsPredicted in March 2021. The pre-registration can be seen here: `https://aspredicted.org/vc8vt.pdf`

possible actions, or with just one action?

Our data show that fraud in the health sector during the COVID-19 pandemic was widespread. Nearly 91 percent of the respondents personally visited or had a household member visit a hospital since the beginning of the pandemic. The majority of them report having paid a bribe (62 percent), having given a gift (59 percent) or having done a favor (68 percent) to a health provider to obtain a medical service. About 46 percent of those who visited a hospital during the pandemic thought that they were overcharged for a medical service. We also find evidence of substantial misalignment of beliefs about others' willingness to protest against corruption in the health sector. While most participants (90 percent) stated their willingness to protest, they believed on average that around 64 percent of others are willing to do so. Moreover, about 60 percent of participants have downward biased beliefs.

The comparison of engagements in the three forms of activism reveals that, at baseline, subjects are least willing to make a donation (27%) and most willing to watch the video (62%), with the signing of the petition in between (39%).[15] When looking at actual activism (absent any treatment manipulation), the percentage who donated a positive amount falls to 20%, the percentage who signed the petition with full name falls to 30%, and the percentage who stayed on the video page for at least 5 minute falls to about 40%.

The effectiveness of our treatments in increasing individual activism depends greatly on the form of activism being considered. The Information and Belief Correction treatments, and their Combination, have a significant and positive impact on individuals' willingness to sign the petition to the Ministry of Health, and actual petition signing. In particular, the likelihood of signing the petition with one's full name increases by 11, 14 and 15.6 percentage points, respectively, in response to the Information, Belief Correction and Combined treatment manipulations. These correspond to 42, 54 and 58% increases over the Control mean. These impacts are large and robust to correcting for multiple hypothesis testing. Further analysis shows that, as expected, it is the individuals with downward-biased beliefs about others that increase their activism when their beliefs about others are corrected, leading to the overall positive impact of the treatment on petition signing.

The analysis of treatment effects on the other actions is less promising. In fact, we find that the Information and Belief Correction treatments, and their combination, have no impact on willingness to make a donation or to willingness to watch the video. Finally, the analysis of each

[15]This reflects the initial decision to engage in the action rather than exiting the survey. After expressing willingness to act, subjects could still decide not to act.

individual action (*Petition*, *Donation* and *Video*) as opposed to the opportunity to choose between the actions (*Choice*) suggests that, within each treatment and overall, individuals are less likely to act when such action is presented together with other actions than when it is presented alone.

Our findings on willingness to sign a petition - the action whose expected costs and benefits are more likely to depend on the number of others signing the petition - provide support to theoretical studies that model activism as a game of strategic complementarities. This is in contrast to the findings of Cantoni et al. (2019), which show evidence of a decrease (rather than an increase) in activism when downward biased beliefs about others' activism are corrected upward. This confirms that the form of activism (petitioning in our case, protesting in Cantoni et al. (2019)), as well as the setting (democracy versus semi-authoritarian government) and the nature of the initiative (one-shot, new movement versus established and long-running movement) are likely to affect how beliefs about others enter individuals' utility function.

Finally, we find that the probability of taking any action increases when subjects are given a choice of actions. The willingness to act increases by in the Choice action group - subjects are less likely to exit the survey when they can choose from multiple actions. However, since subjects cannot coordinate around any single action, the willingness to take each action is lower than in the single action groups. This result potentially highlights the key issue of coordination for any single form of activism to be effective.

Our study contributes to the literature on ways to counteract corruption in settings where corrupt behavior on the part of service providers is widespread and where there is limited awareness on what constitutes illegal behavior and ought to be punished. While increased monitoring and auditing have proven effective in these settings (e.g., Ferraz and Finan, 2008; Olken, 2007), their implementation is often challenged by deficient accountability systems.[16] Recent research has attempted to identify ways to fight corruption by bypassing standard service delivery channels, for instance through the use of e-governance (Banerjee et al., 2020), smart cards (Muralidharan et al., 2016) and direct transfers to mobile accounts (Barnwal, 2014). Studies focusing on ways to mobilize the public in the fight against corruption in the delivery of public services are hard to find. We contribute to this literature by showing that awareness of how and where corruption happens is important, as are beliefs about others' willingness to oppose corruption. However, different forms of activism have different likelihoods of being taken up and can be differently impacted (or not impacted) by anti-corruption campaigns focusing on

[16]For a review of issues related to corruption in developing countries, see Banerjee et al. (2012) and (Olken and Pande, 2012). For a review of issues related to public service delivery and governance in India, see Afridi (2017).

generating awareness on the occurrence of corruption or on the widespread willingness, among the public, to join forces to fight corruption.

2.2 Experiment Design and Implementation

2.2.1 The Online Survey

The study was conducted between March and July 2021 in two Waves - Wave 1 of the online survey conducted about a week prior to the main experiment (Wave 2), as shown in Table 2.A.1. The results presented in this paper pertain to the main experiment in Wave 2 of the survey. We, therefore, discuss the relevance of the Wave 1 survey with reference to the main experiment described below.

Figure 2.A.1 provides an overview of our study design which embedded the experiment within an online survey (Wave 2) aimed at understanding people's behaviours and attitudes during the COVID-19 pandemic.[17] Subjects first answered questions on basic demographics such as age, gender, education, caste and religion, household composition and income, and location of current residence. They then answered a set of questions aimed at generating personality and preference measures, including locus of control,[18] risk, trust, altruism and retaliatory tendencies. We took these non-incentivized measures of individual preferences from the Global Preference Survey, following (Falk et al., 2018). Specifically, we chose questions that have been shown to correlate with the corresponding incentivized measures. We combine the indices of trust, altruism and reverse-coded retaliation to generate a measure of pro-sociality.[19] Questions on experiences with the healthcare system during the pandemic followed.

The next set of questions aimed to measure: (1) awareness about corruption and fraud in the health sector during the pandemic; (2) the extent to which subjects tolerate or justify corruption in the health sector and in other government sectors. These are especially important as we expect the impact of our information and belief correction treatments to likely depend on both subjects' prior information about corruption and their tolerance of corruption. A more detailed discussion of these measures is presented in Section 2.3.1.

The last section of the survey, which preceded the randomization into treatments, included

[17] More details on the recruitment process is given in the Data Appendix section.

[18] The locus of control index captures the degree of control subjects believe they have over outcomes in their lives. Summary statistics are reported in section 2.A and the index construction procedure is listed in section 2.B.

[19] More details can be found in the section 2.B.

questions that allowed subjects to earn bonus money. First, participants engaged in a risk-elicitation incentivized activity, modeled after Eckel and Grossman (2008). Then, they answered questions aimed at eliciting beliefs on others' willingness to act against corruption in health. We followed the methodology introduced by Bursztyn et al. (2020) in the context of female labor force participation in Saudi Arabia. We presented participants with three statements related to the health sector and health-related behaviors, and asked them first to agree or disagree with each statement, and then to guess the percentage of Wave 1 participants who agreed with each statement. The responses of Wave 1 participants were used to generate the correct proportions of subjects who agreed with each of the three statements. This allowed us to incentivize belief elicitation in our main survey.[20]

We incentivized the belief elicitation by rewarding each correct guess with INR 50, for a maximum of INR 150 if all three guesses were correct.[21] In order to facilitate the incentivized elicitation, beliefs were recorded over 10 percentage point ranges, i.e. 0-10, 11-20, 21-30 and so on and so forth. We describe each statement and its relevance in the following section.Participants were not provided feedback on either the outcome of the lottery or their earned bonus earnings, to alleviate the concern of higher bonus earnings leading to higher donations. However, we elicited their (un-incentivized) beliefs regarding the bonus money they accumulated in the survey.

Next, subjects were randomly assigned to either a control group or one of three anti-corruption treatments. A further individual-level randomization, within each treatment group, took place at the conclusion of the survey and determined which action each subject was offered to partake in. We describe each anti-corruption treatment in Section 2.2.2 and each action treatment in Section 2.2.2.

2.2.2 Treatments

Our experiment employs a 4x4 between-subject design, depicted in Figure 2.A.1. In particular, we implemented two independent sets of treatment manipulations by acting on: (1) factors that may increase individuals' willingness to partake in activism, and (2) the types of action(s) made available to subjects. We refer to the former as *Activism Treatments*, and to the latter as *Action Treatments*.

[20] The characteristics of the subjects in the first wave (viz. gender, age and incomes) were the same as in the main study. The data analysis presented in this paper is based on the main survey participants only.

[21] INR stands for Indian Rupee; 1 USD = INR 75 the time of the project implementation.

Activism Treatments

After answering all sections of the survey described in Section 2.2.1, subjects were randomized to either a control group or one of three treatments. The control group reached the end of the survey, whereas the treatment groups were exposed to different stimuli aimed at increasing individuals' willingness to engage in an anti-corruption action.

In the **Information (I)** treatment, subjects were shown a 3-minute video on the cause, i.e., specific instances of corruption in the health sector in India during the COVID-19 pandemic. The video showed and discussed news stories concerning the demand for bribes, the illegal overcharging for medical equipment or hospitalization, and the occurrence of medical hostage taking.[22] The content of the video was taken from corruption cases documented in local newspapers and social media platforms between April 2020 and January 2021.[23] In order to maximize the likelihood that participants would watch the video in its entirety, we made sure that the video could not be forwarded and that subjects could not move on with the survey until the video ended.

The **Belief Correction (BC)** treatment aimed at updating participants' (potentially misaligned) beliefs about others' willingness to act to help the cause. We employed the methodology introduced by Bursztyn et al. (2020), i.e., we first elicited subjects' beliefs about the percentage of Wave 1 survey participants who agreed with the statement "I am willing to raise my voice and participate in a protest against corruption in the provision of health service" - as described in Section 2.2.1. The elicitation took place in all treatments. However, in the BC treatment, at the end of the survey, we presented subjects with a table displaying the three statements for which we elicited beliefs - including the statement of interest - together with the percentage of Wave 1 participants who agreed with that statement.

Similar to Bursztyn et al. (2020), in order to minimize experimenter demand effects, we used three statements, rather than only the statement of interest. We chose the other statements so that they were all about health-related behaviors, but differed in the expected belief mismatch and the hypothesized impact of the belief correction on our outcomes of interest. The first statement was about the use of masks during the pandemic - a health advisory that had been emphasized through public communication channels and that we expect not to generate a belief mismatch.[24]

[22]Hospitals often illegally hold dead bodies or detain patients for non-clearance of hospital bills, as documented here: `https://scroll.in/article/973153/interview-how-should-india-regulate-private-healthcare-to-avoid-pitfalls-exposed-by-the-pandemic`)

[23]The video could be accessed here: `https://youtu.be/8Ud5gla8gVI`

[24]The statement read: "In order to contain the spread of COVID-19, people should wear face masks when they

The second statement concerned the independent oversight of emergency funds set up during the pandemic.[25], and was therefore closer to the statement of interest, in terms of its focus on possible misbehavior within the health sector during the pandemic. However, contrary to the statement of interest, it does not directly address individuals' willingness to act against such misbehavior.

In the **Combined (COM)** treatment, we implemented both the Information and the Belief Correction treatment manipulations. Specifically, subjects were shown both the 3-minute video *and* the table displaying the true percentage of previous survey participants who agreed with each of the three statements.

Action Treatments and Outcome Variables

An important aspect of our experiment design is the way we measure our outcome variables. Given the nature of the data, which made it impossible to follow up survey participants over time and observe subsequent decisions regarding activism to help the cause, we had to devise a way to allow for such decisions to be made within the framework of the survey. In particular, any decision concerning activism should be perceived as a factual decision, and not as an hypothetical survey answer. We achieved this by directing subjects to a final survey page, where we thanked them for their participation in the study. This aimed to create the belief that the survey has ended. In fact, subjects could select an "Exit Survey" button on that page.

However, on the same page, we also gave subjects information about a local non-profit organization - the All India Drug Action Network (A.I.D.A.N) - that had been pressurising local and federal government to better regulate health care in India, fostering transparency in pricing and providing redress to patients who have been illegally overcharged. Following the paragraph with information about A.I.D.A.N., we gave subjects the chance to either exit the survey or to take some action to support the activities of the organization.[26] The different Action treatments experimentally manipulated the action that was offered to subjects to support the non-profit organization. Specifically, subjects were given the chance to either sign a petition to the Ministry of Health, or make a monetary donation to A.I.D.A.N., or watch an informational video on A.I.D.A.N.'s activities which would suggest ways in which subjects could get involved and act

are in public spaces."

[25]The statement read: "I believe that citizens should demand that the usage of relief funds set up during the pandemic should be audited by independent third party organisation."

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

for the cause. A fourth action treatment presented subjects with all three actions and allowed them to choose among them. Exiting the survey was always a choice.

In the **Petition Action Treatment**, subjects are given the chance to sign a petition addressed to the Union Health Minister of India, copying all the state health ministries as well. If subjects click on “Petition", they are shown a new page, which discloses the full 200-word long petition, which we designed in close collaboration with A.I.D.A.N. The letter places demands on the government to (1) fast-track the adoption of regulatory laws of health establishments, (2) clear communication of treatment protocol and implementation of prescription audit, and (3) implement district level grievance redress system for patients. At the bottom of the petition, subjects are given the chance to sign by writing down their name, knowing that the petition, once all signatures have been collected, would be sent to the Health Minister. Subjects can also decide not to sign the petition and instead select the “Exit Survey" button, which appears at the bottom of the same page.

Petitions have been used in a number of studies to measures individuals’ attitudes toward sensitive topics, such as support of pro- or anti-immigration policies (Facchini et al., 2016; Haaland and Roth, 2020) and gender equality in the labor market (Settele, 2019). The usual methodology consists in providing subjects with links to a webpage outside the survey platform, and to then assess changes in the total number of signatures on the platform by treatment, while individual signatures remain inaccessible to the researchers. We departed from this method and instead presented a petition (that we created) to participants *within* the survey platform. This allows us to record whether each individual participant decided to sign the petition, as well as the time spent on the petition page.[27] While we have no way to verify whether the name subject wrote down is his actual name, we assume that whenever a first and last name are provided, the likelihood of them being truthful is high. Another advantage of using our methodology is that, by preventing access to an online petition through an external website, the decision to sign the petition cannot be conditioned on the number of previous signatures, which is usually visible in such websites, and would be outside of our control.

When analyzing activism in the form of petition signing, we consider the following outcome variables: (1) Initial willingness to sign the petition (rather than exit the survey); (2) Willingness to write down at least one name (rather than leaving the name field empty); (3) Willingness to write down a first and a last name (rather than just one name or leaving the field empty).

[27]We placed an invisible time-tracker question attached to the petition action to track how much time the subject spent on reading the petition text. We found that on an average, in the petition action group, subjects spent 39 seconds to read the text, with a standard deviation of 41 seconds in the full sample.

In the **Donation Action Treatment**, once subjects reach the final survey page, subjects are given the same information about the non-profit organization (A.I.D.A.N) as in the Petition Action Treatment. They are then given the chance to either donate to the organization or to exit the survey. If they select the “Donation" button, they are shown a new page where they are asked to select their desired donation level, out of 10 possible levels, i.e., 10%, 20%, 30%, and so on and so forth, up to 100% of their bonus earnings.[28] Importantly, 0 percent is also listed as a possibility, meaning that subjects can still decide to not make a donation to the organization prior to exiting the survey.

A number of recent studies employing online surveys use subjects’ willingness to make donations to specific organizations as their outcome measures of interest. Usually, subjects are presented with some money, e.g., 1 USD, and choose whether to authorize the donation of that amount to an organization presented to them by the researchers, as in Bursztyn et al. (2020). Other studies (e.g., Grigorieff et al., 2020) give subjects an endowment and allow them to keep or donate some or all of the money to the organization of interest. Others, (e.g., Alesina et al., 2018) ask subjects to decide how much to donate out of an amount of money that they have the chance of winning in a lottery that is implemented as part of the study. Our approach is different. To maximize similarities with real life donation decisions, we ask subjects to donate part of the money that they earned by participating in the survey. In fact, while the compensation for completing the survey is fixed, subjects could earn bonus money from an incentivized lottery game and the belief elicitation exercise conducted towards the of the survey. In order to minimize endowment effects, subjects are not informed about their bonus earnings prior to deciding whether and how much to donate, although we did collect data on expected earnings. Recall that donations are expressed in percentage points, rather than actual monetary amounts. When analyzing activism in the form of making donations, we consider the following outcome variables: (1) Initial willingness to make a donation (rather than exit the survey); (2) Percentage of bonus earnings donated.

In the **How-To-Act Video Treatment**, the information on the final survey page is held constant, but subjects are given the chance to watch a 5-minute informational video about A.I.D.A.N’s activities, including examples on how the organization helps citizens fight corruption in the health sector. The video also provides information on how citizens can assist A.I.D.A.N’s efforts to promote transparency and accountability, for instance by sharing information on their

[28] We deduct the contribution from subjects’ earnings and donate the amount to A.I.D.A.N after completion of the study.

own experience with illegal practices in the health sector and by collectivizing in the fight against corruption. Like in the other action treatments, subjects were first given the chance to select either “Exit Survey" or “Video", and then, once the video started in the next page, they could still exit the survey at any time. Similar to the petition action group, we attached an invisible time tracker to record how long the participants watched the 5-minute video. When analyzing activism in the form of video watching, we consider the following outcome variables: (1) Initial willingness to watch the video (rather than exit the survey); (2) number of seconds of video watched.

Choice: In the Choice action treatment, subjects were offered all three actions listed above. They could choose any one action or exit the study without taking any action.[29]

Our decision to experimentally manipulate the types of actions subjects were asked to engage in, was motivated by a desire to examine the collective aspect of activism by varying the nature of the costs and benefits associated with each action, and the extent to which such costs and benefits are perceived as somehow depending on others' activism. In the next subsection we formalize our conceptual framework and derive our empirical predictions.

2.2.3 Theoretical Framework and Predictions

In deriving our theoretical predictions we adapt and extend the model of protest participation introduced by Cantoni et al. (2019). Similar to their benchmark model, we assume that individuals' utility from participating in any form of activism depends on the costs and benefits of participation. As in previous models (Cantoni et al., 2019; Barbera et al., 2016; Passarelli and Tabellini, 2017), we assume that such costs and benefits are affected, negatively and positively, respectively by the participation of other individuals, i.e. we assume strategic complementarity in both the costs and benefits of activism.

The participation decision is denoted by $P_i \in \{0, 1\}$, where 1 (0) denotes participation (non-participation). We augment Cantoni et al. (2019)'s model by assuming that there is uncertainty regarding the state of the world $\theta \in \{H, L\}$ - which we interpret as the severity of the social problem that requires citizen mobilization. In our setting, this would be the level of fraud and corruption in the health sector. Without loss of generality, we assume that severity of the social

[29] In order to check subject attentiveness in the survey, we employed a variety of checks and screening questions within the study. Inattentive subjects were more likely to have a higher number of failed attempts in the training questions, and were more likely give incomprehensible answers in the descriptive questions. We do not find the proportion of inattentive subjects (24% overall) to vary significantly between treatment groups or affect our results. Our analysis sample, therefore, consists only of attentive subjects.

problem, i.e., the level of corruption, θ is high (H). Informed citizens are aware of this, whereas uninformed citizens have a prior probability p on the state of the world being H. We also assume that individuals receive an intrinsic net benefit W_i from participating in activism. This is the difference between the intrinsic benefit from participating, e.g., warm glow, and the intrinsic cost from not participating, e.g., feeling of guilt. We assume that that such net benefit is increasing in the level of corruption, i.e., $\frac{\partial W_i}{\partial \theta} > 0$. For informed types, $W_i(\theta)$ is equal to $W_i(H)$; for the uninformed, it is equal to $pW(H) + (1-p)W(L)$. Below n_{-i} denotes the number of citizens participating in activism excluding i, while $n = n_{-i} + 1$.

Hence, the utility of citizen i from participating in activism, i.e., when $P_i = 1$, is represented by:

$$(U_i|P_i = 1) = W_i(\theta) + V_i(n, S(n,\theta)) - C_i(n, S(n,\theta)) \tag{2.1}$$

where V_i and C_i are the benefits and costs associated with participation, and S denotes the probability of "success" of the form of activism the citizen engages in. The state of the world θ enters the success function, as the probability of success is lower the higher the severity of the social problem ($\frac{\partial S}{\partial \theta} < 0$). The number of other participants n also enter the success function, as we assume strategic complementarities in citizen's actions. In particular, the probability of success is higher the larger the number of participants ($\frac{\partial S}{\partial n} > 0$,), and, as in Cantoni et al. (2019), individuals get more benefits from participating in an event that is more likely to succeed ($\frac{\partial V_i}{\partial S} > 0$) and when more people participate, no matter the outcome ($\frac{\partial V_i}{\partial n} > 0$). Moreover, we assume that also the cost of participating is a function of the number of others participating and the likelihood of success. This is because, for instance, the cost of being punished (e.g., for signing a petition) is likely to be lower the larger the number of other participants and by benefits, as the government is more likely to give in than to crack down on citizens' actions.

The utility associated with not participating is given by:

$$(U_i|P_i = 0) = V_i(n_{-i}, S(n_{-i},\theta)) \tag{2.2}$$

which indicates that by not participating, an individual still enjoys the possible benefits generated by the participation of others, without suffering any costs.

Informed citizens know that the true level of corruption is high ($\theta = H$), i.e., there is no uncertainty. Therefore, an informed citizen i will participate if and only if $(U_i|P_i = 1) - (U_i|P_i = 0) \geq 0$. In contrast, uninformed citizens do not know the true state of the world. Therefore, their utility associated with participation is expressed in expectations over θ, as follows:

$$\begin{aligned} E_\theta(U_i|P=1) &= p\left(W_i(H)+V_i(n,S(n,H))-C_i(n,S(n,H))\right) \\ &+ (1-p)\left((W_i(L)+V_i(n,S(n,L))-C_i(n,S(n,L))\right) \end{aligned} \tag{2.3}$$

and similarly for $E_\theta(U_i|P_i=0)$. Therefore an uninformed citizen i would participate if and only if the expected benefit from participating exceeds the cost of participating, i.e., if $E_\theta(U_i|P_i=1)-E_\theta(U_i|P_i=0)\geq 0$. In other words, participation takes place if the (Expected) Net Marginal Benefit (NMB) of participating is greater than zero.

Assume that when $n_{-i}=0$, i.e. no other citizen is expected to participate, then the (expected) benefit V associated with participation is zero, the activism has no chance of succeeding. On the other hand, both the intrinsic benefit from participating W and the cost from participating are likely to still be greater than zero. It is reasonable to assume that: i) when nobody else participates, the cost of participating exceeds the intrinsic benefit of participating, and ii) the Expected NMB (ENMB) curve is monotonically increasing in n_{-i} (since we assume strategic complementarity). This implies that each individual i will have a threshold value of n_{-i} denoted as $\tilde{n}^i$ such that below the threshold, $P_i=0$ and above the threshold $P_i=1$.

The activism threshold is lower for individuals with high intrinsic motivations to participate. Many factors may affect such intrinsic motivations, hence the threshold level of participation - everything else equal - including attitudes toward the problem (e.g., tolerance of/aversion towards corruption), as well as individual preferences related to pro-sociality, such as trust and altruism. The activism threshold is also lower for individuals for which the cost of acting when $n=0$ is small, and those whose Expected NMB of acting is more responsive to changes in n.

Next, we derive predictions on the impact of our Information, Belief Correction and Combined interventions on the likelihood of participating in activism. Providing individuals information about the state of the world (being H) will increase the intrinsic motivations to act of the uninformed. However, since the chance of success S depends negatively on θ, an increase in p may also lead to lower expected S and may therefore discourage participation. The overall impact on the ENMB curve is ambiguous, hence the effect of increased information on the threshold $\tilde{n}^i$ is also ambiguous. This leads to our first prediction:

Prediction 1: The **Information (I)** intervention will increase activism among previously uninformed individuals if the positive impact on intrinsic motivations to act is larger than the discouragement effect caused by lower expectations of success.

Our predictions regarding the impact of the Belief Correction treatment depend on two factors: i) whether individuals have incorrect beliefs about the number of others willing to act, n, and ii) whether they have a low or a high threshold $\tilde{n}^i$ for participation.

Prediction 2: The **Belief Correction (BC)** intervention will:
(a) increase activism among individuals with downward biased beliefs about n_i;
(b) have no(negative) impact on individuals with upward biased beliefs about n (if beliefs are updated below the threshold $\tilde{n}^i$);
(c) be more likely to impact the decisions of individuals with high initial thresholds $\tilde{n}^i$ [30]

The Combined Treatment provides individuals with information about the true state of the world (High corruption) and corrects beliefs about others' willingness to act. The impact of this treatment on activism depends on three factors: i) whether individuals are already informed about the state of the world θ, ii) whether they have a relatively low or high threshold $\tilde{n}^i$ for participation; and iii) whether they hold incorrect beliefs about n. For individuals who are informed, the impact of the Combined treatment will be the same as the impact of the Belief Correction treatment, i.e., larger for subjects with higher thresholds $\tilde{n}^i$. As in the Information and Belief Correction treatments, the effects of the Combined treatment are larger for uninformed individuals with high thresholds, who are likely to have downward biased beliefs, relative to uninformed with low thresholds.

Prediction 3: The **Combined (COM)** intervention will:
(a) have the same impact as the Belief Correction (BC) treatment on subjects who are already informed about the state of the world;
(b) have the same impact as the Information (I) treatment on uninformed subjects with low threshold for participation $\tilde{n}^i$;
(c) have an impact equal to the sum of the impacts of the I and BC treatments on uninformed subjects with high thresholds for participation.

[30] In this we are guided by our finding that the true percentage of people willing to protest was close to 90%.

An important component of our experimental design is the manipulation of the specific types of activism subjects were presented with at the end of the survey. Conceptually, individuals could engage in different actions sharing the same goal, i.e., the reduction of corruption. Such actions are likely to vary in their benefit and cost functions, therefore leading to different levels of activism and different responsiveness to our treatments of interest. We are particularly interested in actions that vary in the extent to which costs and benefits depend on the (expected) activism of others. Formally, we can assume that different forms of activism differ in the extent to which the expected Net Marginal Benefit of taking action reacts to changes in n_{-i}.

Let us define the expected Marginal Net Benefit of activism as $\Delta(\theta, n_-i)$. To simplify notation, we assume n is large so n_{-i} is approximately equal to n. We can classify different types of activism according to the extent to which $\Delta(\theta, n))$ changes with others' activism, n. Specifically, in the experiment, we employ three specific actions: a Petition (P), a Donation (D), an Informational Video (V). We separate out the parts of the NMB function into those that depend on n (collective action component) and those that do not (intrinsic component). Below we explain why this is the case.

High Collective Action Component - Petition: Signing a petition requires individuals to publicly disclose their support for a cause through the provision of identifying information, e.g., names and contact details. This implies that individuals who sign a petition could be contacted and formally or informally punished. It is reasonable to assume that the likelihood of individual punishment decreases the larger the number of others signing the petition. The benefit function associated with petitioning is also likely to be dependent on n, as the probability of success S increases with the number of people signing the petition. Therefore, the Net Marginal Benefit curve is likely to be increasing in n.

Lower Collective Action Component - Donation: In the case of donations to organizations fighting for a given cause, e.g., against corruption, the cost of acting is independent from n. In fact, donors can keep their identity confidential, hence punishment is unlikely, and the number of others' donating does not impact the individual cost of donating. However, it is still reasonable to assume that the marginal benefit is increasing in n, since the probability that the organization collecting donations will be successful in reaching its goal is increasing in the number of donors, or that the larger the number of other donors, the more likely it is that the NGO is good. Hence, $|\frac{\partial E_\theta(\Delta(n)}{\partial n}|_D$ is greater than zero, yet is it is likely lower than $|\frac{\partial E_\theta(\Delta(n)}{\partial n}|_P$ where the subscripts D and P refer to Donation and Petition, respectively.

Lowest Collective Action Component - Video: We expect watching the informational video to be the action least likely to depend on the (expected) number of others doing the same. In fact, watching the video comes with a purely private cost - the cost of time. As for the expected benefits, it is still possible that individuals find watching the video more likely to be useful for the cause if they think others also watch the video and gain the same information. However, in this case, the probability that the action is successful also depends on the number of people who subsequently act upon the information received through the video. Therefore, the link between the action and number of other acting, n, is especially weak.

Our above assumptions on net benefits of each action are supported by a follow-up survey of 849 Indian men on Qualtrics that we conducted in October-November 2022, as shown in Figure 2.A.2.[31] We expect the different Net Marginal Benefits (NMBs) of the three actions, as well as their differential collective action natures, to affect their responsiveness to our Information, Belief Correction and Combined treatments, as follows:

Prediction 4 - Differential Treatment Effects on the Three Actions

The relative impacts of the treatments on Petition, Donation and Video will depend on the threshold levels associated with each action, with the treatments being most effective on the action with the highest threshold, $\tilde{n}^i$ but lower than true beliefs, and on the elasticity of the NMB curve to the activism of others.

(a) The Belief Correction treatment will be most effective on Petition, and least effective on Video.

(b) The Information treatment will have a larger effect on actions with flatter NMB curves (i.e., less responsiveness of V and C to changes in n) and/or with greater net disutility from acting when $n = 0$, everything else being equal.

(c) The relative impact of the Combined treatment on the different actions is ambiguous.

Prediction 5 - The Choice action vs individual actions Our final action treatment was the choice action where subjects are presented with a choice of the three actions but also can choose to exit the survey as before. Conceptually the choice action might lead to a coordination problem where subjects are uncertain about others' choice and might prefer to take an action only if sufficiently many others are expected to choose it. This logic is most compelling for an action

[31] Specifically, the survey data were collected on 18th, 26th, and 28th October, 2nd - 6th November, and 10th November 2022.

treatment that needed a higher degree of collective action to be successful -i.e. petition as we discussed above. Therefore, we expect that coordination problems lead to lower probability of any one action being chosen in the choice treatment relative to the case when a single action is presented. At the same time, since subjects can self select into the type of action they prefer, the overall likelihood of taking action increases in the choice action relative to exit.

(a) In the choice treatment the likelihood of any one action being chosen is lower relative to the single action treatment.

(b) The overall likelihood of taking any action increases relative to exit.

(c) Conditional on any one action being chosen the treatment effects of Information and belief correction are the same as for the single action groups.

2.2.4 Implementation

In both waves of the study, participation was restricted to Indian subjects who were at-least 18 years of age, with a monthly household income of INR 60,000 or less. We recruited only men, for a number of reasons. First, men are more likely to be in charge of intra-household decision-making regarding health expenditures; they are also more likely to interact with and pay health professionals. They are therefore more likely to have experience with corruption. Second, we expect men to be more likely to engage in activism in India due to patriarchal norms.[32] Finally, we wanted to avoid unnecessary heterogeneities due to differential gender access to computer/mobile devices that would be required for participation in the study.[33][34]

On average, subjects took about 30 minutes to complete the questionnaire from start to finish, and earned a fixed compensation set up by Qualtrics, and an average bonus earning of INR 59.[35]

[32]For example, the sixth round of World Values Survey (2010-2014) shows that in India, 34.2% (22.9%) of male (female) subjects have signed or might sign a petition; 48.3% (29.7%) of male (female) subjects have attended or might attend peaceful demonstrations; 38.2% (22.7%) of male (female) subjects indicate that they have already participated or might participate in “any other forms of protest”. For more information, see `https://www.worldvaluessurvey.org/WVSOnline.jsp`. Additionally, according to Shresth and Verma (2020), the most common motivation for donation is religious beliefs, with men being the key decision-makers in giving to ‘religious organisations’.

[33]64% of subjects participated in the study through a mobile device.

[34]The Wave 1 survey was aimed at understanding individual attitudes and behaviors during the COVID 19 pandemic. This initial survey is used to explore subjects’ (potentially misaligned) beliefs about others’ willingness to act, which then served as the basis of belief correction treatment in the main Wave 2 survey. As shown in Table 2.A.1, Wave 1 survey was conducted approximately a week before Wave 2 survey. We do not find any difference in subjects’ willingness to act between the end of March and the May rounds of Wave 1. Crucially, the initial survey differed from the second wave in one important feature- it did not include any activism treatment, but the action treatments were incorporated in the questionnaire. Thus, the first wave is, on average, about 8 minutes shorter in length than the second wave. Subject recruitment process and the compensation arrangement with Qualtrics were analogous to that of the second wave.

[35]The maximum possible bonus earnings per subject was INR 48 for wave 1, and INR 198 for wave 2.

Individuals were assigned a randomly generated ID and their identities remained unknown to the research team. The payment of the bonus earnings was implemented by Qualtrics within two weeks of the survey completion.

In order to screen out subjects who were not paying attention, the questionnaire included attention checks. In particular, in the middle of the questionnaire, we included a question that, while looking very similar to previous questions (by length and content), asked subjects to select a specific answer choice, to provide confirmation that they read the question, following Oppenheimer et al. (2009). About 24% of participants failed the attention check. While we allowed these subjects to complete the survey, we exclude them from oursample.[36].

2.3 Data and Estimation Strategy

2.3.1 Descriptive Statistics and Balance Tests

Almost 400 Indian men participated in the first wave of the online survey we conducted about a week prior to the main experiment. Table 2.1 shows the number of subjects in each of our treatments in Wave 2, the main sample for our analyses here. Our sample of 1774 men includes subjects from all major states of India as shown in Figure 2.A.3. The majority of our subjects (over 80%) are younger than 45 years of age, unmarried (51%) and with a college degree (78%). Around 49% of the subjects' monthly household income is below INR 30K, i.e., lower than 400 USD. More than half (56%) of the subjects reside with an elderly and 77% had made at least one hospital visit in the 12 months preceding the survey - i.e., from the beginning of the COVID19 pandemic - as shown in Panel A of Table 2.2.

When comparing our sample to a representative sample of urban men from the Periodic Labor Force Survey (2017-18) we see that our average respondent is younger, more educated and belongs to wealthier households than the average Indian urban man, as shown in Table 2.A.2. While this may lead us to individual willingness to engage in activism, under the assumption that wealthier and more educated subjects are more willing to act, we argue that it does not undermine the internal validity of our experiment and its policy relevance. In fact, if wealthier

[36]We also included three comprehension questions prior to the incentivized belief elicitation questions to make sure that subjects understood the payoff structure. This allows us to calculate the number of failed attempts for each subject. Finally, we included in the survey an open-ended question and checked for entries that did not make sense. The very high correlation between failing the attention check, the number of failed attempts for the comprehension questions, and writing ludicrous answers to the open ended question provides further justification to our decision to exclude from the sample the subjects who failed the attention question.

and better educated individuals are more likely to be informed about the social problem and the cause, and have more accurate beliefs about others - a plausible assumption to make - our estimated treatment effects are essentially a conservative measure of the impact of information and belief correction on activism.

Table 2.2 reports balance tests for all our survey measures across the anti-corruption treatment groups. The statistics reported in Panel A, shows that participants' demographics and living standards are balanced across the Activism treatments. In Panel B, we report the average scores of survey-generated indices measuring individual preferences and personality traits, i.e., locus of control, risk preferences, and a pro-sociality index generated from the aggregation of questions measuring trust, altruism and reverse-coded retaliation indices. All indices in Panel B are standardized around the control group mean, as explained in section 2.B, and are therefore expressed in standard deviations from the control group mean. We do not see any imbalances in any of these measures across treatment groups.[37]

Panel C of Table 2.2 reports on four indicators that capture various aspects of corruption in health, i.e., perceptions, information, tolerance, and civic engagement. These indices are also all standardized around the control mean, and therefore expressed in standard deviations from such mean. The *corruption perception* index aggregates answers to three survey questions: (i) personal experience of corruption - in the form of bribery - in the health sector during the pandemic; (ii) individual perception of the prevalence of corruption in the health sector; and (iii) individual opinion on whether the level of corruption has gone up/down since April 2020. The *information* index capture individual awareness of their rights and the occurrence of fraud in the health system. It aggregates answers to a question on knowledge of ongoing rates for intensive care beds in hospitals, and a question on whether subjects (thought that they) had been illegally overcharged by healthcare professionals during a hospital stay. The *tolerance of corruption* combines answers to four questions: (i) the extent to which subjects think that paying a bribe is justifiable, (ii) that avoiding fare on public transportation is justifiable; (iii) that doctors overcharging patients in justifiable; and (iv) subjects' beliefs on how many people in their community would expect them to complain if they were overcharged or asked to pay a bribe by a doctor. Finally, the *civic engagement* index averages subjects' answers to questions regarding their past participation in different types of activism, such as protests, strikes, and petitions, and the extent of their civic involvement through a set of action, such as voting, membership in

[37] Alternatively, balance test by action groups is given in Table 2.A.3.

community groups.

Table 2.2 shows that all individual measures related to corruption and civic engagement are balanced across treatments. The disaggregated data, displayed in Table 3.1, show that nearly all survey participants had personally visited a hospital or had a household member visit a hospital during the pandemic. The majority of them (53%) had experienced corruption in the form of bribery to access health services, 61% of the respondents suspected that they to have been overcharged for a hospital bed, and 71% perceived corruption to have increased during the pandemic. There seems to be considerable level of misinformation about rights and entitlements, with only 34% of the sample knowing about the existence of caps on the prices that can be charged on ICU hospital beds, and only 14% suspecting to have been overcharged for health services. The answers to questions of previous forms of activism show that about one third of the respondents have participated in protests, strikes and/or petitions. A larger proportion (77%) had donated to an organization in the past, although this is not an accurate representation of donations as a form of activism, since our donation question referred to donations to all kinds of organizations.[38]

Panel D of Table 2.2 reports data on subjects' beliefs about other participants' willingness to protest against corruption in the health sector. This is our incentivized measure of beliefs of others' willingness to act, which we then manipulate in the Belief Correction and Combined treatments. The direct measure of individual willingness to act shows that 90% of respondents stated their willingness to act against corruption.[39] However, the average *believed* percentage of others willingness to participate is around 64%, with small differences across treatments (the average believed percentages range from 63 - 66%). A further look at the belief data show that about 60% of the respondents believed the percentage of others willing to act to be lower than the true percentage, and about 20% believed the percentage to be higher than the true percentage. In other words, we observe a substantial misalignment of beliefs in our sample. In contrast, we see very little misalignment in the beliefs regarding the statement on mask wearing, as shown in Panel (a) of Figure 2.A.4. On the other hand, the statement on the need for external auditing of COVID-19 relief funds shows similar overall belief misalignment as our statement of interest.

[38] A recent report by Shresth and Verma (2020) shows that donations towards 'religious organisations' or 'beggars' are the most preferred forms, consisting of roughly 70% and 12% of total market share. Donation towards non-religious organisations- the relevant category for activism- stands at only 5%.

[39] It has been reported that popular protests seem to be on the rise since mid-2000s, all over the world (Ortiz et al., 2022), and India is no exception to this trend. In recent years, tens-of-thousands citizens have shown up to protest against a number of issues, such as citizenship law, farm bill and farmers' rights, slow economic growth, military reform, reservation laws for specific communities etc (Carnegie Endowment for International Peace, 2023).

Panel D of Table 2.2 shows that belief misalignment was generally balanced across treatments, although we do see some evidence of more pronounced upward bias in the Combined treatment than in the Belief Correction treatments (25 versus 21%). We display the cumulative distributions of individual beliefs by treatment in Figure 2.A.5 in the appendix. Kolmogorov-Smirnoff tests of equality of distributions show that the four distributions of beliefs (Control, Information, Belief Correction and Combined) are not significantly different from each other, with the exception of the Combined and the Belief Correction distributions. Finally, we do not see any imbalances in individuals' levels of confidence in their own beliefs, or in their expected bonus earnings from the incentivized sections of the survey.

Overall, we conclude that the individual-level randomization was successful. We account for the slight differences seen in our balance tests by including the full set of individual measures displayed in Table 2.2, in our empirical specification, as discussed in Section 2.3.2.

2.3.2 Estimation Strategy

Our main outcome of interest is subject's "willingness to act" against corruption by either signing the petition, making the donation, watching the how-to-act video, or choosing among these three actions. Our main estimating equation, therefore, is:

$$Y_i = \beta_0 + \beta_1 I_i + \beta_2 BC_i + \beta_3 COM_i + \delta X_i + \varepsilon_i \tag{2.4}$$

where $\mathrm{Y_i}$ is a dummy variable that equals 1 if subject *i* is willing to take an action and 0 otherwise. I_i is an indicator equal to 1 if the individual was assigned to the information treatment, and 0 otherwise. Similarly, BC_i and COM_i are indicators equal to 1 if the individual was assigned to the Belief Correction or the Combined treatment, respectively. The control group is the excluded category. $\mathrm{X_i}$ is a vector of individual characteristics, including demographics (e.g. age, marital status, ethnicity, religion education and household wealth), personality and preference measures, experiences of corruption in the health sector in the previous 12 months, information about and attitudes toward such corruption, as well individual measures of past activism and civic engagement.[40]

[40]Specifically the vector $\mathrm{X_i}$ includes the following variables: (1) locus of control index; (2) The survey-generated indices of risk, trust, altruism and retaliation; (3) indexes of corruption experience, information about corruption and tolerance of corruption; and (4) civic engagement index. Each index is discussed in Section 2.3.1 and summarized in Table 2.2.

Since within each treatment group subjects are randomly assigned to 4 action groups, we estimate equation (1) separately for each anti-corruption action, i.e. for the petition (P), the donation (D), the video (V), and the choice among actions (C) groups. Our main coefficients of interest are β_1, β_2 and β_3, which estimate the impact of each treatment on willingness to engage in a given action, relative to the control group. Heteroskedasticity robust standard errors are reported throughout the analyses. As an alternative specification, we also pool the data and include dummy variables for each action treatment, keeping the donation action (D) as the benchmark, and including interactions between each Action Treatment and each Anti-corruption Treatment. We report estimates from equation (1) in the main text, and estimates from the pooled sample in the appendix.

In order to assess whether it is preferable to give subjects a choice of actions or only one action, within each action treatment (Petition, Donation, Video) we pool the subjects who were only shown one action and those who were given a choice of actions, and we estimate the following equation:

$$\begin{aligned} Y_i =& \beta_0 + \beta_1 I_i + \beta_2 BC_i + \beta_3 COM_i + \theta_1 I_i * C_i + \theta_2 BC_i * C_i + \theta_3 COM_i * C_i \\ &+ \gamma C_i + \delta X_i + \varepsilon_i \end{aligned} \tag{2.5}$$

where Y_i indicates individual i's decision to act within each action treatment - i.e., the decision to sign a petition in the Petition action treatment, to make a donation in the Donation action treatment, and to watch the video in the Video action treatment. C_i is a dummy variable that equals 1 if the subject belongs to the Choice action group, and 0 if he belongs to a single action group. Its estimated coefficient, γ, indicates the impact of giving subjects a choice of actions, rather than presenting one action only, in the Control (anti-corruption) group. Since we include the interactions between each anti-corruption treatment and the Choice action treatment, β_1, β_2 and β_3 are now the impacts of the Information, Belief Correction and Combined treatments, respectively, on willingness to act (i.e., to sign a petition, make a donation or watch the video) when the action is presented on its own rather than as part of the set of action. Finally, θ_1, θ_2 and θ_3 are the differential impacts of each anti-corruption treatment when subjects are given a choice of actions.

As a secondary analysis, we examine heterogeneous effects of the anti-corruption treatments on each action across several individual characteristics that we hypothesize could affect the responsiveness to our treatments: (i) by beliefs about others' willingness to fight corruption; (ii) by information about rights and entitlement; (iii) heterogeneity by perceptions of corruption; and (iv) by tolerance of corruption. When estimating the heterogeneous treatment effects by a given variable of interest, we simply augment equation (1) by adding interactions between that variable and each treatment indicator.

2.4 Results

Our experimental design allows us to test the impact of our Information, Belief Correction and Combined treatments on each of the three actions available to (randomly selected) subjects: signing a petition, making a donation and watching the informational video, as shown in Figure 2.1. When comparing the take-up rates of each action in the Control group, we see that subjects are least likely to donate part of their earnings to the non-profit organization (about 27%) and most likely to be willing to the video (about 62%). Willingness to sign the petition lies in between, with around 39% stating their willingness to sign it. We observe an increase in the willingness to petition due to all three treatments (Panel a), with no significant impacts on donation and watching the how-to-act video. Interestingly, Panel d, the group in which subjects are given a choice of actions suggests a decline in any action taken.

2.4.1 Treatment Effects on Activism

Petition: Table 2.3 presents the estimated treatment effects of our three measures of the Petition action - willingness to sign petition (columns 1-2), signed petition with name (columns 3-4) and signed with full name (columns 5-6). For each outcome we show the estimates without and with controls. Column 2 of Table 2.3 shows that the Information, Belief Correction and Combined treatments increase individuals' willingness to sign a petition by 21.4, 15.1 and 22.2 percentage points, respectively. These correspond to 54.6 percent, 38.5 percent and 56.6 percent increases from the baseline willingness to petition (39.2%) observed in the Control group. The treatment impacts decrease in magnitude but retain statistical significance when refining the outcome variable to account for actual petition signing. In particular, column 4 (6) of Table 2.3 shows that the Information, Belief Correction and Combined treatment manipulations increase the likelihood of signing the petition with a name (with a full name) by 13.7 (11), 15 (14) and 15 (15.6) percentage points, respectively, which correspond to 45.8 (42.6), 50.2 (54.3) and

50.2 (60.5) percent increases over the Control mean.[41] Note that we do not find any significant differences in effect sizes across the three treatment groups as indicated by the p-values of the test of equality of treatment effects in the bottom panel of Table 2.3.

Donation:The estimated impact of our treatments on the donation outcomes are displayed in Table 2.4. Contrary to the positive treatment effects observed for the petition outcomes, we do not see any significant impact of Information and Belief Correction on our three donation outcomes: initial willingness to donate part of one's earnings (columns 1-2); actual decision to donate once on the donation page (columns 3-4) and percentage of earnings donated (columns 5-6). If anything, the combination of information and belief correction seems to lower individuals' tendency to make donations to the non-profit organization with which we partnered, as indicated by the marginally significant negative coefficients on the 'Combined' treatment. While the effect sizes are mostly comparable across treatments, the combined treatment effects are significantly different from the Information and Belief Correction effects for the percentage of earnings donated (column 6).

How-to-act Video: Similar to the other two actions, we employ three measures of willingness to engage in our third form of activism: (1) the initial willingness to watch the 5-minute how-to-act video, as stated in the final survey page; (2) the decision to watch at least 10 seconds of the video; and (3) the number of seconds watched. The estimates, reported in Table 2.5, show that the none of the treatments significantly impacted subjects' willingness to watch the how-to-act video. We hypothesized that the belief correction manipulation would have a more limited impact on this form of activism - as compared to petition and donation - given the more private nature of the costs and benefits associated with the decision to watch the video. This seems to be confirmed by the data. As for the null impact of providing subject with information about the occurrence of corruption in the health sector, as well as their entitlements, it may be partly due to the fact that subjects in the Information and Combined treatments had already watched an informational video (3 minutes long), as part of the study and this may have been disincentivized them from watching another.[42]

[41] We obtain similar results when pooling the data from all the Action Treatments and interacting each Action with each Anti-Corruption treatment, as shown Table 2.A.5 in the appendix.

[42] The minimum detectable effect size (MDES) for the willingness to sign petition outcome is 0.1984, given control group mean=0.3918 & SD=0.4907, significance level=0.05, power=0.8 and assuming equal number of observations in control and treatment group (N=97). The MDES for willingness to donate outcome is 0.1726, given control group mean=0.2667 & SD=0.4443, significance level=0.05, power=0.8 and assuming equal number of observations in control and treatment group (N=105). Finally, the MDES for willingness to watch video is 0.1867, given control group mean=0.6204 & SD=0.4876, significance level=0.05, power=0.8 and assuming equal number of

Robustness: A common issue that arises when employing multiple outcome variables, is that, by increasing the number of inferences made, the likelihood of false positives also increases. In our case, while we do have different measures of activism (Petition, Donation, Video), they are not different proxies for the same variable of interest, generated from the same sample of subjects. Rather, by design, they are different outcomes generated by separate groups of subjects, who were randomly assigned to distinct action treatment groups. Nevertheless, for each action, we employ three outcome measures, as shown in their respective regression tables. To address the possibility of false positives arising from multiple hypothesis testing, we compute the false discovery rate (FDR).[43] and report the sharpened q-values (Benjamini et al., 2006) associated with the impacts of our treatments on the petition outcomes.[44] Table 2.A.6 shows that the our Petition results are robust to the adjustment for multiple hypothesis testing.

Another possible concern stems from the inclusion of a large set of control variables in our empirical specification. Although the results that we obtain with and without controls are highly comparable, we also estimate an alternative specification by using the double LASSO method, which aims to optimise the selection of controls variables when the set of covariates is large (Belloni et al., 2014). The results, reported in Table 2.A.7, show that the impacts of the activism treatments on the three actions are very similar in magnitude and significance to those displayed in our primary regression tables.[45]

2.4.2 Effect of Offering Choice of Actions

Our experimental design allows us to ask whether it is preferable to present subjects with a choice of anti-corruption actions - or more generally, different ways to engage in activism for a given cause - or if presenting one choice only is more likely to affect take-up. In Figure 2.2 we display actual activism in the form of petition signing (panel a), donations made out of one's survey earnings (panel b) and average seconds of how-to-act video watched (panel b) when the corresponding form of activism was presented in isolation or when it was presented together

observations in control and treatment group (N=108).

[43]The FDR is the proportion of rejections that are "false discoveries" (Type I error).

[44]We do not report the q-values generated for the Donation and Video action measures, as the impacts of the treatments were null on such actions.

[45]We also conduct robustness checks by aggregating the variables that compose our preference and corruption-related indices by using the inverse covariance matrix, where the weights are calculated in order to maximize the amount of information captured in each variable, as in Anderson (2008), rather than simple averages. The regression results when we include these differently weighted indexes are unchanged.

with the other actions and subjects were given a chance to engage in one of the actions, or exit the survey. In Table 2.6, for each action (Petition, Donation, Video) we pool the treatment groups that were presented with the individual action and those presented with the full set of actions (Choice treatment) and estimate equation 2 of Section 2.3.2. Figure 2.2 shows that no matter the action under investigation, providing an action within a set of possible actions lowers the likelihood that a subject would engage in that action, as indicated by the significantly lower yellow bars in panels a, b and c. However, when we pool all single action groups, then Figure 2.3 shows higher proportion willing to take any action in the Choice treatment.

This result is confirmed by the regression analysis as well in Table 2.6. The estimated coefficient of the Choice indicator in Table 2.6 is negative and significant in all specifications and Action treatment groups. Focusing on the estimates in columns 1 to 3, for Petition, we also note that while the treatments have significant positive impacts on activism when the petition is presented to subjects in isolation (i.e. the non-interaction coefficients, which confirms the estimates in Table 2.3), such impacts are significantly lower when the petition is presented together with the donation and the how-to-act video (i.e., the negative coefficients on the interaction terms). In fact, the joint presentation of the three actions annuls the impact of the anti-corruption treatments on the willingness to sign the petition. The coefficients on the 'choice' variable is significantly negative for all three actions: petition (columns 1 - 3), donation (columns 4 - 6) and watching how-to-act video (columns 7 - 9).

Overall, our comparison of our Choice versus No Choice treatments indicate that, in order to induce subjects to act on a specific cause, it is beneficial to encourage them to engage with only one action. However, without any intervention, subjects are more likely to take any action when offered choice as shown in Table 2.7. Columns 1 - 3 show the effect of choice, while columns 4 - shows the converse effect on exiting the survey relative to single action treatment groups. The coefficient on choice is insignificant in columns 1-2 and 4-5. But column 3 (6) shows that relative to the control group providing choice increases (decreases) the probability of taking any action (exiting) by 11.9 percentage points. Surprisingly, the probability of taking action (exiting) falls (increases) due to the treatments, as indicated by the interaction terms in column 3 (6).

2.4.3 Heterogeneity of Treatment Effects on Activism

An important hypothesis, which motivated our experiment design, is that subjects may be reluctant to act against corruption if they believe that the number of others willing to join the fight is low. We also assumed, and empirically found, that subjects may hold incorrect beliefs about others' willingness to act against corruption. In Table 2.8, we report estimates generated by regression analyses that include interactions between our anti-corruption treatment and a dummy variable equal to 1 if the respondent held downward biased (about 60 percent of our sample) or correct (about 20 percent of our sample) beliefs and 0 if he held upward biased beliefs about the percentage of other participants willing to protest against fraud in the health sector (according to our incentivized belief measure). Thus the coefficients on the uninteracted treatment dummies in Table 2.8 indicate the impacts of the treatments on subjects holding downward biased or correct beliefs. The estimated coefficients show that the Belief Correction treatment operated - at least on the Petition action (columns 1-3) - as hypothesized, i.e., by increasing the likelihood to act among subjects that held incorrect downward-biased beliefs about others. We note that the impact on the Belief Correction treatment on the propensity of these subjects to sign the petition is substantial, i.e. 25.9 - 30.3 percentage point higher than the Control mean, which translates into a 100% increase in the likelihood to act in the Petition Action group.[46]The impacts of the Information and Combined treatments are also large, corresponding to a 56% and a 61% increase in the likelihood of signing the petition with the full name, as shown in column 3.

The negative and significant coefficients on the interaction between Belief Correction and the upward bias dummy indicates that the impact of the treatment on subjects with upward-biased beliefs was significantly lower than the impact on the downward-biased individuals (columns 1-3). In fact, the sum of the relevant coefficients indicate that the Belief Correction induced the upward biased individuals to adjust their beliefs downward and, consequently, lower their propensity to sign the petition. The results obtained for the upward- and the downward-biased individuals are consistent with our model of strategic complementarities in the decision to act through petition signing. We do not find a similar effect on donation and video action groups in Table 2.8(columns 4 - 9).[47]

Naturally, we expect the provision of information on individual entitlements in the context of health services and on the occurrence of corruption in the health sector to have a larger impact on uninformed subjects, and on subjects who erroneously perceive corruption in the health sector to be low. In Table 2.9 and Table 2.10, we test these hypotheses by interacting our anti-corruption

[46]For example, from column 3 of Table 2.8, we find an almost 25 percentage point increase in actual signing with full name than the control mean (0.258), which translates in a 100% increase in the likelihood to act by signing with the full name in the Petition Action group.

[47]When breaking up the subjects into 3 groups- those who held downward biased beliefs, those with correct beliefs, and those who had upward biased beliefs, we get somewhat similar results in Table 2.A.8, but likely under-powered because adding more interactions.

treatments with, respectively, our indicator for *information* on own rights in the health sector and our indicator of *perceptions of corruption*.

The estimates displayed in Table 2.9 for the Petition outcomes (columns 1-3) confirm that the uninformed are significantly and positively impacted by all treatments. While the coefficients of the interaction terms are not statistically significant, the tests conducted on the linear combinations of the estimated coefficients show that the Information and Combined treatment are not effective on the most ex-ante informed subjects, whereas the Belief Correction treatment remains effective no matter the initial level of information. Similarly, the estimates displayed for the petition action group in Table 2.10 reveal that perceptions of corruption do not affect subjects' responsiveness to any of the treatments, i.e. no matter their perceptions of corruption in the health sector, subjects become more likely to sign the petition in the information and belief correction treatment as compared to the control group. Columns 4 to 6 of Table 2.10 also show that the negative impact of the Combined treatments on the decision to make a donation is driven by subjects who perceive the level of corruption in the health sector to be low. Finally, perceptions of corruption in the health sector also affect responsiveness to treatments in the Video action group (columns 7 - 9), where we see that the higher the perceptions of corruption, the lower the responsiveness to the Information and Belief Correction manipulations, as indicated by the negative coeffcients on the interaction terms.

Finally, we test whether subjects' tolerance or justification of corruption may soften the effects of our anti-corruption treatments. To this end, we interact our treatments with the *tolerance of corruption* index. Table 2.11 confirms that the treatments positively impact the willingness to sign the petition of the individuals who are less tolerant of corruption (columns 1 -3). The total impacts of the treatments on the more tolerant subjects, however, are not statistically significantly different from zero, as shown by the high p-values in the bottom panel.[48]

2.5 Discussion

The above findings indicate that the relative costs and benefits of modes of activism can vary and interventions that create awareness or correct beliefs can be effective in increasing activism depending on the relative net benefits. Our results confirm the theoretical prediction that in

[48] We also conducted exploratory analyses of heterogeneous treatment effects by subjects' household income, education, pro-sociality, and past activism. Results can be found in Appendix Tables 2.A.9, 2.A.10 2.A.11 and 2.A.12.

our setting, activism in the form of petition signing can be modeled as a game of strategic complements rather than substitutes.

However, offering subjects the choice of multiple actions significantly increases the probability of any action being taken by the subject relative to the control group. By presenting three actions and asking subjects to choose among them, we generated the need for respondents to coordinate on one action. Hence no single action could be successfully taken up by a large enough mass of participants. The interventions along with choice of actions lowered the probability of any action being taken possibly because the subjects became aware of coordination issues.

Further, the heterogeneity results show that people with upward biased beliefs have high thresholds of participation. Thus, correcting their belief or providing information lowers their activism. But since the majority hold downward biased beliefs, the overall effect of both interventions significantly raises the petition action.

2.6 Conclusion

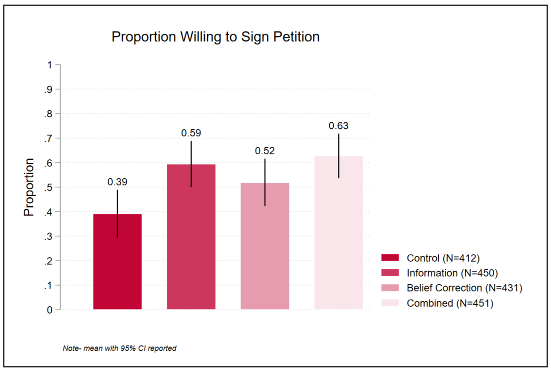
We designed and implemented an online experiment embedded in a survey involving 2000 Indian men to examine whether raising awareness about a specific cause – reducing fraud in the health sector during the COVID-19 pandemic – or correcting beliefs about others' willingness to act for the cause, or both, could affect citizens' participation in activism. Within each activism treatment arm, we experimentally varied the type of activism subjects were given a chance to engage in. We chose three actions that vary in their actual and expected costs and benefits, and, in particular, the extent to which their costs and benefits depend on (beliefs about) others' willingness to engage in the same action. These were: 1) signing a petition to the Ministry of Health (which we assumed to be the most dependent on beliefs), 2) watching a 5-minute video on how to act (assumed to be the least dependent on beliefs), and 3) making a donation to an organization involved in anti-corruption (assumed to be in between the other two). We also randomly selected one fourth of our survey participants to be presented with all actions and be given the chance to choose one of them.

Our results show heterogeneity in the extent to which information and beliefs about others affect one's decision to act. In particular, the decision to donate to an organization fighting for the cause and the decision to watch a 5 minute video on possible ways to help the cause are unaffected by both information about the occurrence of corruption, and by information about the percentage of others' willingness to act. In contrast, both providing information and correcting downward-biased beliefs about others' activism (and the combination of information and belief correction) significantly impacted individuals' likelihood to sign a petition to the Ministry of Health, i.e., the form of activism that we assumed to be most affected by collective action problems. Our findings on the role that beliefs about others play in individuals' decision to sign a petition provide empirical support to recent theoretical studies that model social activism as a game of strategic complements. Finally, the comparison of observed activism when subjects are asked to engage in one action versus when they are presented with a set of actions reveals that providing a choice of actions is undesirable as it significantly reduces subjects' willingness to engage in any of the actions, as compared to presenting the action in isolation.

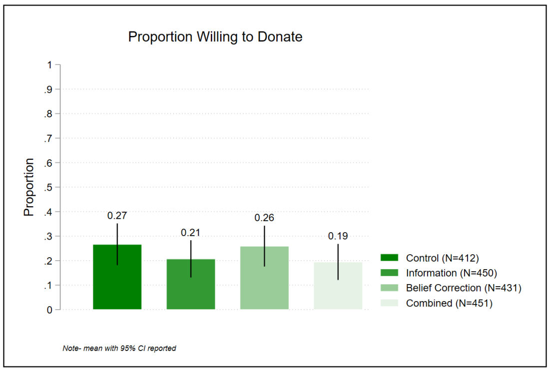
2.7 Tables and Figures

Figure 2.1: Activism Treatments and Willingness to Take Action

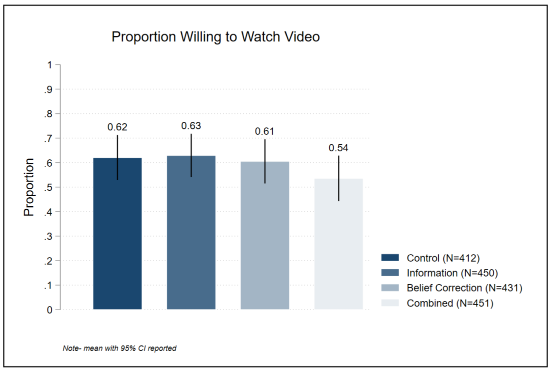
(a): Petition



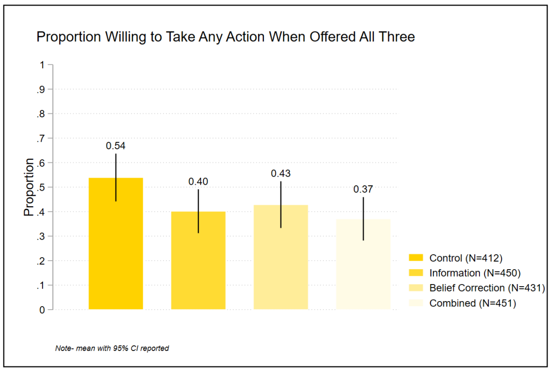
(b): Donation



(c): Watch Video



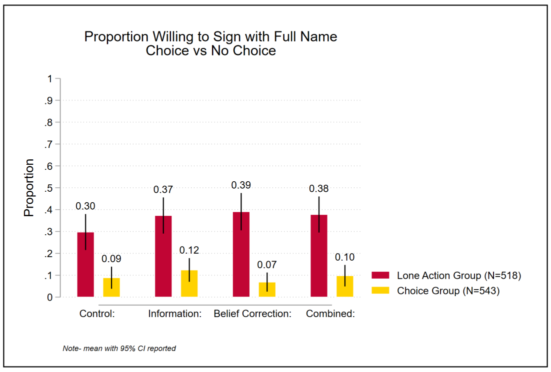
(d): Offered All Three Actions



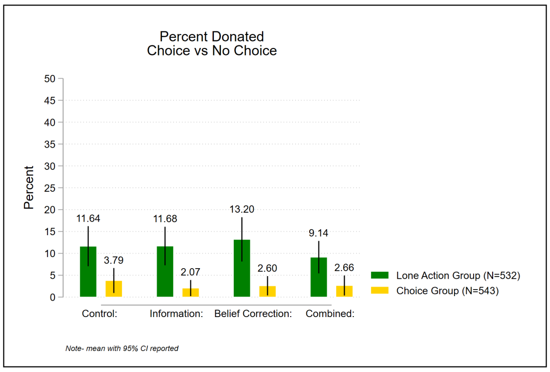
Notes: The four figures show the percentages of participants willing to sign a petition (a), make a donation (b), watch an informational video (c) and engage in any of the three actions when given the choice (1), in each activism treatment (Control, Information, Belief Correction and Combined). Subjects were presented with one of the three actions or given a choice between the actions, at the end of the survey, as part of our experimental design. The figures display percentages and 95% confidence intervals.

Figure 2.2: Activism with or without a Choice of Actions

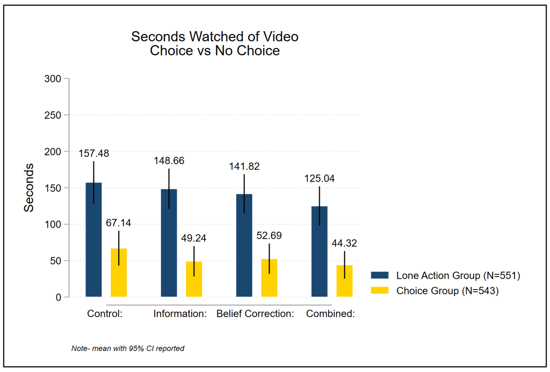
(a) Petition



(b) Donation

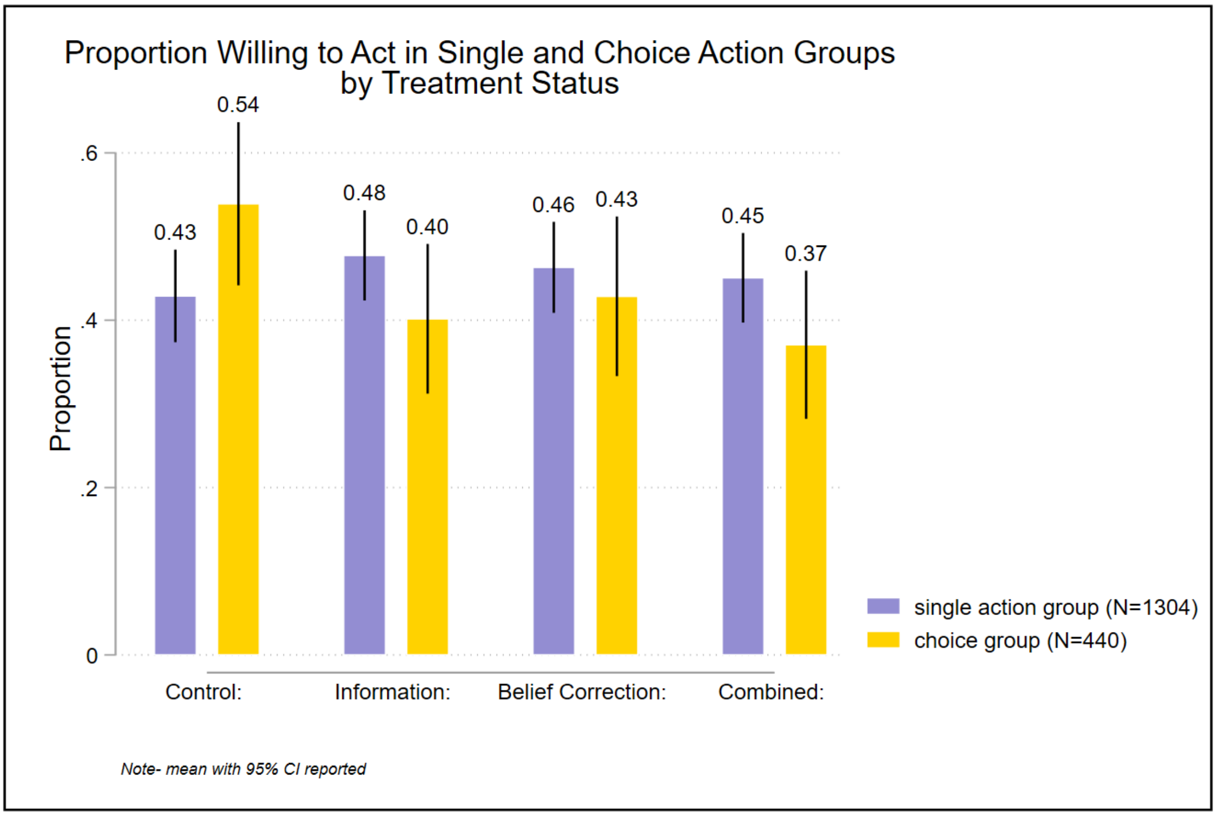


(c) Watch Video



Notes: The three figures show (a) the percentage of participants who signed a petition with their full name (b), the percentage of earnings donated (c), the average number of seconds of the 5 minute video watched in each activism treatment (Control, Information, Belief Correction and Combined), when the action was presented in isolation versus when subjects were given a choice of actions. The figures display percentages and 95% confidence intervals.

Figure 2.3: Proportion Willing to Act in Single and Choice Action Groups by Treatment Status



Source: The figure shows the percentages of participants willing to act instead of exiting, in each activism treatment (Control, Information, Belief Correction and Combined), & by the type of action offered (Choice, or no choice (i.e., Petition, Donation, or How-to-act video)). Subjects were presented with the option of exiting, or taking part in one of the three actions or given a choice between the actions, at the end of the survey, as part of our experimental design. The figures display percentages and 95% confidence intervals.

Table 2.1: Treatments

	Action Treatments				
	Petition	Donation	Video	Choice	All
Activism Treatments					
Control (C)	97	105	108	102	412
Information (I)	106	111	116	117	450
Belief Correction (BC)	104	108	114	105	431
Combined (COM)	110	113	112	116	451
Total	417	437	450	440	1744

Notes: Table shows the number of subjects assigned randomly into each of the Activism and Action treatment cells in the 4 x 4 experimental design. All 1744 subjects passed the attention check criteria.

Table 2.2: Balance on Observable Characteristics

Variable	Total (1)	Control (2)	Information (3)	Belief Correction (4)	Combined (5)	Difference (2)-(3)	 (2)-(4)	 (2)-(5)	 (3)-(4)	 (3)-(5)	 (4)-(5)
A. Demographics											
Age 45+	0.145	0.129	0.149	0.144	0.157	-0.020	-0.015	-0.029	0.005	-0.009	-0.014
Married	0.490	0.464	0.480	0.503	0.512	-0.016	-0.040	-0.049	-0.023	-0.032	-0.009
SC\ST	0.264	0.272	0.264	0.246	0.275	0.007	0.026	-0.003	0.019	-0.011	-0.029
Hindu	0.769	0.784	0.769	0.740	0.783	0.015	0.044	0.001	0.029	-0.014	-0.043
College	0.782	0.779	0.802	0.763	0.780	-0.023	0.016	-0.001	0.039	0.022	-0.017
Income	0.494	0.517	0.513	0.480	0.466	0.004	0.037	0.051	0.033	0.048	0.015
Elderly	0.563	0.563	0.549	0.538	0.599	0.014	0.025	-0.036	0.011	-0.050	-0.060*
B. Preferences											
Locus of Control	0.059	0.000	0.039	0.099	0.093	-0.039	-0.099	-0.093	-0.060	-0.054	0.006
Risk	0.001	-0.000	-0.044	0.028	0.022	0.044	-0.028	-0.022	-0.072	-0.065	0.006
Pro-sociality	-0.034	-0.000	-0.029	-0.041	-0.062	0.029	0.041	0.062	0.012	0.032	0.021
C. Corruption											
Perception	0.053	-0.000	0.067	0.043	0.097	-0.067	-0.043	-0.097	0.024	-0.029	-0.053
Information (Rights)	0.027	-0.000	0.002	-0.000	0.102	-0.002	0.000	-0.102	0.002	-0.100	-0.103
Tolerance	0.052	-0.000	0.038	0.087	0.081	-0.038	-0.087	-0.081	-0.050	-0.043	0.006
Civic Engagement	0.064	-0.000	0.054	0.040	0.157	-0.054	-0.040	-0.157**	0.015	-0.102	-0.117*
D. Belief and Earning from Survey											
Bias (↑)	0.222	0.238	0.213	0.255	0.184	0.025	-0.017	0.054*	-0.042	0.029	0.071**
belief about others' willingness to protest (%)	64.077	64.709	63.044	65.986	62.705	1.664	-1.277	2.004	-2.942*	0.339	3.281**
Confidence	4.268	4.260	4.251	4.316	4.246	0.009	-0.056	0.014	-0.064	0.005	0.069
Expected Bonus Earning	138.801	138.532	136.778	142.497	137.534	1.754	-3.965	0.997	-5.719	-0.757	4.962
N	1744	412	450	431	451						
F-test of joint significance [p-value]						[0.994]	[0.841]	[0.522]	[0.830]	[0.892]	[0.303]

*Notes:*SC (Schedule Caste) and ST (Scheduled Tribe) are socio-economically deprived individuals in India; 'income' indicates subjects with monthly household income below INR 30 thousand in the previous month; 'elderly' indicates subjects who say 'yes' to the question "In your household, do you have elderly (above 60) living with you?"; Locus of control, risk and pro-sociality indices are standardized measures of self-assessment as explained in subsection 3.B.1 of the Appendix; indices of corruption perception, information (rights), corruption tolerance and civic engagement are created by aggregating standardised responses of relevant survey questions as described in subsection 3.B.1 ; 'bias(↑)' is a dummy equal to 1 if the subject overestimated the true willingness to protest, 0 otherwise; 'belief about others' willingness to protest' indicates subjects' guess about percentage of previous participants agreeing with the statement "I am willing to raise my voice and participate in a protest against corruption in the provision of health service."; 'confidence' indicates how confident a subject is, in his aforementioned belief on a scale of 1 to 5, with 5 being the most confident; 'expected bonus earning' is the subject's guess about his bonus earnings from this experiment. p-values of F-tests of joint significance of variables reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.3: Treatment Effects on Activism: Petition

	Sign Petition?		Signed with Name		Signed with Full Name	
	(1)	(2)	(3)	(4)	(5)	(6)
Information	0.203***	0.214***	0.116*	0.137**	0.091	0.110*
	(0.069)	(0.070)	(0.067)	(0.070)	(0.064)	(0.066)
Belief Correction	0.127*	0.151**	0.134**	0.150**	0.127*	0.140**
	(0.070)	(0.072)	(0.068)	(0.073)	(0.065)	(0.069)
Combined	0.236***	0.222***	0.137**	0.150**	0.142**	0.156**
	(0.068)	(0.071)	(0.067)	(0.072)	(0.065)	(0.069)
Equality of treatment effects [p-value]						
Information = Belief Correction	[0.275]	[0.368]	[0.797]	[0.859]	[0.595]	[0.656]
Information = Combined	[0.621]	[0.912]	[0.753]	[0.852]	[0.441]	[0.498]
Belief Correction = Combined	[0.111]	[0.324]	[0.957]	[0.995]	[0.819]	[0.822]
Control Outcome Mean	0.392	0.392	0.299	0.299	0.258	0.258
Controls	NO	YES	NO	YES	NO	YES
Observations	417	417	417	417	417	417
R^2	0.032	0.163	0.013	0.105	0.013	0.133

Notes: Controls include demographics: age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home. We also control for indices of: locus of control, risk, pro-sociality, perceptions of corruption perception, information about rights and entitlements, tolerance of corruption, past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies included. Robust standard errors in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.4: Treatment Effects on Activism: Donation

	Make Donation?		Donated Positive Amount		Percent Donated	
	(1)	(2)	(3)	(4)	(5)	(6)
Information	-0.059	-0.053	-0.068	-0.055	1.637	3.044
	(0.058)	(0.055)	(0.058)	(0.055)	(3.361)	(3.142)
Belief Correction	-0.007	-0.026	-0.026	-0.044	2.971	0.624
	(0.061)	(0.055)	(0.060)	(0.053)	(3.594)	(2.966)
Combined	-0.072	-0.107*	-0.099*	-0.134**	-2.635	-5.028*
	(0.057)	(0.055)	(0.056)	(0.053)	(2.867)	(2.623)
Equality of treatment effects [p-value]						
Information = Belief Correction	[0.365]	[0.629]	[0.449]	[0.840]	[0.720]	[0.479]
Information = Combined	[0.816]	[0.323]	[0.563]	[0.131]	[0.157]	[0.006]
Belief Correction = Combined	[0.254]	[0.143]	[0.183]	[0.081]	[0.088]	[0.054]
Control Outcome Mean	0.267	0.267	0.267	0.267	9.714	9.714
Controls	NO	YES	NO	YES	NO	YES
Observations	437	437	437	437	437	437
R^2	0.006	0.281	0.008	0.299	0.007	0.343

Notes: Controls include demographics: age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home. We also control for indices of: locus of control, risk, pro-sociality, perceptions of corruption perception, information about rights and entitlements, tolerance of corruption, past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies included. Robust standard errors in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.5: Treatment Effects on Activism: Informational Video

	Watch Video?		Watched $>$ 10 Seconds		Seconds Watched	
	(1)	(2)	(3)	(4)	(5)	(6)
Information	0.009	-0.026	0.029	-0.001	9.657	-1.487
	(0.065)	(0.066)	(0.066)	(0.067)	(22.752)	(23.516)
Belief Correction	-0.015	-0.062	-0.013	-0.045	-11.319	-25.540
	(0.066)	(0.068)	(0.067)	(0.069)	(22.283)	(23.566)
Combined	-0.085	-0.084	-0.083	-0.080	-11.567	-12.699
	(0.067)	(0.069)	(0.067)	(0.069)	(22.566)	(23.621)
Equality of treatments [p-value]						
Information = Belief Correction	[0.709]	[0.580]	[0.520]	[0.520]	[0.336]	[0.296]
Information = Combined	[0.153]	[0.379]	[0.088]	[0.243]	[0.337]	[0.624]
Belief Correction = Combined	[0.293]	[0.748]	[0.291]	[0.619]	[0.991]	[0.577]
Control Outcome Mean	0.620	0.620	0.574	0.574	149.198	149.198
Controls	NO	YES	NO	YES	NO	YES
Observations	450	450	450	450	450	450
R^2	0.006	0.120	0.007	0.119	0.003	0.098

Notes: Controls include demographics: age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home. We also control for indices of: locus of control, risk, pro-sociality, perceptions of corruption perception, information about rights and entitlements, tolerance of corruption, past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies included. Robust standard errors in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.6: Treatment Effects on Action (Choice vs. No Choice of Action)

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Choice	-0.237***	-0.151**	-0.157***	-0.196***	-0.195***	-5.354**	-0.292***	-0.243***	-81.478***
	(0.061)	(0.059)	(0.054)	(0.046)	(0.045)	(2.282)	(0.067)	(0.068)	(20.990)
Information	0.217***	0.140**	0.114*	-0.052	-0.057	2.880	-0.016	0.009	3.513
	(0.068)	(0.067)	(0.064)	(0.054)	(0.054)	(3.074)	(0.065)	(0.066)	(22.683)
Belief Correction	0.143**	0.151**	0.137**	-0.018	-0.037	1.807	-0.050	-0.039	-20.929
	(0.070)	(0.069)	(0.066)	(0.054)	(0.052)	(2.956)	(0.066)	(0.067)	(22.464)
Combined	0.238***	0.156**	0.164**	-0.088*	-0.115**	-3.616	-0.094	-0.090	-14.889
	(0.068)	(0.068)	(0.065)	(0.052)	(0.050)	(2.400)	(0.067)	(0.068)	(22.824)
Information x *Choice*	-0.212**	-0.144*	-0.088	0.018	0.023	-5.686	-0.114	-0.135	-20.927
	(0.085)	(0.082)	(0.076)	(0.062)	(0.062)	(3.543)	(0.089)	(0.090)	(28.767)
Belief Correction x *Choice*	-0.212**	-0.228***	-0.180**	-0.028	-0.010	-5.224	0.033	0.017	6.795
	(0.085)	(0.082)	(0.077)	(0.061)	(0.059)	(3.404)	(0.096)	(0.097)	(29.178)
Combined x *Choice*	-0.257***	-0.180**	-0.152**	0.087	0.111*	3.030	-0.074	-0.077	-12.340
	(0.084)	(0.082)	(0.077)	(0.061)	(0.059)	(3.137)	(0.091)	(0.091)	(28.768)
Control Outcome Mean	0.266	0.171	0.216	0.164	0.164	6.763	0.481	0.457	110.773
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	857	857	857	877	877	877	890	890	890
R^2	0.273	0.181	0.184	0.282	0.288	0.300	0.196	0.171	0.154

Note: Each column includes the sub-sample of the relevant action group (Petition: columns 1-3; Donation: columns 4-6; Video: columns 7-9) and the choice group. The outcome variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), or if signed with full name (col 2) or if signed with any name (col 3); is a dummy that equals 1 if willing to donate (col 4), is a dummy that equals 1 if donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); is a dummy that equals 1 if willing to watch video (col 7), is a dummy that equals 1 if the subject watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.7: Exit and Engagement Rates by Treatment Status

	Willing to Take Any Action			Willing to Exit		
	(1)	(2)	(3)	(4)	(5)	(6)
Choice	-0.017	-0.017	0.119**	0.017	0.017	-0.119**
	(0.027)	(0.027)	(0.055)	(0.027)	(0.027)	(0.055)
Information		0.001	0.049		-0.001	-0.049
		(0.033)	(0.038)		(0.033)	(0.038)
Belief Correction		-0.010	0.027		0.010	-0.027
		(0.034)	(0.039)		(0.034)	(0.039)
Combined		-0.041	0.008		0.041	-0.008
		(0.033)	(0.039)		(0.033)	(0.039)
Information x *Choice*			-0.192**			0.192**
			(0.075)			(0.075)
Belief Correction x *Choice*			-0.146*			0.146*
			(0.079)			(0.079)
Combined x *Choice*			-0.192**			0.192**
			(0.075)			(0.075)
Control Outcome Mean	0.432	0.432	0.432	0.568	0.568	0.568
Controls?	YES	YES	YES	YES	YES	YES
Observations	1744	1744	1744	1744	1744	1744
R^2	0.087	0.088	0.093	0.087	0.088	0.093

Note: The dependent variable for columns 1 to 3 is a dummy equal to 0 if the subject clicked on the exit button; 1 if he chose to take any action. The dependent variable for columns 3 to 6 is a dummy equal to 1 if the subject clicked on the exit button; 0 if he chose to take any action. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.8: Heterogeneity by Belief Mismatch

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information	0.262***	0.164**	0.156**	-0.058	-0.067	1.841	0.001	0.025	9.016
	(0.080)	(0.079)	(0.075)	(0.064)	(0.064)	(3.630)	(0.075)	(0.075)	(27.192)
Belief Correction	0.303***	0.260***	0.259***	-0.030	-0.044	0.102	-0.043	-0.035	-15.529
	(0.082)	(0.083)	(0.079)	(0.066)	(0.064)	(3.811)	(0.077)	(0.076)	(26.123)
Combined	0.307***	0.191**	0.182**	-0.114*	-0.148**	-5.862*	-0.063	-0.063	-5.596
	(0.080)	(0.081)	(0.076)	(0.066)	(0.063)	(3.229)	(0.076)	(0.076)	(25.787)
Information x Bias (↑)	-0.096	-0.043	-0.134	0.016	0.046	4.614	-0.131	-0.123	-52.085
	(0.162)	(0.162)	(0.154)	(0.123)	(0.122)	(7.378)	(0.163)	(0.170)	(56.104)
Belief Correction x Bias (↑)	-0.541***	-0.396**	-0.421***	0.014	-0.010	1.549	-0.104	-0.055	-51.301
	(0.157)	(0.166)	(0.154)	(0.120)	(0.114)	(5.777)	(0.166)	(0.180)	(58.141)
Combined x Bias (↑)	-0.305*	-0.135	-0.068	0.032	0.065	3.248	-0.115	-0.085	-34.895
	(0.161)	(0.167)	(0.163)	(0.118)	(0.116)	(5.038)	(0.182)	(0.191)	(63.447)
Bias (↑)	0.233**	0.092	0.052	-0.051	-0.044	-3.183	0.188	0.131	54.865
	(0.114)	(0.115)	(0.109)	(0.083)	(0.081)	(3.188)	(0.118)	(0.131)	(42.205)
I + I x Bias (↑) [p value]	[0.242]	[0.391]	[0.875]	[0.697]	[0.840]	[0.321]	[0.369]	[0.519]	[0.375]
BC + BC x Bias (↑) [p value]	[0.078]	[0.347]	[0.221]	[0.873]	[0.569]	[0.700]	[0.317]	[0.584]	[0.204]
COM + COM x Bias (↑) [p value]	[0.988]	[0.704]	[0.432]	[0.400]	[0.390]	[0.517]	[0.286]	[0.402]	[0.489]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.192	0.122	0.152	0.281	0.300	0.344	0.122	0.120	0.101

*Notes:*The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). The symbols I, BC and COM stand for information, belief correction and combined treatments respectively. 'Bias(↑)' is a dummy equal to 1 if the subject overestimated the true willingness to protest, 0 otherwise. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.9: Heterogeneity by Information about Rights and Entitlements

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information	0.213***	0.139**	0.115*	-0.054	-0.056	3.022	-0.026	-0.002	-1.711
	(0.071)	(0.070)	(0.067)	(0.055)	(0.055)	(3.154)	(0.067)	(0.068)	(23.490)
Belief Correction	0.170**	0.171**	0.155**	-0.025	-0.045	0.619	-0.062	-0.046	-24.896
	(0.071)	(0.072)	(0.069)	(0.055)	(0.053)	(2.970)	(0.069)	(0.069)	(23.574)
Combined	0.234***	0.162**	0.167**	-0.102*	-0.132**	-5.092*	-0.084	-0.078	-11.619
	(0.071)	(0.072)	(0.069)	(0.056)	(0.054)	(2.629)	(0.069)	(0.070)	(23.581)
Information x Information (Rights)	-0.040	0.026	0.040	0.051	0.045	1.548	0.009	0.005	-10.542
	(0.076)	(0.076)	(0.068)	(0.052)	(0.051)	(2.979)	(0.067)	(0.068)	(23.773)
Belief Correction x Information (Rights)	0.099	0.150**	0.104	0.072	0.047	2.660	-0.002	0.001	-18.168
	(0.068)	(0.071)	(0.067)	(0.065)	(0.060)	(3.411)	(0.073)	(0.074)	(24.646)
Combined x Information (Rights)	-0.128**	-0.109*	-0.096	-0.003	0.013	1.844	0.007	-0.020	-22.244
	(0.064)	(0.066)	(0.063)	(0.049)	(0.048)	(2.281)	(0.068)	(0.069)	(23.047)
Information (Rights)	0.093**	0.051	0.044	-0.007	-0.005	0.096	0.044	0.075	30.677
	(0.047)	(0.048)	(0.043)	(0.043)	(0.043)	(1.946)	(0.050)	(0.051)	(18.639)
I + I x Information (Rights) [p value]	[0.103]	[0.137]	[0.122]	[0.964]	[0.877]	[0.289]	[0.858]	[0.977]	[0.728]
BC + BC x Information (Rights) [p value]	[0.006]	[0.002]	[0.009]	[0.581]	[0.976]	[0.455]	[0.500]	[0.641]	[0.211]
COM + COM x Information (Rights) [p value]	[0.235]	[0.569]	[0.424]	[0.120]	[0.075]	[0.352]	[0.403]	[0.302]	[0.320]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.184	0.132	0.151	0.286	0.302	0.344	0.121	0.119	0.101

*Notes:*The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). The symbols I, BC and COM stand for information, belief correction and combined treatments respectively. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Information (rights) is created by aggregating standardised responses of survey questions related to individual's initial information of rights and entitlements in healthcare, as described in subsection 3.B.1 of the Appendix. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.10: Heterogeneity by Perception of Corruption

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information	0.209***	0.129*	0.104	-0.056	-0.057	3.050	-0.021	0.003	0.031
	(0.072)	(0.070)	(0.067)	(0.055)	(0.055)	(3.175)	(0.066)	(0.067)	(23.484)
Belief Correction	0.147**	0.143*	0.134*	-0.025	-0.044	0.625	-0.053	-0.035	-23.113
	(0.073)	(0.074)	(0.070)	(0.054)	(0.053)	(2.982)	(0.068)	(0.069)	(23.661)
Combined	0.221***	0.155**	0.165**	-0.104*	-0.130**	-4.852*	-0.076	-0.070	-10.393
	(0.073)	(0.073)	(0.070)	(0.054)	(0.052)	(2.605)	(0.068)	(0.069)	(23.645)
Information x Perception	0.055	0.093	0.077	0.089*	0.068	1.156	-0.041	-0.034	-21.885
	(0.062)	(0.065)	(0.064)	(0.053)	(0.054)	(3.415)	(0.058)	(0.061)	(23.448)
Belief Correction x Perception	0.012	0.078	0.063	0.063	0.068	2.316	-0.125**	-0.120*	-33.304
	(0.067)	(0.073)	(0.071)	(0.055)	(0.052)	(3.047)	(0.062)	(0.065)	(22.543)
Combined x Perception	0.001	-0.035	-0.065	0.152***	0.156***	5.766**	-0.136**	-0.154**	-44.913**
	(0.064)	(0.071)	(0.071)	(0.052)	(0.051)	(2.647)	(0.063)	(0.066)	(22.389)
Perception	-0.046	-0.092*	-0.084	-0.151***	-0.140***	-5.333**	0.095**	0.071	11.246
	(0.049)	(0.051)	(0.051)	(0.040)	(0.040)	(2.103)	(0.047)	(0.051)	(17.124)
I + I x Perception [p value]	[0.002]	[0.016]	[0.041]	[0.626]	[0.866]	[0.297]	[0.461]	[0.730]	[0.491]
BC + BC x Perception [p value]	[0.098]	[0.028]	[0.040]	[0.599]	[0.728]	[0.448]	[0.045]	[0.097]	[0.073]
COM + COM x Perception [p value]	[0.009]	[0.195]	[0.260]	[0.511]	[0.718]	[0.801]	[0.022]	[0.021]	[0.089]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.165	0.116	0.145	0.295	0.315	0.350	0.133	0.134	0.107

*Notes:*The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). The symbols I, BC and COM stand for information, belief correction and combined treatments respectively. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. 'Perception' is created by aggregating standardised responses of survey questions related to individual's perception of corruption in healthcare, as described in subsection 3.B.1 of the Appendix. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.11: Heterogeneity by Tolerance of Corruption

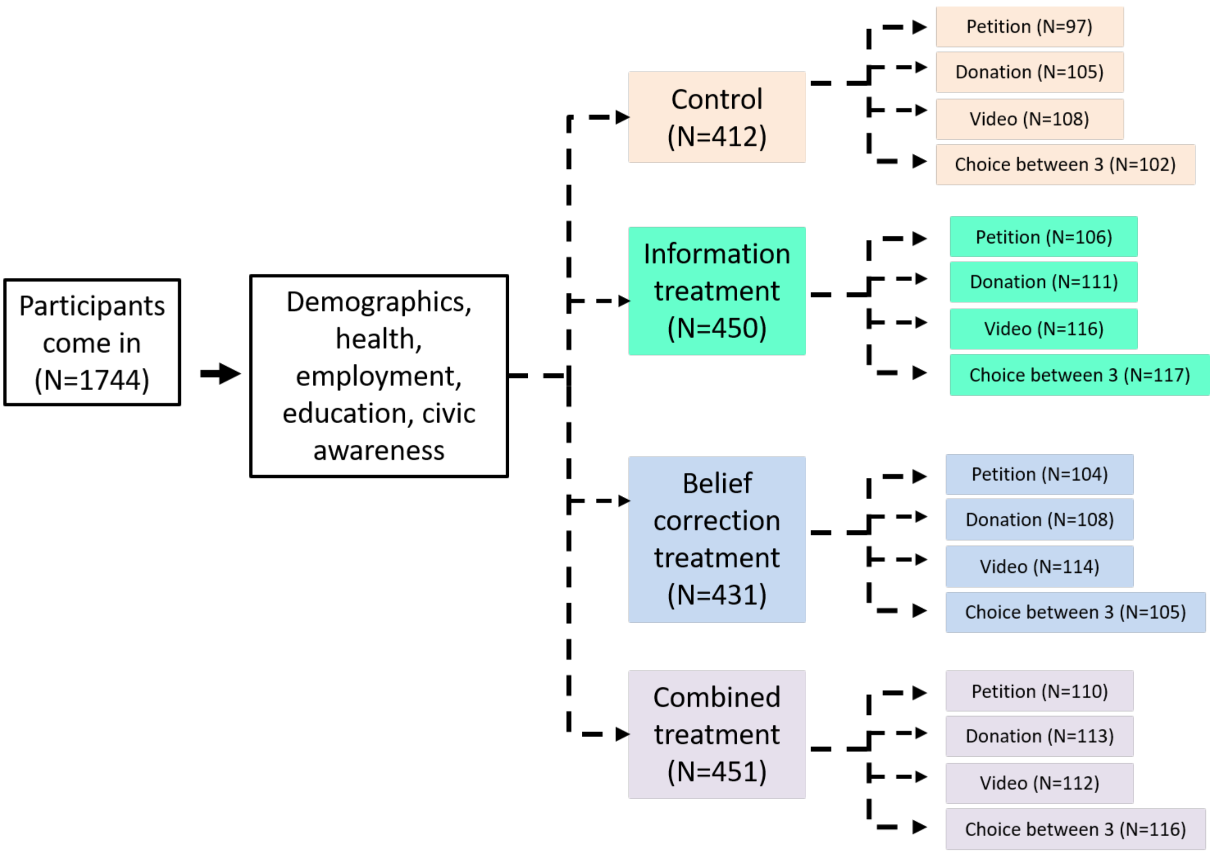
	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information	0.211***	0.137*	0.111*	-0.055	-0.058	2.879	-0.030	-0.006	-4.839
	(0.070)	(0.070)	(0.066)	(0.055)	(0.055)	(3.158)	(0.067)	(0.067)	(23.402)
Belief Correction	0.150**	0.149**	0.140**	-0.027	-0.045	0.464	-0.066	-0.050	-27.517
	(0.072)	(0.073)	(0.069)	(0.055)	(0.053)	(2.988)	(0.069)	(0.069)	(23.590)
Combined	0.223***	0.153**	0.160**	-0.104*	-0.132**	-5.059*	-0.085	-0.079	-12.509
	(0.071)	(0.072)	(0.068)	(0.055)	(0.054)	(2.660)	(0.069)	(0.070)	(23.713)
Information x Tolerance	0.021	-0.033	-0.085	0.036	0.030	3.760	-0.042	-0.038	-40.949*
	(0.063)	(0.066)	(0.064)	(0.050)	(0.049)	(3.078)	(0.067)	(0.070)	(24.658)
Belief Correction x Tolerance	-0.092	-0.111	-0.101	0.021	0.012	3.515	0.040	0.052	5.310
	(0.069)	(0.072)	(0.069)	(0.054)	(0.053)	(3.171)	(0.067)	(0.069)	(24.349)
Combined x Tolerance	-0.068	-0.094	-0.114*	0.002	-0.000	2.824	-0.002	-0.018	-31.329
	(0.063)	(0.069)	(0.068)	(0.049)	(0.048)	(2.278)	(0.070)	(0.071)	(23.887)
Tolerance	-0.005	0.011	0.037	0.037	0.040	-1.476	-0.023	-0.025	10.781
	(0.048)	(0.050)	(0.048)	(0.037)	(0.036)	(1.669)	(0.052)	(0.054)	(19.107)
I + I x Tolerance [p value]	[0.009]	[0.259]	[0.763]	[0.798]	[0.711]	[0.106]	[0.457]	[0.657]	[0.194]
BC + BC x Tolerance [p value]	[0.548]	[0.712]	[0.688]	[0.941]	[0.664]	[0.310]	[0.779]	[0.978]	[0.518]
COM + COM x Tolerance [p value]	[0.093]	[0.542]	[0.629]	[0.160]	[0.059]	[0.455]	[0.350]	[0.304]	[0.204]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.171	0.113	0.141	0.282	0.300	0.347	0.124	0.123	0.112

Notes: The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). The symbols I, BC and COM stand for information, belief correction and combined treatments respectively. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. 'Tolerance' is created by aggregating standardised responses of survey questions related to individual's tolerance of corruption in healthcare and in general, as described in subsection 3.B.1 of the Appendix. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Appendix

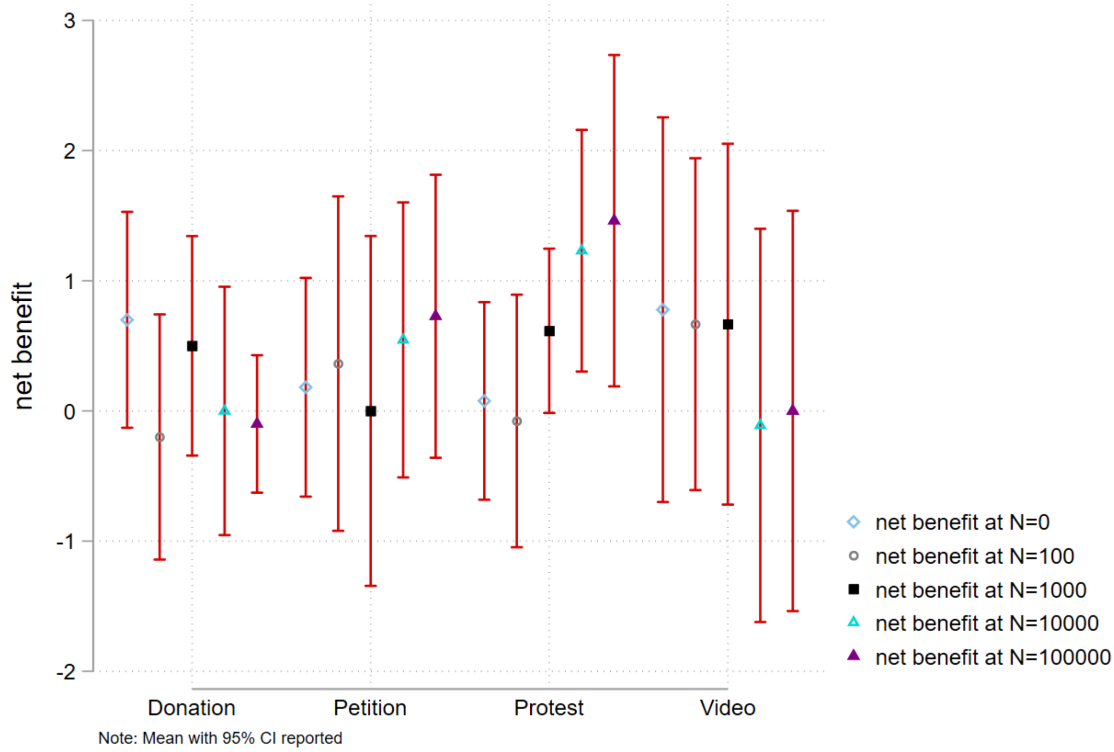
2.A Additional Figures and Tables

Figure 2.A.1: Experiment Design (Wave 2)



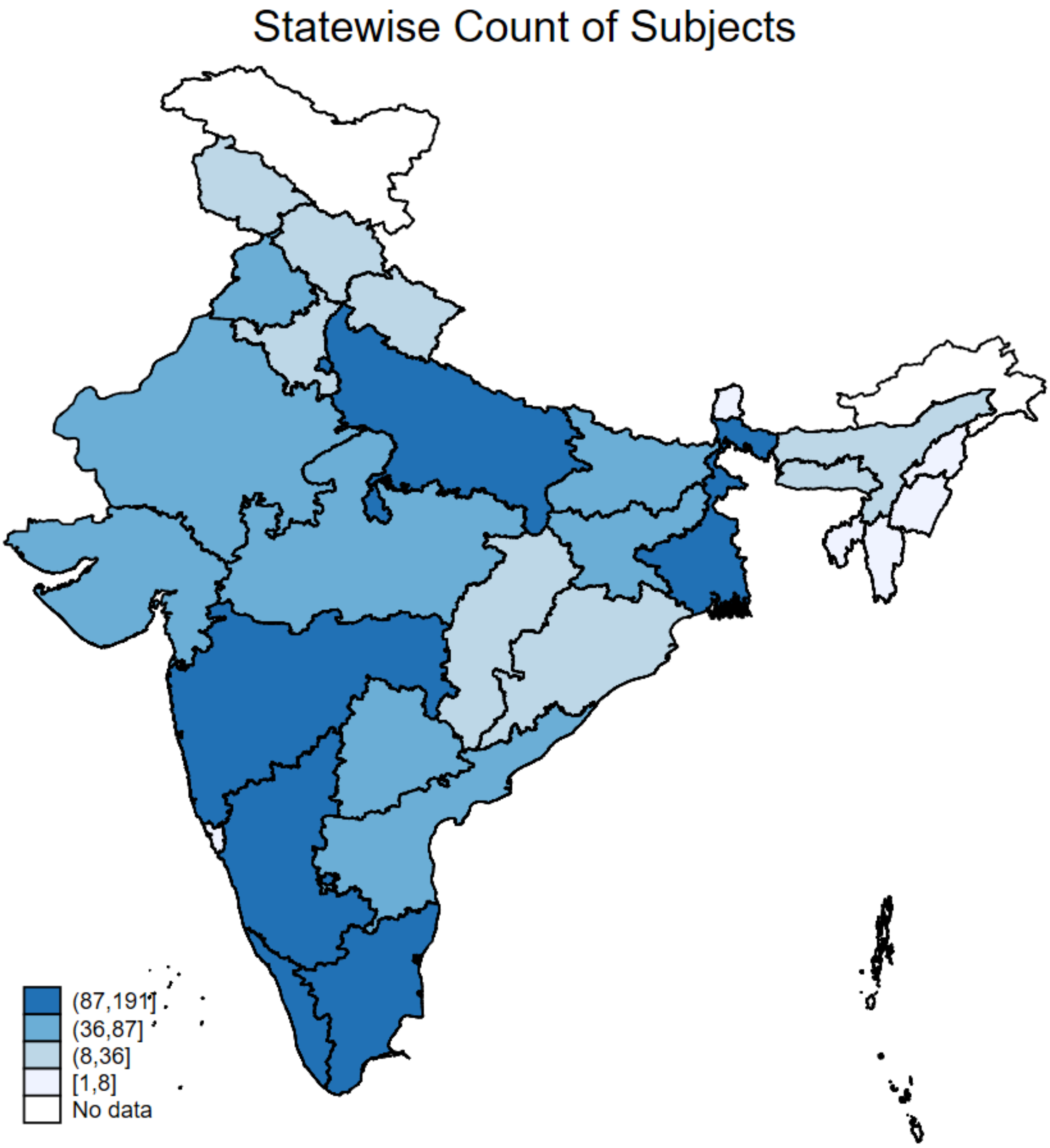
Notes: Flow-chart of the experimental design. The dashed lines are used to indicate random allocation of subjects into the anti-corruption treatment conditions, and then again into the action treatment groups.

Figure 2.A.2: Net Benefit of Actions



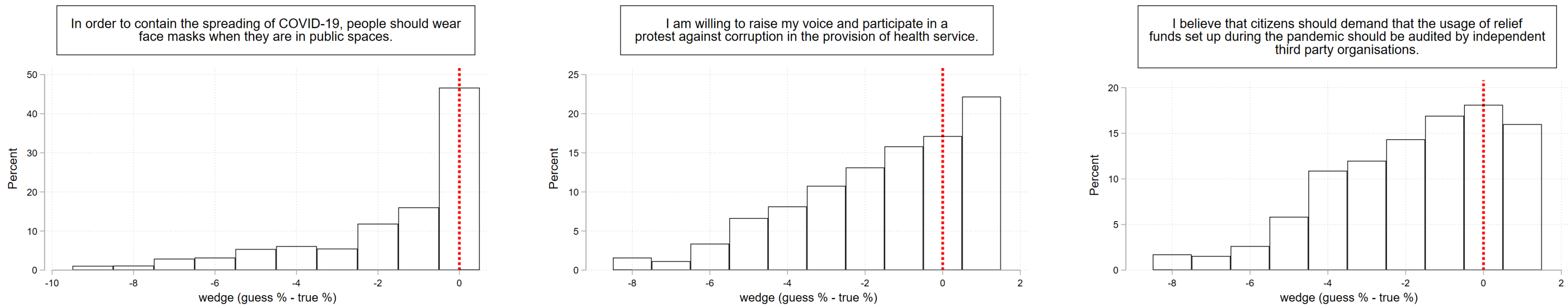
Notes: This graph shows the net benefit of different actions, for a comparable sample of 849 Indian men collected in 2022. To calculate the benefit of doing every action, we ask subjects if 'N' number of people decided to take the action, then how likely it is that this action will induce the government to act on corruption on a scale of extremely unlikely (1) to extremely likely (5), where 'N'= 0/ 100/ 1000/ 10,000/100,000. Thus, benefit is the simple aggregate of survey responses at 5 different group sizes. Similarly for capturing cost associated with an action, we ask subjects if 'N' number of people decided to take the action, then how likely it is that this action will induce the government to punish citizens on a scale of extremely unlikely (1) to extremely likely (5), where 'N'= 0/ 100/ 1000/ 10,000/100,000. The net benefit is calculated as (benefit - cost) of every action.

Figure 2.A.3: Geographic Distribution of Study Sample (by State of Residence)



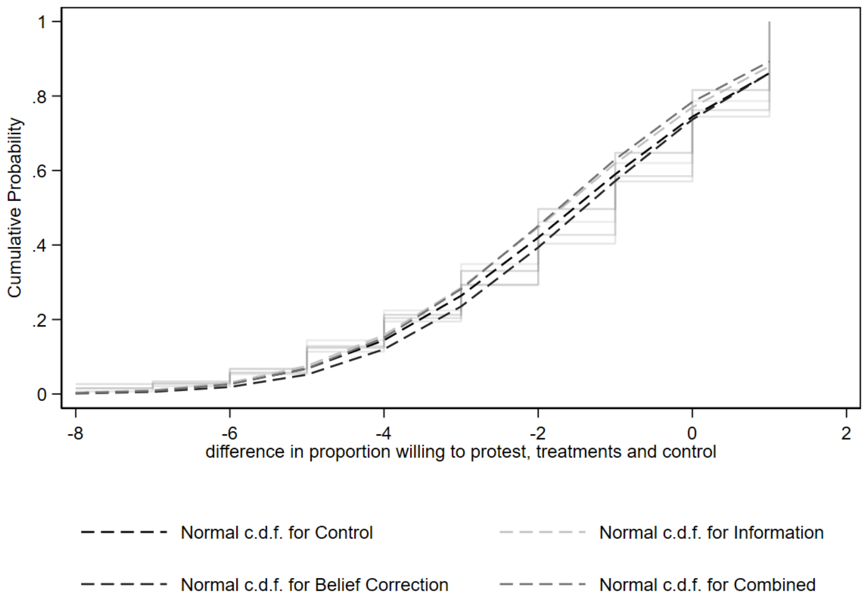
Source: Authors' own calculation

Figure 2.A.4: Belief Mismatch



Notes: The figure shows the distribution of wedges in perception of (1) “In order to contain the spread of COVID-19, people should wear face masks when they are in public spaces." (2) “I believe that citizens should demand that the usage of relief funds set up during the pandemic should be audited by independent third party organisation." and (3) “I am willing to raise my voice and participate in a protest against corruption in the provision of health service." For each of these statements, wedges are calculated as the difference between subject’s guess about the % of Stage 1 participants agreeing with the statement and the true % of Stage 1 participants agreeing with the statement (Bursztyn et al., 2020).

Figure 2.A.5: Distribution of Beliefs about Others' Willingness to Protest, by Treatment



Note: The figure plots the cumulative distributions of individual beliefs about others' willingness to protest against corruption, by activism treatment. The value 0 in x axis indicates the '80-90%' category, which contained the true willingness to protest. Each unit below or above 0 indicates belief mismatch by 10 percentage points. For instance, -2 indicates the beliefs that 50-60% of others agreed with the statement on willingness to protest against corruption in health.

Kolmogorov-Smirnov Test of Equality of Belief Distributions (p value)

control=information	0.529
control=belief correction	1.000
control=combined	0.250
information=belief correction	0.438
information=combined	0.952
belief correction= combined	0.044

Table 2.A.1: Timeline of Study

Data Collection Date	Survey Round	Sample Size
24th-25th March 2021, 2nd-7th April 2021, 19th May 2021, 26th May 2021	Wave 1	N=582 (full sample) / N = 391 (attentive sample)
21st-22nd April 2021, 1st-3rd June 2021, 15th-18th June 2021, 30th June-1st July 2021	Wave 2	N = 2296 (full sample) / N = 1744 (attentive sample)

Notes: This table shows the timeline of the interview rounds. All study participants were adult Indian men. The wave 1 was a preliminary round conducted to understand baseline beliefs about willingness to protest. The analysis sample comes from only the subjects of wave 2 who passed the attention check criteria, conducted shortly after the first wave.

Table 2.A.2: Comparison between National and Experimental Sample

characteristics	*Proportion*	
	national sample	experimental sample
Age (45 years and above)	36	14
College educated	27	79
Married	69	51
Income	92	48
Hindu	79	78
SC or ST	18	28

Note: Income indicates the percentage with less than Rs 30K in monthly income. SC (Schedule Caste) and ST (Scheduled Tribe) are socio-economically deprived individuals in India. The sample of adult (18 years and above) urban men from the Periodic Labor Force Sample (PLFS) 2017-2018 are used for the national figures and experimental figures are from own experimental sample.

Table 2.A.3: Balance on Observable Characteristics (by Action Treatments)

Variable	Total (1)	Petition (2)	Donation (3)	Video (4)	Choice (5)	Difference (2)-(3)	(2)-(4)	(2)-(5)	(3)-(4)	(3)-(5)	(4)-(5)
A. Demographics											
Age 45+	0.145	0.134	0.142	0.158	0.145	-0.008	-0.023	-0.011	-0.016	-0.004	0.012
Married	0.490	0.468	0.483	0.504	0.505	-0.015	-0.037	-0.037	-0.022	-0.022	-0.000
SC\ST	0.264	0.252	0.245	0.296	0.264	0.007	-0.044	-0.012	-0.051*	-0.019	0.032
Hindu	0.769	0.765	0.751	0.749	0.811	0.014	0.016	-0.046*	0.002	-0.061**	-0.062**
College	0.782	0.784	0.762	0.791	0.789	0.022	-0.007	-0.004	-0.029	-0.027	0.002
Income	0.494	0.472	0.517	0.500	0.484	-0.045	-0.028	-0.012	0.017	0.033	0.016
Elderly	0.563	0.566	0.574	0.520	0.591	-0.008	0.046	-0.025	0.054	-0.017	-0.071**
B. Preferences											
Locus of Control	0.059	0.083	0.091	0.056	0.005	-0.008	0.027	0.078	0.035	0.086	0.051
Risk	0.001	-0.028	0.046	0.019	-0.034	-0.074	-0.047	0.006	0.027	0.080	0.053
Pro-sociality	-0.034	-0.010	-0.051	-0.014	-0.059	0.041	0.005	0.049	-0.037	0.008	0.045
C. Corruption											
Perception	0.053	0.070	0.011	0.059	0.073	0.059	0.011	-0.002	-0.048	-0.061	-0.014
Information (Rights)	0.027	-0.029	0.013	0.067	0.053	-0.041	-0.096	-0.082	-0.055	-0.040	0.015
Tolerance	0.052	0.028	0.118	0.029	0.034	-0.090	-0.001	-0.006	0.089	0.083	-0.006
Civic Engagement	0.064	0.066	0.056	0.015	0.122	0.010	0.052	-0.056	0.041	-0.066	-0.107*
D. Belief and Earning from Survey											
Bias (↑)	0.222	0.242	0.233	0.202	0.211	0.009	0.040	0.031	0.031	0.022	-0.009
Confidence	4.268	4.276	4.314	4.242	4.241	-0.038	0.034	0.035	0.071	0.073	0.001
Expected Bonus Earning	138.801	137.002	139.963	139.087	139.059	-2.961	-2.084	-2.057	0.877	0.904	0.028
belief about others' willingness to protest (%)	64.077	65.468	64.508	63.444	62.977	0.960	2.023	2.490	1.064	1.531	0.467
N	1744	417	437	450	440						
F-test of joint significance [p-value]						[0.946]	[0.723]	[0.868]	[0.540]	[0.487]	[0.497]

*Notes:*SC (Schedule Caste) and ST (Scheduled Tribe) are socio-economically deprived individuals in India; 'income' indicates subjects with monthly household income below INR 30 thousand in the previous month; 'elderly' indicates subjects who say 'yes' to the question "In your household, do you have elderly (above 60) living with you?"; Locus of control, risk and pro-sociality indices are standardized measures of self-assessment as explained in subsection 3.B.1 of the Appendix; indices of corruption perception, information (rights), corruption tolerance and civic engagement are created by aggregating standardised responses of relevant survey questions as described in subsection 3.B.1 ; 'bias(↑)' is a dummy equal to 1 if the subject overestimated the true willingness to protest, 0 otherwise; 'belief about others' willingness to protest' indicates subjects' guess about percentage of previous participants agreeing with the statement "I am willing to raise my voice and participate in a protest against corruption in the provision of health service."; 'confidence' indicates how confident a subject is, in his aforementioned belief on a scale of 1 to 5, with 5 being the most confident; 'expected bonus earning' is the subject's guess about his bonus earnings from this experiment. p-values of F-tests of joint significance of variables reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.A.4: Summary Statistics

	N	Mean	Std. Dev
A. Demographics			
Age 45+	1744	0.15	0.35
Married	1744	0.49	0.50
SC\ST	1744	0.26	0.44
Hindu	1744	0.77	0.42
College	1744	0.78	0.41
Income	1744	0.49	0.50
Asset	1744	5.99	2.31
Elderly	1744	0.56	0.50
Hospital Visits	1744	0.77	0.42
B. Preferences			
Locus of Control	1744	0.06	1.00
Risk	1744	0.00	1.06
Pro-sociality	1744	-0.03	0.99
C. Corruption			
Ever given a Gift?	1744	0.51	0.50
Ever did a Favor?	1744	0.60	0.49
Ever Paid a Bribe?	1744	0.53	0.50
Know ICU Rate?	1744	0.34	0.47
Charged Extra in Hospital?	1744	0.14	0.34
Opinion: Corruption has increased	1744	0.71	0.46
Opinion: Corruption a Problem?	1744	0.82	0.38
Prior Protest	1744	0.37	0.48
Prior Walkouts or Strike	1744	0.29	0.46
Prior Boycott	1744	0.33	0.47
Prior Petition	1744	0.36	0.48
Prior Lodging Complaints	1744	0.39	0.48
Prior Marching	1744	0.26	0.44
Prior Donation	1744	0.77	0.42

*Notes:*SC (Schedule Caste) and ST (Scheduled Tribe) are socio-economically deprived individuals in India; ‘income’ indicates subjects with monthly household income below INR 30 thousand in the previous month; ‘elderly’ indicates subjects who say ’yes’ to the question “In your household, do you have elderly (above 60) living with you?"; Locus of control, risk and pro-sociality indices are standardized measures of self-assessment as mentioned in subsection 3.B.1 in the Appendix; questions related to corruption are described in subsection 3.B.1 in the Appendix.

Table 2.A.5: Treatment Effects on Decision to Act, Conditional on Type of Action

	(1)	(2)	(3)
Information	0.001	-0.000	-0.042
	(0.033)	(0.032)	(0.056)
Belief Correction	-0.010	-0.011	-0.010
	(0.034)	(0.032)	(0.056)
Combined	-0.041	-0.041	-0.080
	(0.033)	(0.032)	(0.054)
Petition		0.322***	0.133**
		(0.031)	(0.063)
Choice		0.216***	0.298***
		(0.030)	(0.063)
Video		0.374***	0.387***
		(0.030)	(0.063)
Information x *Petition*			0.273***
			(0.087)
Information x *Choice*			-0.103
			(0.085)
Information x *Video*			0.014
			(0.086)
Belief Correction x *Petition*			0.152*
			(0.088)
Belief Correction x *Choice*			-0.111
			(0.089)
Belief Correction x *Video*			-0.032
			(0.087)
Combined x *Petition*			0.314***
			(0.087)
Combined x *Choice*			-0.102
			(0.084)
Combined x *Video*			-0.034
			(0.086)
Controls?	YES	YES	YES
Observations	1744	1744	1744
R^2	0.088	0.169	0.184

Notes: The dependent variable is a dummy that equals 1 if the respondent chose to take any action when offered to sign a petition or donate or watch a video or choose any one of the three actions, and 0 otherwise. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.A.6: Petition: Correction for Multiple Hypothesis Testing

	Willing to sign	Signed with full name	Signed with name
Information	0.214	0.11	0.137
	(0.003)	(0.098)	(0.05)
FDR-adjusted p-value	[0.012]	[0.06]	[0.046]
Belief Correction	0.151	0.14	0.15
	(0.037)	(0.044)	(0.042)
FDR-adjusted p-value	[0.046]	[0.046]	[0.046]
Combined	0.222	0.156	0.15
	(0.002)	(0.024)	(0.037)
FDR-adjusted p-value	[0.012]	[0.046]	[0.046]

Note: Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Conventional p-values are given in parentheses, under the coefficients. FDR-adjusted p-values, computed following Anderson (2008) are reported in square brackets below.

Table 2.A.7: Robustness: Treatment effects on Activism - Double LASSO Method

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information	0.207***	0.130*	0.105	-0.059	-0.065	2.086	-0.030	-0.003	0.231
	(0.071)	(0.069)	(0.066)	(0.056)	(0.056)	(3.222)	(0.066)	(0.067)	(23.468)
Belief Correction	0.147**	0.151**	0.147**	-0.021	-0.041	0.477	-0.057	-0.041	-25.151
	(0.073)	(0.072)	(0.068)	(0.056)	(0.054)	(3.017)	(0.068)	(0.069)	(23.239)
Combined	0.236***	0.156**	0.156**	-0.091*	-0.119**	-3.845	-0.097	-0.095	-16.965
	(0.069)	(0.070)	(0.067)	(0.054)	(0.052)	(2.500)	(0.069)	(0.070)	(23.560)
Equality of treatments [p-value]									
Information = Belief Correction	[0.393]	[0.768]	[0.527]	[0.497]	[0.649]	[0.639]	[0.679]	[0.565]	[0.269]
Information = Combined	[0.667]	[0.709]	[0.446]	[0.551]	[0.288]	[0.043]	[0.306]	[0.169]	[0.456]
Belief Correction = Combined	[0.204]	[0.944]	[0.896]	[0.181]	[0.109]	[0.125]	[0.550]	[0.439]	[0.724]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450

*Notes:*The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). Controls are selected by the double lasso method. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.A.8: Heterogeneity by Belief Mismatch (Separating Unbiased and Downward Biased)

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information x Correct	0.226	0.172	0.220	0.116	0.092	1.646	-0.004	-0.019	-1.479
	(0.223)	(0.226)	(0.209)	(0.187)	(0.185)	(9.088)	(0.218)	(0.227)	(76.987)
Belief Correction x Correct	0.447**	0.385*	0.426**	0.194	0.231	13.744	-0.145	-0.195	-36.042
	(0.213)	(0.214)	(0.194)	(0.177)	(0.170)	(9.063)	(0.240)	(0.253)	(82.478)
Combined x Correct	0.248	0.146	0.142	0.227	0.248	10.121	0.075	0.071	11.621
	(0.210)	(0.225)	(0.214)	(0.185)	(0.183)	(7.037)	(0.242)	(0.251)	(82.015)
Information x Bias (↓)	0.076	0.013	0.108	-0.058	-0.090	-6.918	0.167	0.159	62.215
	(0.164)	(0.166)	(0.160)	(0.128)	(0.127)	(7.806)	(0.168)	(0.175)	(58.457)
Belief Correction x Bias (↓)	0.573***	0.409**	0.437***	-0.088	-0.067	-6.946	0.158	0.108	71.102
	(0.164)	(0.175)	(0.164)	(0.124)	(0.117)	(6.044)	(0.172)	(0.184)	(59.571)
Combined x Bias (↓)	0.331**	0.132	0.040	-0.089	-0.131	-6.744	0.125	0.088	38.088
	(0.168)	(0.172)	(0.170)	(0.124)	(0.122)	(5.574)	(0.186)	(0.195)	(65.249)
Information	0.162	0.118	0.019	-0.040	-0.020	6.554	-0.132	-0.099	-42.900
	(0.141)	(0.142)	(0.135)	(0.108)	(0.107)	(6.553)	(0.145)	(0.153)	(48.654)
Belief Correction	-0.236*	-0.139	-0.169	-0.016	-0.053	1.638	-0.149	-0.091	-67.303
	(0.136)	(0.145)	(0.133)	(0.101)	(0.094)	(4.302)	(0.147)	(0.163)	(52.566)
Combined	-0.001	0.055	0.114	-0.087	-0.089	-2.828	-0.179	-0.150	-40.127
	(0.142)	(0.148)	(0.146)	(0.098)	(0.098)	(4.097)	(0.167)	(0.176)	(58.841)
Bias (↓)	-0.286**	-0.097	-0.026	0.075	0.068	5.439	-0.210*	-0.155	-69.203
	(0.115)	(0.119)	(0.115)	(0.089)	(0.087)	(3.825)	(0.122)	(0.134)	(43.324)
Correct	-0.121	-0.096	-0.126	-0.021	-0.029	-3.243	-0.098	-0.035	7.322
	(0.161)	(0.154)	(0.135)	(0.120)	(0.116)	(4.332)	(0.161)	(0.175)	(58.347)
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.207	0.125	0.155	0.296	0.323	0.358	0.128	0.127	0.110

*Notes:*The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.A.9: Heterogeneity by Income

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information x Income	0.099	-0.123	-0.114	-0.125	-0.104	-5.232	0.154	0.181	78.866*
	(0.143)	(0.139)	(0.133)	(0.108)	(0.107)	(5.849)	(0.130)	(0.134)	(47.183)
Belief Correction x Income	-0.082	-0.206	-0.240*	-0.053	-0.056	-3.443	-0.056	0.005	50.117
	(0.142)	(0.141)	(0.133)	(0.114)	(0.110)	(5.761)	(0.139)	(0.142)	(46.678)
Combined x Income	-0.120	-0.212	-0.145	-0.161	-0.179*	-7.779	-0.099	-0.016	42.967
	(0.142)	(0.140)	(0.134)	(0.110)	(0.106)	(4.936)	(0.140)	(0.143)	(48.333)
Information	0.163	0.196**	0.164*	0.011	-0.001	5.758	-0.114	-0.102	-44.710
	(0.099)	(0.096)	(0.091)	(0.072)	(0.072)	(3.567)	(0.097)	(0.096)	(33.032)
Belief Correction	0.189**	0.248***	0.252***	0.000	-0.016	2.404	-0.040	-0.054	-52.647
	(0.094)	(0.094)	(0.090)	(0.078)	(0.075)	(3.409)	(0.093)	(0.094)	(32.074)
Combined	0.277***	0.250***	0.226**	-0.025	-0.043	-1.069	-0.040	-0.076	-35.699
	(0.092)	(0.094)	(0.092)	(0.076)	(0.075)	(2.809)	(0.095)	(0.096)	(32.390)
Income	-0.043	0.069	0.011	0.106	0.099	5.904	0.037	-0.006	-39.332
	(0.099)	(0.095)	(0.089)	(0.083)	(0.083)	(3.998)	(0.101)	(0.104)	(36.365)
I + I x Income [p value]	[0.010]	[0.470]	[0.602]	[0.162]	[0.200]	[0.915]	[0.649]	[0.401]	[0.308]
BC + BC x Income [p value]	[0.323]	[0.699]	[0.904]	[0.510]	[0.348]	[0.823]	[0.344]	[0.643]	[0.941]
COM + COM x Income [p value]	[0.150]	[0.720]	[0.419]	[0.020]	[0.003]	[0.036]	[0.175]	[0.376]	[0.837]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.170	0.112	0.140	0.285	0.305	0.346	0.129	0.125	0.105

*Notes:*The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). The symbols I, BC and COM stand for information, belief correction and combined treatments respectively. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.A.10: Heterogeneity by Education

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information x College	0.105	0.243	0.203	-0.096	-0.105	4.922	-0.201	-0.093	-21.052
	(0.175)	(0.167)	(0.163)	(0.137)	(0.136)	(7.058)	(0.168)	(0.173)	(60.129)
Belief Correction x College	0.077	0.134	0.178	-0.064	-0.046	-1.783	-0.110	-0.045	-49.755
	(0.180)	(0.180)	(0.166)	(0.129)	(0.122)	(7.787)	(0.168)	(0.169)	(54.987)
Combined x College	0.097	0.064	0.085	-0.079	-0.075	-1.448	-0.233	-0.233	-69.103
	(0.167)	(0.172)	(0.164)	(0.130)	(0.122)	(5.897)	(0.173)	(0.172)	(58.722)
Information	0.132	-0.056	-0.050	0.021	0.026	-0.845	0.140	0.076	15.367
	(0.154)	(0.143)	(0.142)	(0.121)	(0.121)	(5.898)	(0.152)	(0.155)	(53.142)
Belief Correction	0.091	0.043	-0.000	0.022	-0.010	1.960	0.029	-0.004	14.090
	(0.155)	(0.152)	(0.140)	(0.111)	(0.103)	(7.027)	(0.149)	(0.149)	(47.923)
Combined	0.147	0.101	0.091	-0.047	-0.078	-3.962	0.106	0.111	43.830
	(0.146)	(0.147)	(0.140)	(0.109)	(0.102)	(4.983)	(0.153)	(0.151)	(51.986)
College	-0.002	-0.025	-0.078	0.035	0.038	-1.230	0.010	-0.043	5.291
	(0.124)	(0.125)	(0.123)	(0.096)	(0.094)	(4.647)	(0.131)	(0.130)	(41.282)
I + I x College [p value]	[0.003]	[0.022]	[0.045]	[0.229]	[0.202]	[0.275]	[0.408]	[0.816]	[0.831]
BC + BC x College [p value]	[0.047]	[0.042]	[0.032]	[0.515]	[0.373]	[0.957]	[0.293]	[0.538]	[0.188]
COM + COM x College [p value]	[0.003]	[0.050]	[0.029]	[0.056]	[0.018]	[0.082]	[0.102]	[0.123]	[0.343]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.164	0.110	0.136	0.282	0.301	0.345	0.125	0.123	0.102

*Notes:*The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). The symbols I, BC and COM stand for information, belief correction and combined treatments respectively. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.A.11: Heterogeneity by Civic Engagement

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information x Civic Engagement	-0.078	-0.024	-0.027	0.117**	0.087	6.491*	-0.050	-0.052	-31.240
	(0.057)	(0.070)	(0.069)	(0.058)	(0.058)	(3.801)	(0.075)	(0.080)	(25.219)
Belief Correction x Civic Engagement	-0.184***	-0.160**	-0.106	0.020	0.019	0.851	-0.046	-0.049	-15.578
	(0.066)	(0.071)	(0.069)	(0.047)	(0.045)	(2.719)	(0.075)	(0.076)	(24.606)
Combined x Civic Engagement	-0.131**	-0.118	-0.068	0.027	0.024	0.011	0.061	-0.006	-1.959
	(0.060)	(0.072)	(0.071)	(0.049)	(0.047)	(2.483)	(0.073)	(0.079)	(27.016)
Information	0.210***	0.131*	0.107	-0.056	-0.058	2.885	-0.023	-0.001	-1.088
	(0.070)	(0.069)	(0.066)	(0.055)	(0.055)	(3.099)	(0.067)	(0.067)	(23.614)
Belief Correction	0.148**	0.147**	0.138**	-0.027	-0.046	0.542	-0.063	-0.047	-26.464
	(0.072)	(0.073)	(0.069)	(0.054)	(0.053)	(2.939)	(0.068)	(0.069)	(23.665)
Combined	0.225***	0.155**	0.157**	-0.109**	-0.136**	-5.031*	-0.092	-0.084	-15.214
	(0.070)	(0.071)	(0.068)	(0.055)	(0.053)	(2.602)	(0.069)	(0.070)	(23.659)
Civic Engagement	0.136***	0.110**	0.070	-0.004	-0.005	2.037	0.004	0.001	13.022
	(0.047)	(0.056)	(0.054)	(0.032)	(0.031)	(1.384)	(0.060)	(0.062)	(20.110)
I + I x Engagement [p value]	[0.129]	[0.300]	[0.419]	[0.445]	[0.708]	[0.074]	[0.470]	[0.616]	[0.350]
BC + BC x Engagement [p value]	[0.718]	[0.901]	[0.750]	[0.920]	[0.698]	[0.730]	[0.286]	[0.356]	[0.229]
COM + COM x Engagement [p value]	[0.299]	[0.722]	[0.370]	[0.247]	[0.104]	[0.167]	[0.752]	[0.388]	[0.645]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.179	0.121	0.139	0.289	0.304	0.352	0.127	0.121	0.103

Notes: The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). The symbols I, BC and COM stand for information, belief correction and combined treatments respectively. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 2.A.12: Heterogeneity by Pro-sociality

	Petition			Donation			Video		
	Willing to Sign	Signed with Name	Signed with Full Name	Willing to Donate	Donated Positive Amount	Percent Donated	Willing to Watch Video	Watched > 10 Seconds	Seconds Watched
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Information x Pro-sociality	0.102	0.086	0.079	0.004	0.022	2.022	0.046	0.035	15.293
	(0.070)	(0.069)	(0.067)	(0.060)	(0.059)	(3.790)	(0.071)	(0.071)	(23.309)
Belief Correction x Pro-sociality	-0.032	-0.020	0.018	0.029	0.034	-0.171	0.029	0.018	13.137
	(0.069)	(0.073)	(0.069)	(0.047)	(0.047)	(2.686)	(0.075)	(0.075)	(24.236)
Combined x Pro-sociality	0.087	0.115	0.118	-0.053	-0.033	-2.422	0.001	0.019	8.811
	(0.072)	(0.072)	(0.073)	(0.050)	(0.049)	(2.171)	(0.072)	(0.071)	(23.175)
Information	0.218***	0.142**	0.113*	-0.052	-0.054	3.257	-0.027	-0.002	-1.960
	(0.071)	(0.070)	(0.066)	(0.055)	(0.055)	(3.168)	(0.067)	(0.068)	(23.655)
Belief Correction	0.156**	0.154**	0.142**	-0.025	-0.044	0.611	-0.062	-0.045	-25.510
	(0.072)	(0.073)	(0.069)	(0.055)	(0.053)	(2.962)	(0.068)	(0.069)	(23.665)
Combined	0.227***	0.158**	0.164**	-0.113**	-0.139***	-5.298**	-0.086	-0.080	-13.084
	(0.071)	(0.072)	(0.069)	(0.055)	(0.053)	(2.590)	(0.069)	(0.070)	(23.756)
Pro-sociality	-0.081	-0.053	-0.055	-0.012	-0.014	0.081	-0.018	-0.016	-2.674
	(0.050)	(0.050)	(0.048)	(0.035)	(0.035)	(1.632)	(0.052)	(0.052)	(16.799)
I + I x Pro-sociality [p value]	[0.001]	[0.020]	[0.040]	[0.564]	[0.695]	[0.333]	[0.843]	[0.722]	[0.677]
BC + BC x Pro-sociality [p value]	[0.217]	[0.177]	[0.093]	[0.953]	[0.890]	[0.915]	[0.750]	[0.792]	[0.716]
COM + COM x Pro-sociality [p value]	[0.003]	[0.009]	[0.007]	[0.025]	[0.017]	[0.025]	[0.396]	[0.542]	[0.894]
Control Outcome Mean	0.392	0.299	0.258	0.267	0.267	9.714	0.620	0.574	149.198
Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	417	417	417	437	437	437	450	450	450
R^2	0.175	0.118	0.142	0.285	0.303	0.346	0.122	0.119	0.099

*Notes:*The dependent variable is a dummy that equals 1 if the respondent was willing to sign a petition (col 1), signed with a name (col 2) or with full name (col 3); dummy indicating the subject was willing to donate (col 4), donated a positive amount of their experimental earnings (col 5) or percent donated (col 6); dummy indicating the subject was willing to watch the video (col 7), watched more than 10 seconds of the video (col 8) or seconds spent watching the video (col 9). The symbols I, BC and COM stand for information, belief correction and combined treatments respectively. Controls include indicators of age, marital status, religion, education, SC/ST dummy, income, presence of elderly at home, indices for: locus of control, risk, pro-sociality, corruption perception, information about corruption and about rights and entitlements, attitude towards corruption and past civic engagement; belief about others' willingness to protest, confidence in that belief, expected earning from the experiment, time and state of residence dummies. Robust standard errors in parentheses; p-values reported in square brackets. * $p < .10$, ** $p < .05$, *** $p < .01$.

2.B Data Appendix

The pre analysis plan of this study is registered at AsPredicted.org. #60725. Ethics approval was obtained from the Institutional Review Board of King's College, London, U.K.; registration number MRA-19/20-20739 dated 10th August, 2020.
Subjects were recruited through Qualtrics Panel, which is a subdivision of Qualtrics. The Qualtrics Panel participants are recruited through multiple market research panels, or "vendors". We contacted Qualtrics for subject recruitment via email, and they provided an estimate of about 6 USD per complete response. Subjects were paid directly through Qualtrics.

2.B.1 Sampling

In order to measure whether the subjects are paying attention to the survey, 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 incentivised, to make sure that subjects understand how much they're going to earn from the incentivised 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 1744, from 2296.

2.B.2 Procedure for Standardisation and Index Construction

We constructed indices for capturing perception of corruption, information on rights and entitlements and tolerance of corruption, and civic engagement of subjects. These are the average of the relevant standardised 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 sample 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 group mean is 0 and the standard deviation is 1.

Preferences

The questions on preferences are listed in section B of Table 2.2.

- *Locus of control index* (a personal belief about whether outcomes of behavior are determined by one's actions or by forces outside one's control) is the internal sub-scale of the KMKB measure of locus of control (Kovaleva, 2012). It comprises of a five-point Likert response scale, ranging from positive to negative pole, for the statements:
  - I like taking responsibility
  - I find it best to make decisions myself, rather than to rely on fate

  - When I encounter problems or opposition, I usually find ways and means to overcome them

The self-assessment indices of risk, trust, retaliation and altruism are calculated 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).”
  - “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 pro-sociality index using the same process described above.

Corruption Perception

The corruption perception index aggregates the following survey questions, for which the corresponding summary statistics are listed in section C of Table 3.1.

- "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)." [49]
- "In your opinion, has the level of corruption in the health sector during the COVID-19 pandemic - (increased a lot/ increased somewhat/ stayed the same/ decreased somewhat/ decreased a lot)" [50]?
- "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)" [51].

Information (Rights)

Subjects' information on rights and entitlements are captured through this index, which aggregates the following survey questions. The corresponding summary statistics are listed in section C of Table 3.1.

- "Do you know what is the rate you have to pay per day for an ICU bed at your local hospital?" [52]
- "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)" [53]

Corruption Tolerance

The corruption tolerance index aggregates the following survey questions, for which the corresponding summary statistics are listed in section C of Table 3.1.

[49]response coded into a continuous variable.
[50]response coded into a continuous variable with higher value indicating increase in corruption.
[51]response coded into a continuous variable with higher value indicating bigger problem.
[52]response coded into a dummy=0 if subject answered with 'don't know', 1 otherwise.
[53]response coded into a dummy=1 if subject answered with a 'yes.

- “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)[54]."
  - avoiding fare on a public transport
  - doctors overcharging for a hospital bed during COVID-19 pandemic
  - someone accepting a bribe in course of their duties.
- “How many people in your community do you think expects you to complain if you are overcharged or asked to pay a bribe by a doctor? (nobody/ a few people/ many people/ most people/ everybody)"[55].

Civic Engagement

The civic engagement index aggregates the following survey questions[56], for which the corresponding summary statistics are listed in section D of Table 3.1.

engagement “Do you agree or disagree with the following statements, on a scale of: strongly agree/ somewhat agree/ neither agree nor disagree/ somewhat agree/ strongly agree".

- you play an active role in one/more voluntary organisations
- you don’t like to discuss politics with other people (reverse-coded)
- being involved in your neighbourhood is important to you
- you don’t get involved in political protests (reverse-coded)
- you generally vote in elections

past action “Prior to COVID-19 pandemic (since April 2020 till date), have you ever been involved in any of the following actions to help solve a problem that mattered to you? - with answer choices: never/ yes, 1-3 times/ yes, 4-6 times/ yes, 7-10 times/ more than 10 times".

- protests
- walkouts or strike
- boycott

[54]responses coded into a continuous variable.
[55]response coded into a dummy=1 if subject answered with ‘nobody’.
[56]responses for each set were coded into continuous variables.

- petition
- lodging complaints
- marching
- donation to an organisation

Chapter 3

Do Crises Affect Citizen Activism? Evidence from a Pandemic[1]

3.1 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.[2] While this literature has studied citizens' self-reported beliefs, there is less rigorous evidence available on the effect of crises on citizen's anti-corruption activism.

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

[1]This chapter is joint work with Farzana Afridi (ISI-Delhi), Amrita Dhillon (King's College London) and Danila Serra (Texas A&M University).

[2]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).

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 widespread 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 898 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.[3] Data on total daily cases between March 1st and July 31st show that the 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.[4] We then compare the experiences, beliefs and willingness to act to fight corruption in the health sector for these two groups.[5]

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

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

[4]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.

[5]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.

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.[6] 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, 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.[7] 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) show that stock market experiences affect stock-

[6]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.

[7]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`).

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.[8] Overall, our study is consistent with the previous literature which documents that economic or political 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.

[8]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).

3.2 Background and Context

3.2.1 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).[9] 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).[10] 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%.[11]

Private healthcare business has been steadily on the rise in India, with a strong presence in virtually all medical sub-markets, even though they face minimal de-facto regulation and poorer training than public sector personnel.[12] 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.[13] 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

[9] 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%.

[10] 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).

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

[12] 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.

[13] 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).

as compared to the first wave (Panneer et al., 2022; Hindustan Times, 2021a).[14] Additionally, we condition our sample on 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).[15]

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 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.[16] Moreover, the standards for registration of hospitals have not been notified by the federal government, suggesting that the act is not

[14]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.

[15]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`).

[16]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`.

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.

3.2.2 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).[17]

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).[18] However, there is significant variation in healthcare provision among Indian states, particularly in their ability to scale it up during an emergency (Garg and

[17] 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.

[18] Health is a state subject in India.

Karan, 2009; Choutagunta et al., 2021).[19] 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., 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 3.A.1, (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 nationwide 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 3.A.2). 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 3.A.3), 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.

[19]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.

3.3 Data and Methodology

3.3.1 Data

Our data come from the web and phone based Qualtrics survey for adult Indian men conducted over March-July 2021.[20] [21] 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.[22] 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 this information. In Figure 3.A.4, 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.[23]

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 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 3.A.1, 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.

[20] The questionnaire is attached in Appendix I.

[21] 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.

[22] 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.

[23] The state-wise peak in daily cases is given in Table 3.A.1. The national peak in daily cases was on May 8 2021. In Table 3.A.2, 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.

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'.[24]

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.[25] 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 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.[26] 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 6-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.[27] Note that we focus on individuals' decision to

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

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

[26] 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.

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

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 any 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.[28] (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 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.[29] We, thus, expect that the real-effort measure carries lower experimenter demand effects and is likely to reveal the true preferences of subjects.[30] 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 3.1.

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

[29] 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 6-minute video.

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

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.[31]

From Figure 3.1, we find that roughly 37% of our subjects were willing to take an anti-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.[32]

To assess whether exposure to crises affects individuals' beliefs and preferences, we use a series of measures constructed from our survey.[33] These measures include: standardized indices for corruption perception, information (rights and entitlements), tolerance and civic engagement, 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.[34]

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

[32]We also explore the impact by the 4 different types of action (petition/ donation/ video/ choice) in Figure 3.A.5. 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.

[33]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. The civic engagement index was created by averaging over subject's past participation in anti-corruption actions such as protests, strike, petitions, marching etc. and the extent of their willingness to be involved in community actions like discuss politics, vote, get involved in the neighborhood etc. All four 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 3.B.1.

[34]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.

3.3.2 Empirical Methodology

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 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[35]

$$Y_{ist} = \gamma + \beta_0 \; Post_{ist} + \beta_1 X_{ist} + \alpha_s + \varepsilon_{ist} \tag{3.1}$$

where 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). $Post_{ist}$ 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.[36] Hence, β_0 is our main coefficient of interest, capturing the effect of the second wave of pandemic on outcomes. 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 ε_{ist}.[37] Standard errors are clustered at the state-month level to account for unobserved heterogeneity over time and space.

[35] 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).

[36] To illustrate the main results graphically, we extend this model by replacing the $Post_{ist}$ 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.

[37] 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 absorb the impact of such stringency of lock-downs.

3.4 Identification

Since the experience of the pandemic or its timing is not randomized, we utilize data staggered over time that allow us to compare impact trajectories 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. 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. 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 outside their ability to choose.[38] Hence, the independence of being assigned in either pre or post group and willingness to act, is plausible.

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 3.A.3) that the respondent pool is quite similar in terms of observable characteristics.[39] Additionally, as a robustness check, we repeat the main analysis by using

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

[39] 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 3.A.6 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

weights derived from entropy balancing (Hainmueller, 2012).[40] Next, as a second robustness check, we introduce a control for a running variable that measures the difference of interview date from peak date to our main specification, in order to separate the part of the variation in outcomes that doesn't come from change in Post_{ist}. 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 3.1 at successive bandwidths around the moment of the shock, capturing the impact dissemination over time. Finally, we use equation 3.1 to provide some suggestive evidence about whether the exposure to crises also shifted individual's beliefs and preferences.

3.5 Results

We first report the results from equation 3.1 in Table 3.2. 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

including subjects who select the correct response to the attention check question. The precise screener question is given in section 3.B.

[40]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". Propensity score methods are often used in observational studies to pre-process the data prior to estimation of treatment effects under the assumption of selection on observables. In contrast to most other pre-processing methods, entropy balancing involves a re-weighting scheme that directly incorporates co-variate balance into the weight function that is applied to the sample units. An advantage of this method is that unlike the traditional coarsened exact matching, entropy balancing does not require enormous data sets or drop large portions of the sample. Column 4 of Table 3.A.3 confirms that after re-weighting, balance is achieved.

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.[41] In the balanced sample, the coefficient is 0.094. These increases are all significant at 1 percent level.[42]

These results are also supported by time paths plotted in Figure 3.3. To graphically illustrate our results, we dis-aggregate the pre and post time periods as distance (in months) from the month containing the state peak. Figure 3.2a reveals that the real-effort measure of willingness to act indeed shows an increase on the subsequent three months after the peak. Similarly, Figure 3.2b shows that the hypothetical measure of willingness to protest also increases steadily in those months.

3.5.1 Robustness

We begin by estimating if the increase in citizens' anti-corruption activism happened immediately after the peak.[43] 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.[44] Simply put, this variable measures the difference between the interview days before and after the peak for each subject. In other words, we estimate

$$Y_{ist} = \gamma + \beta_0 \, Post_{ist} + \beta_1 \, D_{ist} + \beta_2 \, D_{ist} \; \times \; Post_{ist} + \beta_1 X_{ist} + \alpha_s + \varepsilon_{ist} \tag{3.2}$$

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.

[41]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.

[42]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 3.2 is 0.112 translates to an increase of 0.231 SD. Figure 3.A.7a 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 3.A.7b). This indicates that our study is adequately powered and the estimated effects are meaningful.

[43]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.

[44]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.

Columns 1 and 2 of Table 3.3 captures the estimates of equation 3.2 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.[45] The interactive term 'Days x Post' indicates that in the full sample, 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 3.2) 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 $\pm$ 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 $\pm$ 18 days with the current data at hand.[46] The results are presented in Figure 3.4 shows that the estimated impact of exposure to peak is consistently positive and stable over time, for both willingness to act (Figure 3.4a) and willingness to protest (Figure 3.4b). The observed stability also indicates that time trends or other events are not likely driving the estimated effects.[47]

[45] 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 3.1 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 method (Roodman et al., 2019). This translates into a 61% increase over the control mean immediately after exposure. Table 3.A.4 shows that our main results are robust to clustering by state.

[46] 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 3.1 for each of the bandwidths.

[47] The Table 3.A.5 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 3.A.8 (Figure 3.A.8a for willingness to act and for Figure 3.A.8b for willingness to protest), which lends support to our claim.

3.5.2 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 3.1) 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.[48] 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 3.3.

In Figure 3.3a, we find that real-effort willingness to act increases in the months after being exposed to the peak. Similarly, Figure 3.3b shows the same result for the hypothetical measure of willingness to protest, but the magnitude is somewhat smaller than Figure 3.3a. In contrast, the time paths for late-peak sub-sample show a less obvious pattern; Figure 3.3d 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 3.3c) 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.[49]

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 on this information, we created a dummy (‘*high corruption states*’) indicating the states with high corruption level as 1; 0 otherwise.[50] By interacting this dummy with ‘Post’ in Table 3.A.6, 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

[48] Table 3.A.1 provides a list of state level peaks of confirmed cases.

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

[50] 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.

peak significantly increased the willingness to act.[51] 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 3.A.7, which shows that an increase in hospital density is positively correlated with the real-effort measure of willingness to take action against corruption.

3.6 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 3.4, we explore 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 3.4, 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.[52] [53]

The second wave of COVID in India was a highly salient event. A significant impact on

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

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

[53] Since we are estimating equation 3.1 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 3.A.9. The significance of all our main outcomes are preserved after the correction.

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 3.A.8). 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 exposed to COVID-19.[54]

A question that remains is whether the initial increase in willingness to take action against corruption would persist or fade out over time. The short fieldwork time of the main study facilitates the as-if random assignment to treatment without needing adjustments for time-related concerns, & a threat of simultaneous events is also likely to be lower. However, we conducted a second, not directly related Qualtrics survey in the months of October-November 2022 for a comparable sample, which gave us the opportunity to check if the increase in the hypothetical willingness to protest persisted almost a year after the main study.

We extend the sample by adding 849 observations from the 2022 survey. From columns 1, 3, 5, and 7 of Table 3.A.10, we find that for the extended sample, the effect of being exposed to the COVID case peak is significant, even after introducing controls, time fixed effects, and state-specific linear time trends. In columns 2, 4, 6, and 8, we consider only the 'long term' sample, which compares the long term impact of exposure to the shock, in the 2022 group, vis-a-vis the 'pre' group. We find that the point estimate becomes statistically insignificant after the inclusion of time fixed effects and state specific linear time trends, indicating that in the long term, the impact of exposure has likely petered out.

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

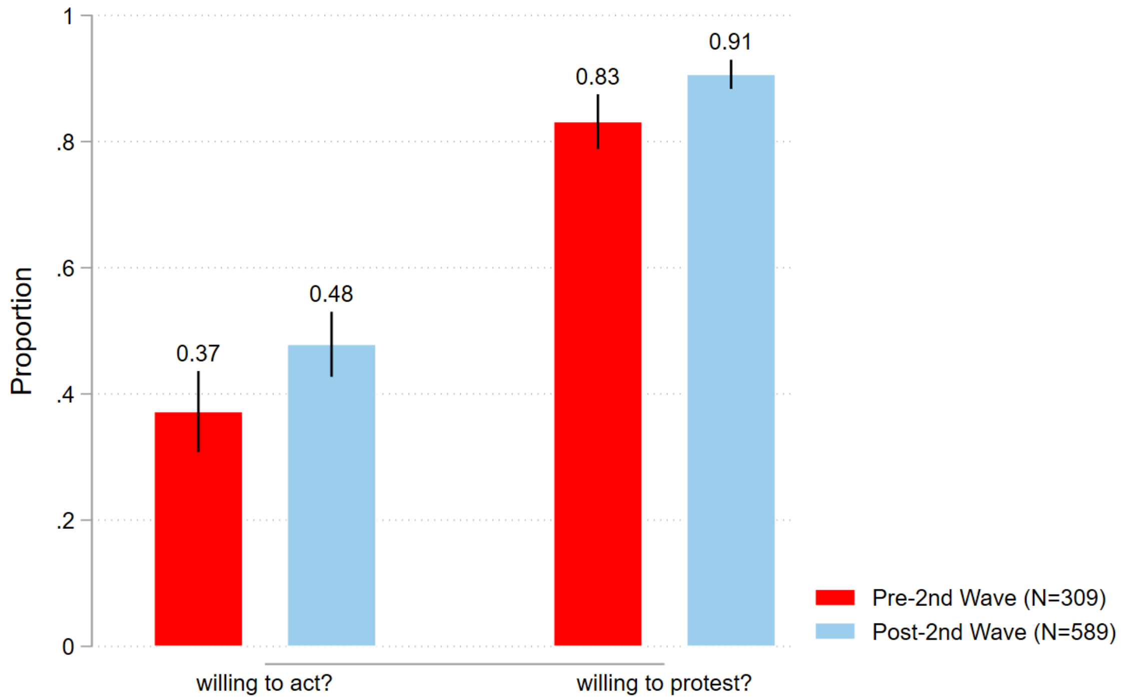
3.7 Conclusion

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.

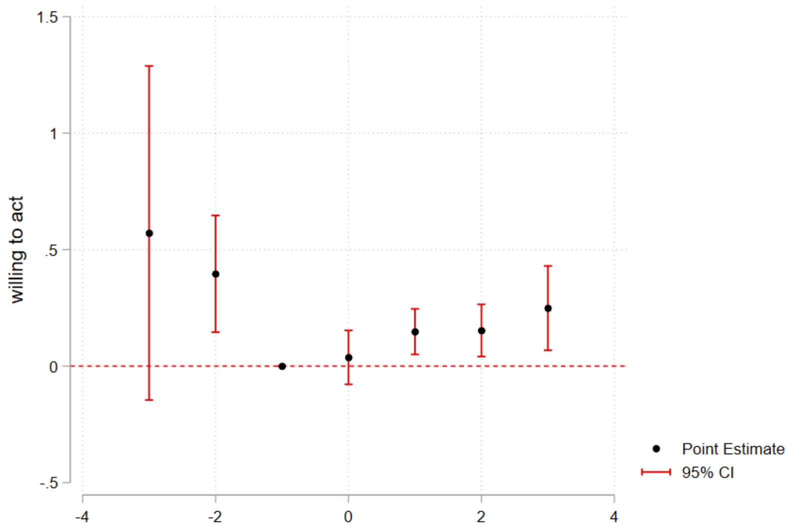
3.8 Tables and Figures

Figure 3.1: COVID-19 and Willingness to Act, Protest, Corruption Perception and Information

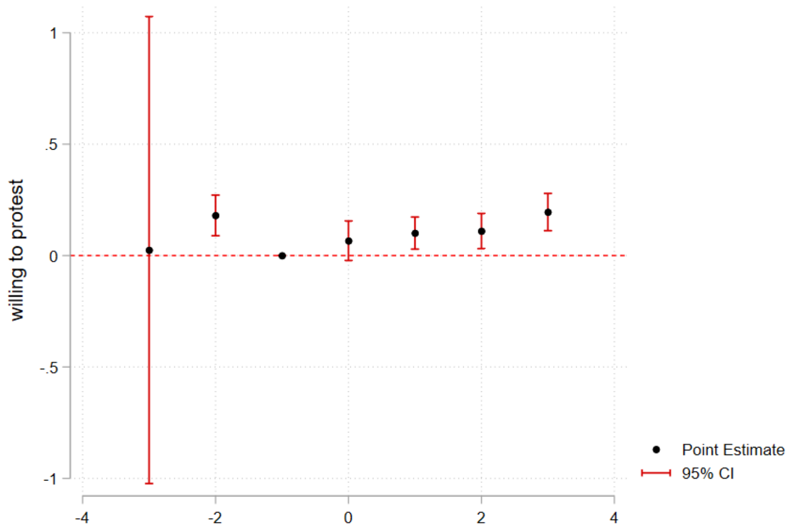


Notes: Figure shows, respectively, the percentages of subjects willing to take anti-corruption action ('willing to act?') and willing to participate in protest ('willing to protest?'), pre and post 2nd wave peak. Total count of subjects=898. The figure displays percentages and 95% confidence intervals.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

Figure 3.2: Willingness to Act and Protest, by Month of Survey



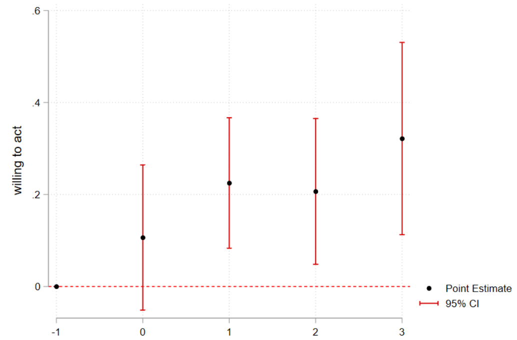
(a) Willingness to Act



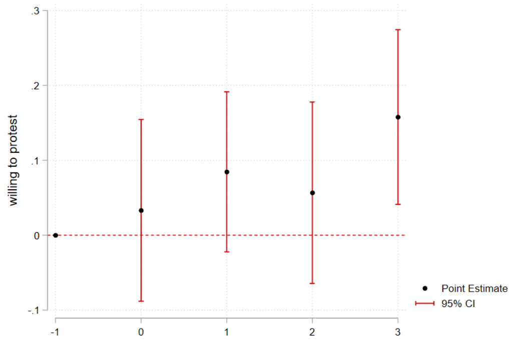
(b) Willingness to Protest

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.

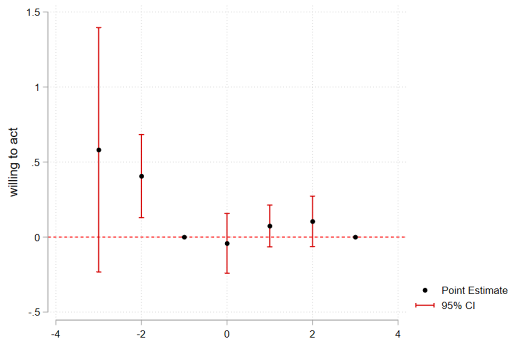
Figure 3.3: Willingness to Act and Protest, by Month of Survey



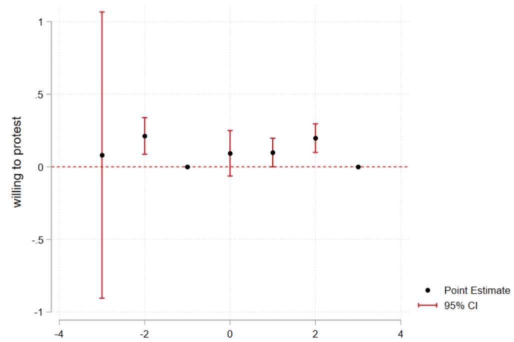
(a) Willingness to Act (Early Peak)



(b) Willingness to Protest (Early Peak)



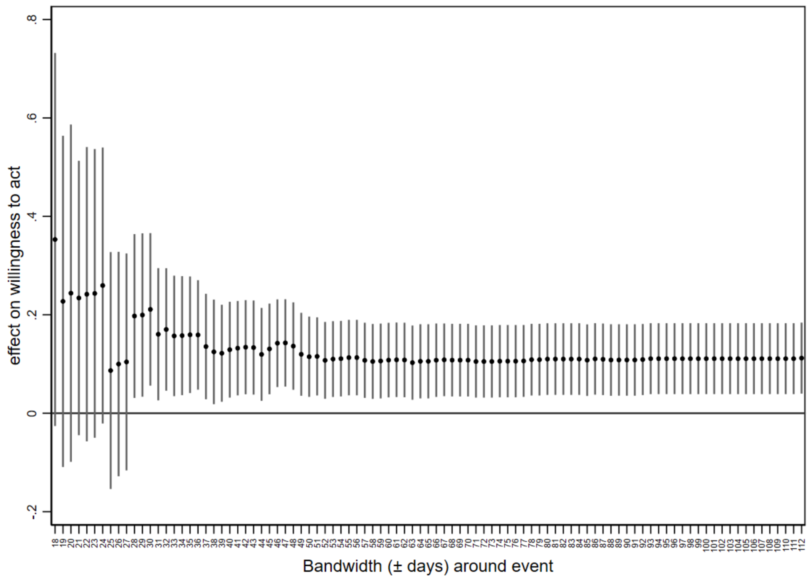
(c) Willingness to Act (Late Peak)



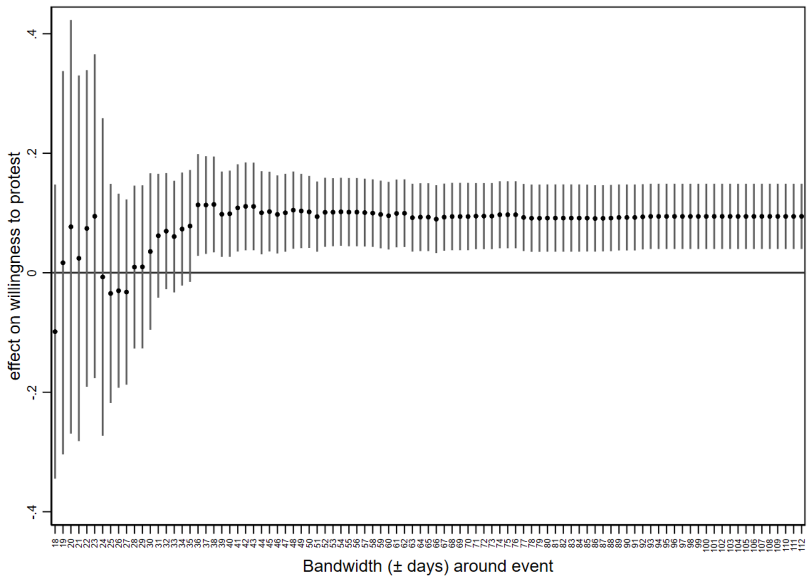
(d) Willingness to Protest (Late Peak)

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 3.4: 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 3.1 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 3.1: 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 3.2: 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 3.3: 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 3.4: Impact of Second-wave of COVID Cases on Beliefs, Information about Rights and Entitlements, Corruption Perception and Risk

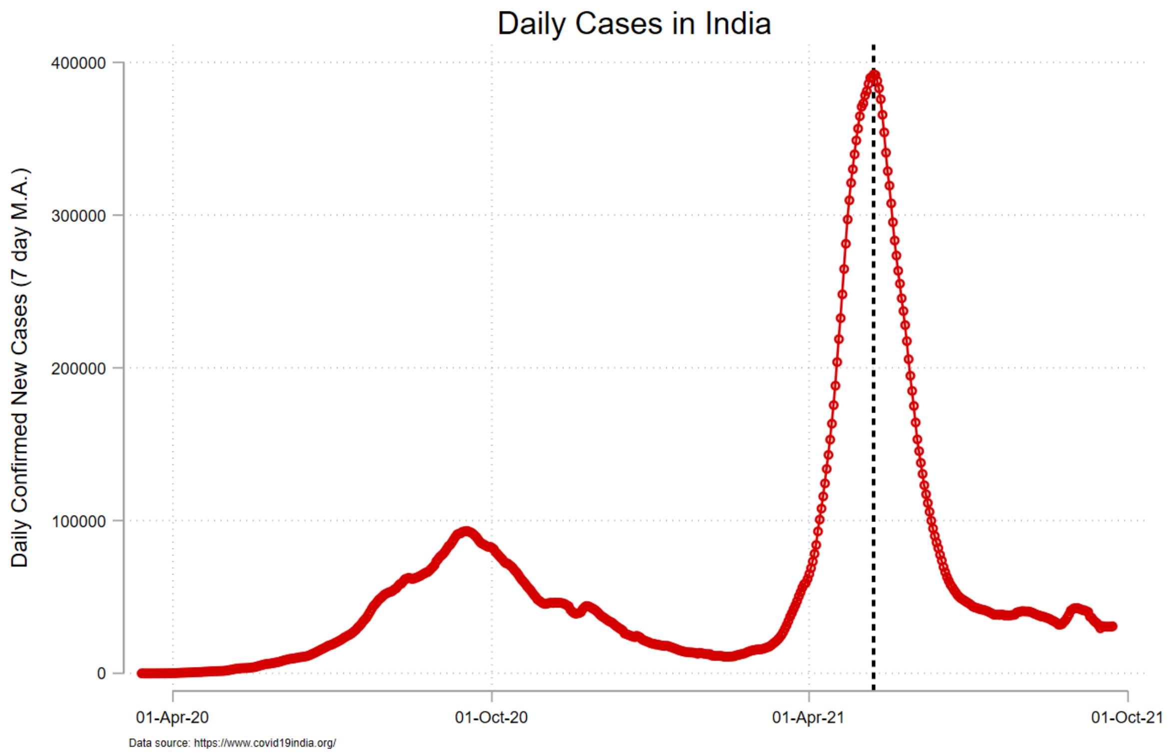
	Bias in Belief	Information (Rights)	Corruption Perception	Risk
	(1)	(2)	(3)	(4)
Post	-0.091***	0.287***	0.238***	0.223***
	(0.028)	(0.070)	(0.086)	(0.065)
Observations	898	898	898	898
Control Mean	0.702	0.000	-0.000	-0.000
Controls?	yes	yes	yes	yes
Balanced?	yes	yes	yes	yes
R^2	0.092	0.172	0.122	0.103

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 3.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. * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix

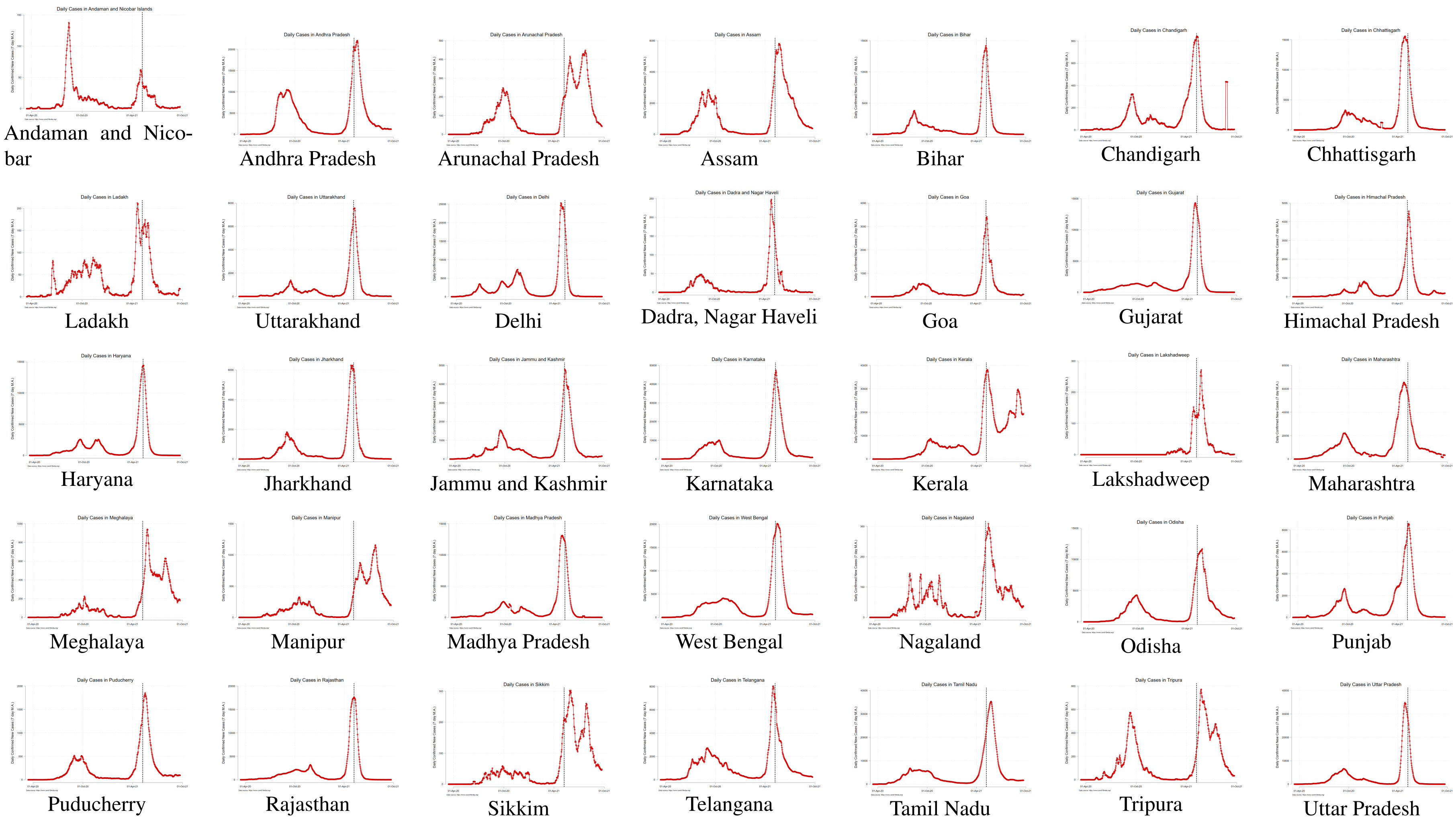
3.A Additional Analysis

Figure 3.A.1: Daily COVID Cases



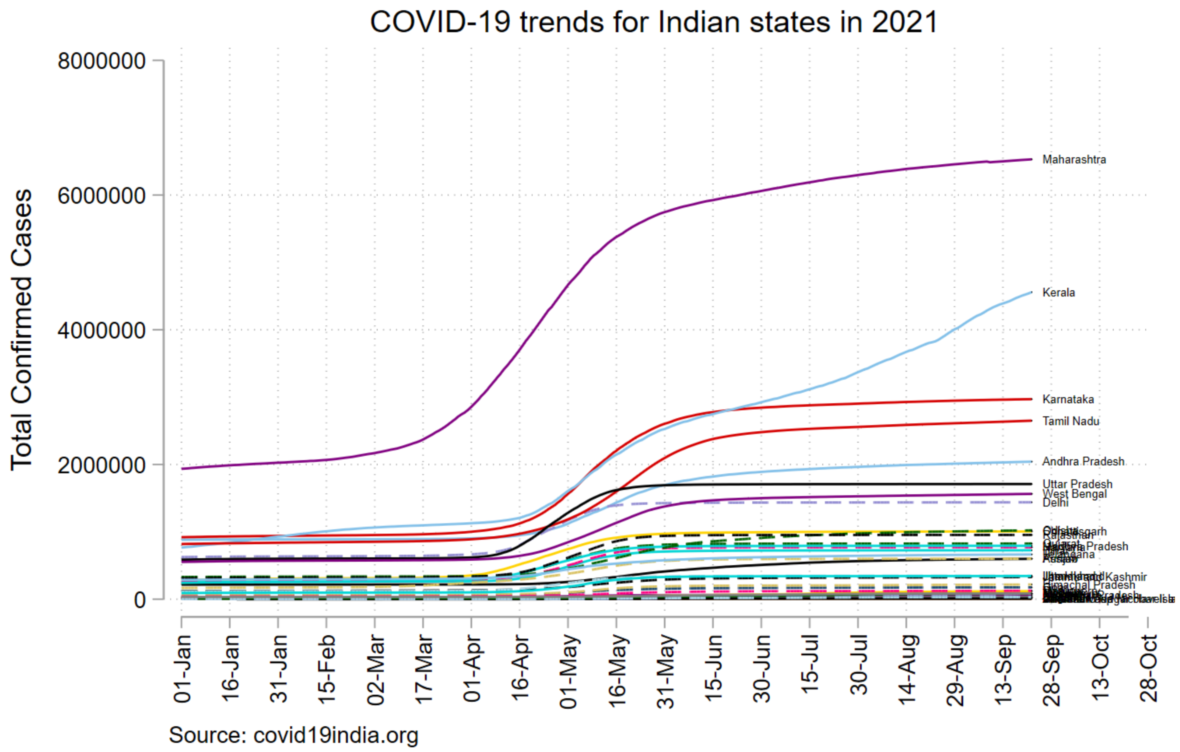
Notes: Figure shows the peak in daily confirmed cases (7 day moving average) for April 2020 to October 2021. The black line corresponds to the national peak. Data taken from covid19india.org.

Figure 3.A.2: Daily COVID Cases - Indian States



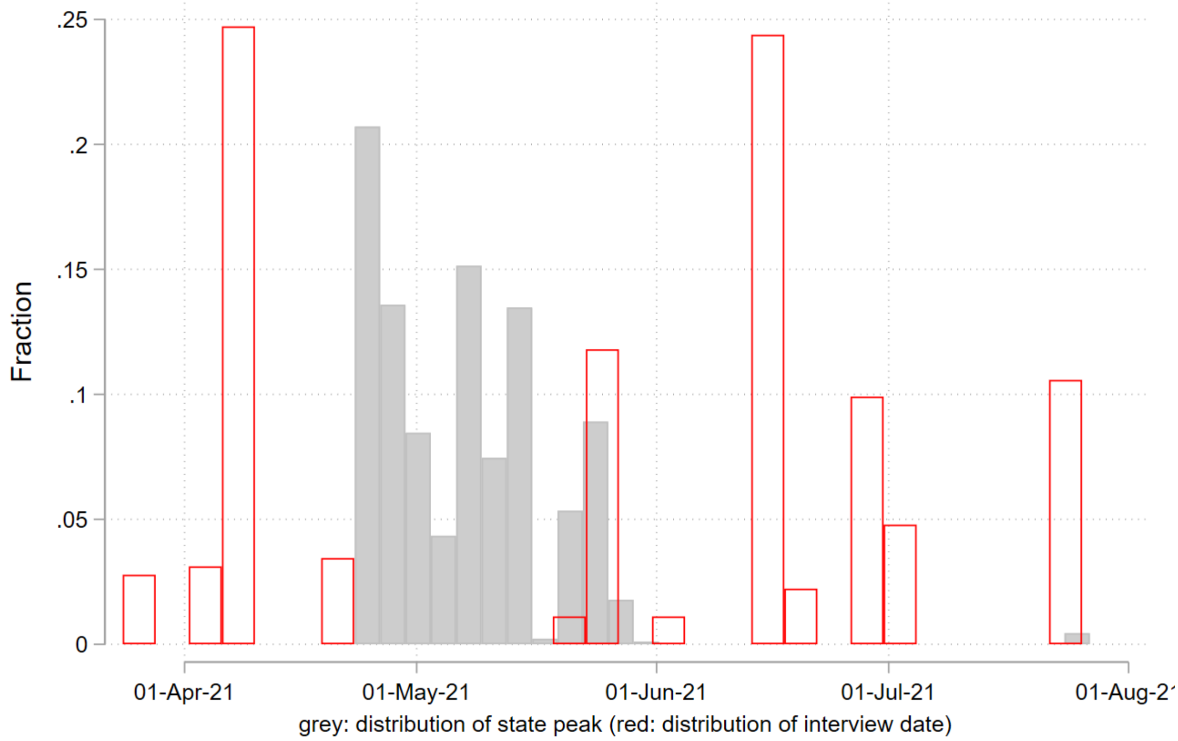
Notes: Figure shows the state-wise trend in daily confirmed cases (7 day moving average) for April 2020 to October 2021. The black line corresponds to the national peak. Data taken from covid19india.org.

Figure 3.A.3: Total COVID Cases - Indian States



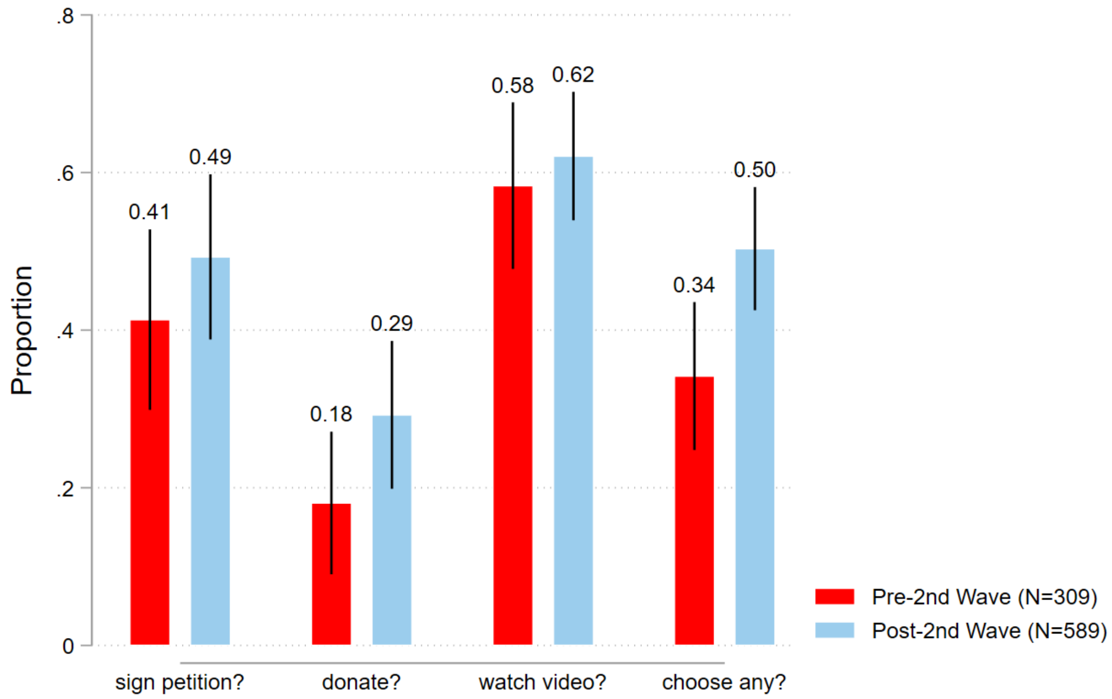
Notes: Figure shows the total confirmed cases for Indian states, from January to October 2021. Data taken from covid19india.org.

Figure 3.A.4: Distribution of Subjects According to Interview Dates and Case-peak in State of Residence



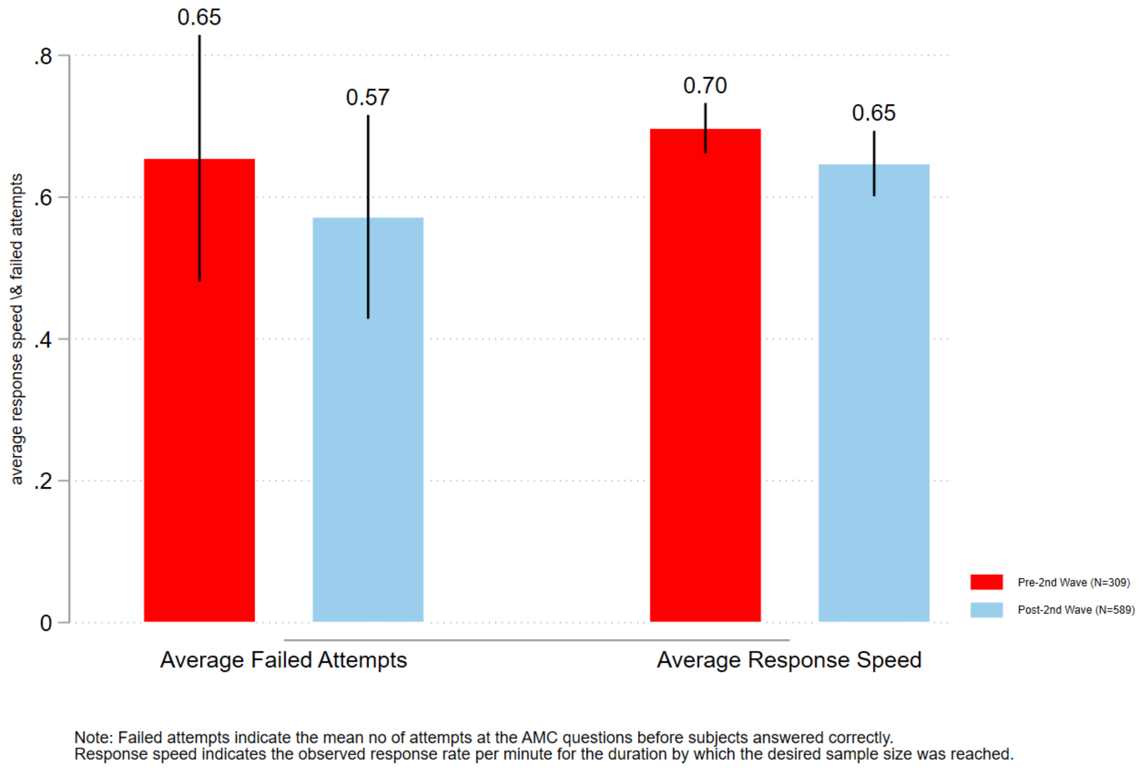
Notes: The distribution of subjects according to date of case peak is captured in grey, while the distribution of interview dates of subjects is in red. N=898.

Figure 3.A.5: Impact of Second-wave on Willingness to Sign Petition, Donate, Watch Video or Choose Any Action When Offered All Three



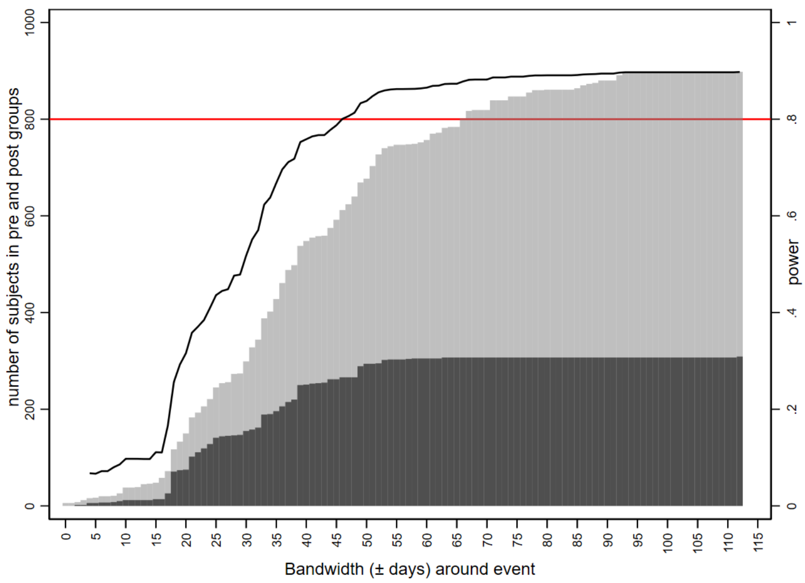
Notes: Figure shows, respectively, the percentages of subjects willing to sign a petition to the Ministry of Health, donate a portion of their earnings to the non-profit organization, gather information online by watching a 6-minute video on how to fight corruption in health or choose any when offered 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 3.A.6: Data Quality Checks Before & After COVID Case-peak

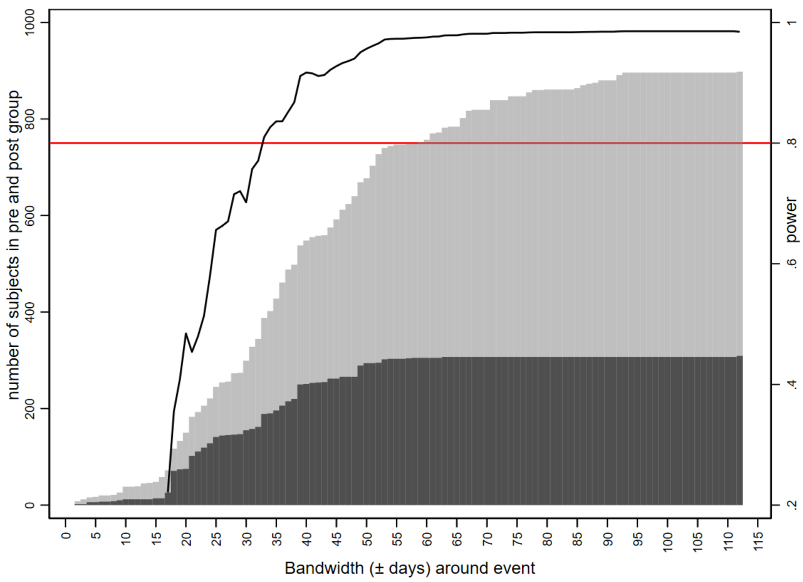


Notes: Failed attempt is a continuous variable indicating the number of attempts at the attention manipulation check question before answering it correctly. The average number of failed attempts is close to 1 in both pre and post groups, and not statistically different. The response speed captures the average speed (surveys completed per minute) at which the desired sample size was obtained, in pre & post group. N=898.

Figure 3.A.7: Statistical Power



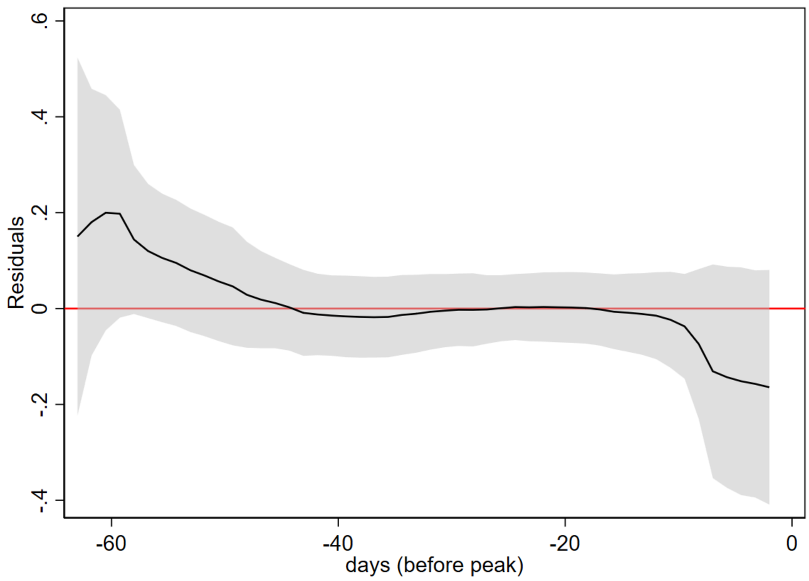
(a) On Willingness to Act



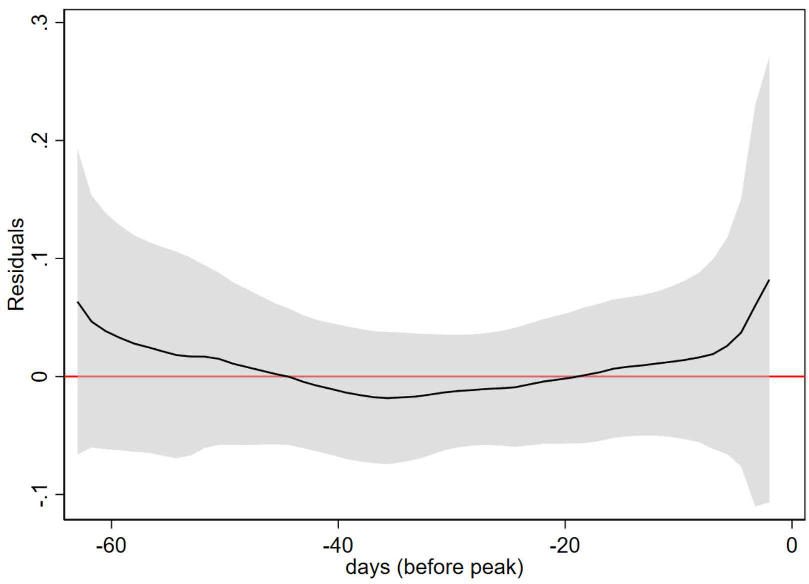
(b) On Willingness to Protest

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 3.A.8: 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 3.A.1: 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 3.A.2: 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 3.A.3: 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 3.A.4: 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 3.A.5: 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 3.A.6: 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 3.A.7: 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 3.A.8: Impact of Second-wave of COVID Cases on Pro-sociality and Tolerance of Corruption

	Pro-sociality	Tolerance
	(1)	(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. Corruption experience, pro-sociality and risk are standardized measures computed from relevant questions, as described in subsection 3.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 3.A.9: 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	0.002
Willing to Protest	0.094	0.000	0.002
Corruption Perception	0.238	0.007	0.004
Information (Rights)	0.287	0.000	0.002
Civic Engagement	0.300	0.000	0.002
Risk	0.223	0.001	0.002
Bias	-0.091	0.001	0.002
Pro-sociality	-0.053	0.304	0.439
Corruption Tolerance	0.073	0.280	0.439

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.

Table 3.A.10: Long Term Impact of Second-wave on Willingness to Protest

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post (full sample)	0.111***		0.094***		0.572***		0.088***	
	(0.025)		(0.019)		(0.107)		(0.029)	
Post (long term sample)		0.136***		0.091***		0.049		1.744
		(0.024)		(0.022)		(0.077)		(1.471)
Observations	1747	1158	1747	1158	1747	1158	1747	1158
Control Mean	0.832	0.832	0.832	0.832	0.832	0.832	0.832	0.832
Controls?	no	no	yes	yes	yes	yes	yes	yes
Balanced?	no	no	yes	yes	yes	yes	yes	yes
State FE	no	no	yes	yes	yes	yes	yes	yes
Time FE	no	no	no	no	yes	yes	yes	yes
State Specific Linear Time Trend	no	no	no	no	no	no	yes	yes
Sample	full	long term	full	long term	full	long term	full	long term
R^2	0.025	0.057	0.123	0.181	0.157	0.231	0.149	0.225

Notes: Post (full sample) 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. Post (full sample) is a dummy equal to 1 for subjects interviewed a year after the COVID case peaks, in 2022; 0 for subjects interviewed before the peak. Controls include age, education, marital status, religion, income, 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.A.11: Heterogeneity in Long Term Impact of Second-wave on Willingness to Protest

	(1)	(2)
Post (full sample) x *low performing health*	0.049	
	(0.041)	
Post (full sample)	0.560***	
	(0.108)	
low performing health	-0.027	-0.086*
	(0.044)	(0.049)
Post (long term sample) x *low performing health*		0.122**
		(0.046)
Post (long term sample)		0.009
		(0.078)
Observations	1747	1158
Control Mean	0.832	0.832
Controls?	yes	yes
Balanced?	yes	yes
State FE	yes	yes
Time FE	yes	yes
Sample	full	long term
R^2	0.159	0.235

Notes: '*low performing health*' is a dummy equal to 1 for the states of West Bengal, Bihar, Uttar Pradesh, Madhya Pradesh, and Rajasthan (accounting for about 25% of the sample), which are designated as states having 'low performing health' as per UNDP health index ranking, according to Transparency International India (2005). Post (full sample) 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. Post (full sample) is a dummy equal to 1 for subjects interviewed a year after the COVID case peaks, in 2022; 0 for subjects interviewed before the peak. Controls include age, education, marital status, religion, income, 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. * $p < .10$, ** $p < .05$, *** $p < .01$

3.B Sampling

In order to measure whether the subjects are paying attention to the survey, 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 make sure that subjects understand 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.

3.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.

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)."[55]
- "In your opinion, has the level of corruption in the health sector during the COVID-19 pandemic - (increased a lot/ increased somewhat/ stayed the same/ decreased somewhat/ decreased a lot)"[56]?
- "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)"[57].

Information (Rights)

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

[55] response coded into a continuous variable.

[56] response coded into a continuous variable with higher value indicating increase in corruption.

[57] response coded into a continuous variable with higher value indicating bigger problem.

- "Do you know what is the rate you have to pay per day for an ICU bed at your local hospital?"[58]

- "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)"[59]

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)."[60]
  - avoiding fare on a public transport
  - doctors overcharging for a hospital bed during COVID-19 pandemic
  - someone accepting a bribe in course of their duties.

- "How many people in your community do you think expects you to complain if you are overcharged or asked to pay a bribe by a doctor? (nobody/ a few people/ many people/ most people/ everybody)."[61]

Civic Engagement

The civic engagement index aggregates the following survey questions.[62]

engagement "Do you agree or disagree with the following statements, on a scale of: strongly agree/ somewhat agree/ neither agree nor disagree/ somewhat agree/ strongly agree".
  - you play an active role in one/more voluntary organizations
  - you don't like to discuss politics with other people (reverse-coded)
  - being involved in your neighborhood is important to you

[58]response coded into a dummy=0 if subject answered with 'don't know', 1 otherwise.
[59]response coded into a dummy=1 if subject answered with a 'yes.
[60]responses coded into a continuous variable.
[61]response coded into a dummy=1 if subject answered with 'nobody'.
[62]responses for each set were coded into continuous variables.

- you don't get involved in political protests (reverse-coded)
- you generally vote in elections

past action "Prior to COVID-19 pandemic (since April 2020 till date), have you ever been involved in any of the following actions to help solve a problem that mattered to you? - with answer choices: never/ yes, 1-3 times/ yes, 4-6 times/ yes, 7-10 times/ more than 10 times".

- protests
- walkouts or strike
- boycott
- petition
- lodging complaints
- marching
- donation to an organization

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).”
- “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 pro-sociality index using the same process described above.

Chapter 4

Electoral Cycles in Road Building: Evidence from India[1]

4.1 Introduction

An influential theoretical literature starting from Nordhaus (1975) argues that economic outcomes will follow the electoral calendar due to fiscal manipulation by opportunistic politicians to boost their re-election prospects (Lindbeck 1976; Rogoff and Sibert 1988; Rogoff 1990; Persson and Tabellini 1990). However, empirical evidence on physical outcomes such as unemployment has been mixed at best: moving to cycles in policy variables, however has produced some credible evidence, in particular on budgetary and monetary variables[2]. The literature initially consisted mostly of either cross-country studies[3] or studies focused on developed countries.[4] Recently, however some progress has been made for developing countries at the sub-national

[1]This chapter is joint work with Farzana Afridi (ISI-Delhi), Amrita Dhillon (King's College London) and Arka Roy Chaudhuri (Shiv Nadar University).

[2]Dubois (2016) provides a survey.

[3]See, for example, Shi and Svensson (2006); Brender and Drazen (2005); Streb et al. (2009); Persson et al. (2003); Michelitch and Utych (2018) among others.

[4]See, for example, McCallum (1978), Klein (1996), Galli and Rossi (2002), Veiga and Veiga (2007), Grier (2008), Potrafke (2010), Aidt et al. (2011), Efthyvoulou (2012), Katsimi and Sarantides (2012), Potrafke (2012), Mechtel and Potrafke (2013), Aidt and Mooney (2014), Stolfi and Hallerberg (2016), Bove et al. (2017) among others.

level.[5] An underlying theme running through these results is that political cycles should logically be more apparent in outcomes where there is greater discretion and control of instruments by the government, and where targeting to pivotal groups of voters is possible.[6]

In this paper, we provide evidence for electoral cycles in public infrastructure - road building - even when the state government does not control the budget on roads, when there are multiple levels of government involved, and when targeting of roads to particular constituencies is ruled out. Despite these constraints, state legislators can still affect program outcomes through informal lobbying with the local bureaucracy (Jensenius and Suryanarayan 2015; Bussell 2019) and in the specific case that we consider i.e. road building, through more formal channels such as participating in the planning stage (N.R.R.D.A 2012; Lehne et al. 2018). We show that state-level incumbents are able to manipulate the road building process such that roads that are likely to be ready by the next election are built at the expense of roads that take longer to build. It is possible that this lowers welfare if e.g. “easy to build" roads come at the expense of roads that connect possibly very remote areas to highways.

The *Pradhan Mantri Gram Sadak Yojna* (PMGSY) was introduced in December 2000- it is the world’s largest rural roads program, with a budget of $41 billion, with built in accountability and transparency features. The 2001 census formed the basis of determining whether villages qualified for the program, on the basis of stated population thresholds (Goyal, 2019). This federally sponsored scheme aimed to provide all weather road connectivity to previously unconnected habitations of India, ensuring that all habitations with population over 1000 get a road by 2003 and the ones with population over 500 get a road by 2007. The funding for this program comes from the federal government and is overseen by a national agency, but the actual execution of the program falls in the hands of the state government. Therefore, multiple decision-makers are involved in various stages of this program.

We use unique data that map all roads built under PMGSY over a decade (2000-01 to 2012-13), to census villages and then to state-level constituencies using geo-coded location and constituency shape files. Another distinctive feature of our data is information on initial and subsequent stages of a road’s construction from administrative records - sanction, award of road construction contracts (or award) and finally road construction (or completion). We are, thus,

[5]See, for example, Akhmedov and Zhuravskaya (2004), Khemani (2004), Brender and Drazen (2005), Cole (2009), Vergne (2009), Drazen and Eslava (2010), Aidt and Eterovic (2011), Baskaran et al. (2015), Mironov and Zhuravskaya (2016), Klomp and de Haan (2016) among others.

[6]Although there is a lot of evidence for electoral cycles, there is also some documentation of null results, such as- Jensen et al. (2020); Berger and Woitek (1997) among others.

able to observe detailed program implementation at each stage, at the road level, within each constituency. Therefore, we show that electoral cycles exist not only in allocation but also in real outcomes.

Our identification strategy exploits the staggered nature of constitutionally mandated scheduled state level elections in India to estimate the effect of an incumbent politician's tenure on rural road construction under PMGSY. We, thus, rely on constitutionally mandated scheduled elections for our analysis since scheduled elections cannot be strategically timed by politicians. This ensures timing of elections are exogenous to road-building outcomes. Our empirical analysis shows that in the fourth year of an incumbent's term, i.e. two years before the elections are due in the five-year fixed term of the incumbent, 2 extra roads are sanctioned under PMGSY, the initial stage of the program. This represents a 40% increase over the mean. Although formal involvement of politicians is largely limited to the sanctioning stage, we should see an electoral cycle in subsequent stages of the road building program either because the spike in sanctioning translates into awards and completion or because of informal involvement of politicians in the final two stages (award and construction) (Lehne et al. 2018) of road building. We, thus, turn to the subsequent stages of the PMGSY program to find that following the spike in sanctioning outcomes in the fourth year of an incumbent's term, award and completion outcomes spike significantly on the fifth year (last year) of the incumbent's term. Our findings are robust to alternative empirical strategies - (1) we drop from the sample all the term years leading up to a midterm election; (2) we use an instrumental variable strategy where scheduled election dummies serve as instruments for the actual election dummies.

To understand whether increases in road building before elections translate into efficiency losses or increased costs, we turn to other measures of road building such as quality, delay, expenditure per kilometre and stipulated construction time, available in the administrative data. Using these measures, we demonstrate that the spike in outcomes before election does not systematically worsen the quality of or increase construction delay and costs for roads that are completed. However, we find that the stipulated construction time of roads decreases right before elections, hinting that politicians might target easier to build roads before elections. The opportunity cost of building roads that have shorter stipulated times, is that roads that are more difficult e.g. roads in geographically difficult terrain get delayed.

To explain these results we build on the model of electoral cycles in Shi and Svensson (2006). We show that when voters care about politician competence, misallocation of road spending towards those roads that have lower stipulated times for completion, can take place in periods before elections even when voters fully anticipate this. We also show theoretically that misallocation is likely to be driven by those constituencies that have a higher share of uninformed voters. The reason is that informed voters know the competence level of the incumbent, while uninformed have to infer the competence of the incumbent from the roads that are built in period t and knowing the equilibrium strategy of the incumbent.

In line with the model's predictions, we find that electoral cycles are more pronounced in electoral constituencies with a larger share of uninformed voters as measured by the fraction of illiterate population in the constituency. We find that the magnitude of electoral cycle is higher in areas where voters don't particularly have the ability to assess incumbent's competence, i.e., in areas with higher share of uninformed voters. We also rule out the competing channel of a learning effect on the part of an incumbent legislator with less administrative experience. Specifically, we look at constituencies with first-time legislators where we would expect the learning effect to be more salient, if it exists. We find no such evidence.[7]

Our paper primarily contributes to the literature on electoral cycles at the subnational level in developing countries. Studies have shown that electoral cycles are larger in developing countries relative to developed countries (Shi and Svensson 2006). India, as a developing country, a federation and a democracy, is a particularly interesting context to study electoral cycles. In the Indian context, Khemani (2004) studies state budgets and documents no strong impact on aggregate fiscal variables but on individual budget components. Cole (2009) observes electoral cycle in public sector bank loans, and finds that election year credit booms induced substantially higher default rates. Min and Golden (2014) and Baskaran et al. (2015) examines electoral cycles in electricity losses and electricity provision respectively. Fagernäs and Pelkonen (2020) finds that teacher transfers and hiring increases after state elections and Bhattacharjee (2022) uncovers evidence of electoral cycles in child health outcomes.

We extend this literature, first, by uncovering evidence of electoral cycles in a novel context. Unlike previous research that has focused on more macroeconomic outcomes and fiscal instruments such as state budgets, credit or more narrowly targetable outcomes such as teacher hiring and transfers, we look at a broad-based public good, viz. infrastructure building. Infrastructure provision is poor in developing countries (Banerjee et al. (2006)).[8] Since infrastructure is one of

[7]We do not find evidence of effect of electoral cycles in PMGSY on re-election probability of incumbents. There is no heterogeneity in our results by electoral competition or center-state political alignment.

[8]Andres et al. (2014) find that countries in South Asia need to invest between 6.6 and 9.9 percent of 2010 gross domestic product per year till 2020 to close their infrastructure gap compared to the 6.9 percent of gross domestic

the key drivers of economic growth, a large-scale rural road building program like PMGSY is particularly important for broad-based development, and finding electoral cycles in this context is particularly concerning. Apart from the large scale of the program[9], it is worthwhile to note that PMGSY is amongst the more rule-based (Aggarwal 2018) programs in India, with little scope for manipulation. Further, unlike the other outcomes studied in the literature such as state budgets, agricultural credit, health expenditure, which come under the purview of either state governments or the federal government, in the case of PMGSY both the state governments and the federal government have joint decision-making powers making it a particularly interesting context to study,

Second, we show exact strategic timing on the part of the incumbent politicians in infrastructure programs that have long gestation periods between inception and completion. To the best of our knowledge, no other paper in the literature shows electoral cycles in successive stages of a program. Our results indicate that politicians time their effort strategically in the phase of PMGSY where they have the most significant formal role, i.e. sanctioning during the fourth year of their terms so that there is a boost in the more visible aspects of road building, i.e. awards and completion right before elections. Moreover, we are also able to show the exact mechanism through which politicians achieve this; they do so by targeting easier to build roads i.e. roads with lower stipulated construction time before elections. Our results further suggest that the overall welfare implication of such strategic timing are ambiguous since electoral cycles in magnitude of road building do not have any corresponding electoral cycles in unit costs and other efficiency measures of road building such as quality and delay. However, our results suggest that this spike in road building is achieved by targeting easier to build roads before elections, leading to delays in roads that might potentially have led to greater increases in productivity.

Finally, unlike most papers in this literature, which either use state-level (Khemani 2004) or district-level data (Cole 2009), we are able to provide more reliable estimates of election cycles due to more disaggregated spatial level panel data at the constituency level. Constituency level panel data allow us us to study electoral cycles at the level at which state elections are held, by including constituency fixed effects to account for unobserved (time invariant) heterogeneity in constituency characteristics.

A growing literature has emerged in the context of *Pradhan Mantri Gram Sadak Yojna*, the

product invested in infrastructure by South Asian countries in 2009.

[9]More than 550,000 kms of rural roads having been constructed at a cost of US$ 40 billion over 19 years (2000-2018) since the program's roll out (Goyal (2019)).

world's largest rural public road delivery program. Almost all the papers in this literature show positive effects of rural road infrastructure on critical measures of development such as market integration (Aggarwal 2018), occupational choice (Asher and Novosad 2020), education (Adukia et al. 2020), healthcare utilization (Aggarwal 2021) and agricultural production (Shamdasani 2021). We show evidence of manipulation of program's functioning, i.e. how election timing influences the implementation of PMGSY, which can potentially impede program benefits.

The remainder of the paper is organized as follows. In Section 4.2, we describe the institutional background. Section 4.3 provides a theoretical model. The datasets are described in Section 4.4 and the empirical strategy in section 4.5. The main results are contained in Section 4.6 while Section 4.7 discusses the possible mechanisms behind our results. Finally, Section 4.8 concludes.

4.2 Institutional background

4.2.1 The PMGSY program

The *Pradhan Mantri Gram Sadak Yojna* (PMGSY) was introduced in December 2000. This federally sponsored scheme aimed to provide all weather road connectivity to previously unconnected habitations of India, ensuring that all habitations with population over 1000 get a road by 2003 and the ones with population over 500 get a road by 2007.

The program has been described as 'unprecedented' in scale and scope - between 2001 - 2010, it provided paved roads to over 100 million people, about 14.5% of rural population, or 47% of rural unconnected population of India, as of 2001 census (Aggarwal, 2018). The funding for this program comes from the federal government and is overseen by a national agency, but the actual execution of the program falls in the hands of the state government. Therefore, multiple decision-makers are involved in various stages of this program. We are interested in the role of state legislator or MLA (Member of Legislative Assembly), but first we outline the process of road planning, approval and clearance of road work, in order to profile the true scope of this program, and then argue that MLAs play an important role in all the stages of road building.

The framework of PMGSY consists of two distinct stages - an initial one-time preparation of road plan, and a yearly planning and clearance activity. Each of these stages involve multiple players at the local, state and federal levels, as outlined below.

4.2.2 Preparation of Road Plan

A simplified overview of the key phases of the program is given in Figure 4.1. The program begins at the block and district[10] level, with the formation of District Rural Roads Plan (DRRP) and the core network, under the supervision of district Program Implementation Units (PIUs) which are set up by the state level road development agency (also known as SRRDA or the State Rural Road Development Agency).,[11] These two planning documents are created for identifying eligible roads that could be constructed to improve the existing all-weather road connectivity at the district level.[12]

The plans are initially approved by the *Intermediate Panchayat*, and then overseen by the *District Panchayat*.[13] At this stage, it is also simultaneously shared with the Members of Parliaments and Legislative Assembly of the state (MP and MLA, respectively) for their feedback. Note that this marks the first instance of involvement from political actors. After ensuring that the suggestions of the politicians (MLAs and MPs) are given full consideration, the plan is forwarded to the state level standing committee.[14] This committee finalizes the DRRP, and also sends a copy of the plan to the federal government for approval.

Once the core network is ready, the states are required to prepare a comprehensive priority list of all proposed road links under PMGSY. The list is updated annually, by removing roads taken up under PMGSY or other programs, and a copy of this list is sent along with the annual proposals to all elected representatives in the state (N.R.R.D.A, 2005).

[10]A district is an administrative unit of an Indian state. Districts can be sub-divided into *tehsils* or blocks, which can further be sub-divided into *Gram Panchayats* or village councils. The electoral district at the state level, on the other hand, is known as assembly constituency (AC), from where members of *state level* legislative assemblies (MLAs) are directly elected to serve five year terms. Each district is divided into several ACs in order to facilitate elections. At the *national level*, each state is divided into several national electoral districts called parliamentary constituencies (PCs), from where members of parliament (MPs) are directly elected to serve five year terms in the Indian House of Commons. Each PC consists of two to three ACs from within a state. Election of MPs are held concurrently at national level, whereas state level elections of MLAs are staggered.

[11]The DRRP consists of the existing network of roads in the district and the proposed new roads for PMGSY, while the core network identifies new roads required to assure all-weather connectivity for previously unconnected habitations (N.R.R.D.A, 2012) .

[12]For a detailed description of the entire process of road formation, clearance, disbursal and monitoring, see N.R.R.D.A (2005).

[13]In India, *Panchayati Raj* Institutions is a system of local governments at three levels: the top-level *District Panchayat* at the (administrative) district level; the intermediate (block) level *Panchayat Samiti* or *Intermediate Panchayat*; and the village level *Gram Panchayat*. Direct elections in India are held at the *Gram Panchayat* level, state level (for MLAs) and at national level (for MPs).

[14]The state level standing committee is headed by the Chief Secretary/ Additional Chief Secretary in each state. It is created for the purpose of overseeing PMGSY road construction.

4.2.3 Annual Planning and Clearance of Road Work

The annual flow of activity in PMGSY is summarized via Figure 4.2. Once the core network is prepared, it is possible to estimate the length of roads in each district. The list of road works is finalized each year at the district level. The funds for road construction are released at the federal level on a quarterly basis, subject to the satisfactory implementation of the program (i.e. subject to implementation of all the steps of Figure 4.1).[15] Every year, the list of roads is finalized at the district level through a consultative process involving lower level local governments and other elected representatives. Then, the state level agency for road development, State Rural Road Development Agency (SRRDA) vets the annual proposals so that they are in accordance with all guidelines, and then places it in front of the state level standing committee. This committee is in charge of finalising detailed reports for each prospective road. The proposals are then sent to the national agency for road development (the National Rural Roads Development Agency or the NRRDA), which operates under the supervision of the federal government.[16]

Road Clearance

At the federal level, the roads pass through the Ministry of Rural Development (MoRD) for clearance. The ministry then communicates the sanctioning of roads to the state governments. This sanctioning marks the first step of the process that is observable in our database (Figure 4.2).

After the cleared proposals have been communicated by the federal ministry, the implementation process begins at the state level. The state level agency invites tenders to award roads to contractor (observed in the "award of sanctioned roads through tenders" step, in bold in Figure 4.2). Upon successful completion of tendering, the contractors commence work on the roads. These last two steps are also observed in our database.

Disbursement of Funds

Under PMGSY, roads have to be completed within a stipulated time period. The cost of the sanctioned roads is made available to the state level agency in instalments, subject to fulfillment

[15]Over the period we consider, the costs of implementation are borne entirely by the federal government. However, any cost overruns are borne by the state government.

[16]The National Rural Road Development Agency (NRRDA) is the federal level agency, set up under the chairmanship of the Minister of Rural Department (MoRD) to manage overall implementation. Before sending them to the national agency, the proposals are also technically assessed by expert institutions, appointed by the federal government.

of completion conditions.[17]

Funds are released from the federal ministry subject to implementation of all the steps of Figure 4.1. Each year, the states distribute the allocated fund among the districts and also communicate this district-wise allocation to the federal ministry. The state level agency authorizes a high-ranking officer, only who can draw and disburse funds to the contractors.

Hence, the federal government is in charge of sanctioning funds, but fund disbursement and road execution lie within the state's purview, with the federal government overseeing it all through the centralized monitoring system in place.[18]

4.2.4 Maintenance and Quality Control

Ensuring the quality of roads is primarily the responsibility of the state governments, in particular, the executive engineer of the district level program implementation units. Periodic inspections are carried out by the Quality Control Units set up by the state governments, as well as by the federal government who engage independent monitors for inspection, at random, for doing a thorough quality control check and rate the checked roads as poor/ average/ satisfactory.

The online management and monitoring system or OMMS is the chief mechanism for monitoring; a case of continued failure to update data on the OMMS actually affects the fund release to the states. This software is directly provided by the NRRDA and not allowed to be modified by the states, which makes it an excellent source of information on the many aspects of the program. Further, it covers all aspects of the program planning, implementation, quality control measures and maintenance.

The roads constructed under this program are expected to be of very high standard, requiring no major repairs for at least five years after completion of construction. To this end, the state government obtains guarantees, valid for five years, from the contractor. After five years, the responsibility of maintenance is transferred to relevant local government institution.

[17] The first instalment in a particular year amounting to 25% of the value of roads cleared by the Ministry is released after the road has been cleared by the Ministry. The release of remaining instalments is subject to utilization of 60% of the total available funds as well as completion of at least 80% of the road works up to the previous year.

[18] The Online Management and Monitoring System or the OMMS is the online software where officials are required to furnish all information related to the program as prescribed by the national level agency NRRDA. For more details, see `http://omms.nic.in/`.

4.2.5 Role of State Legislators

The program outcomes are measured at the level of the state or assembly constituency in our analysis. Our aim is to estimate the electoral cycle resulting from state elections in PMGSY provision. The staggered nature of election timing at the state level provides the necessary variation to estimate electoral cycles. In the next few paragraphs, we elaborate on the role of the Member of Legislative Assembly (MLA), directly elected by voters in their assembly constituencies (ACs), in general and in the PMGSY program.

In the wider context of Indian polity, the role of MLAs in their constituencies is multifaceted. As Jensenius and Suryanarayan (2015) notes -

> “Officially, the main task of local Indian politicians is to represent their constituents in the state assembly. In reality, however, the work in the legislative assembly is a minor part of their work."

Jensenius and Suryanarayan (2015) further point out that much more important to the MLAs are all their unofficial tasks of delivering pork and helping people out with their individual problems. MLAs are often approached by their constituents, party workers and other elected officials for their assistance in a variety of issues- future roads, delivery of government benefits and services, and request to appeal to the local bureaucrats etc. These leaders often provide assistance to their constituents by writing letters, helping them overcome bureaucratic bottlenecks and can even threaten bureaucrats with an unfavorable transfer/ harm (Jensenius and Suryanarayan, 2015; Bussell, 2019).

Specifically, for PMGSY road work, the suggestions of MLAs are requested during the process of drawing up the rural roads plan and considered fully before approval. Further, they are often present in district planning meetings to make sure that the interests of their constituents are not overlooked in the plan.[19] MLAs also play a ceremonial role in laying the foundation or in the inauguration ceremony of roads, which are public events. Within 15 days of the issue of work order to the contractor, standardized signboards with PMGSY logo are erected on either end of the road, containing information on length, estimated cost etc. These activities help to attribute the credit of delivery to them. [20]

[19] Recall that the district level committees play a significant role in road planning, both through the one-time preparation and the annual proposal of roads, as outlined in section 4.2.2 and section 4.2.3. See N.R.R.D.A (2012) for more details.

[20] See Goyal (2019) for a more detailed description of attribution of PMGSY roads.

4.3 Theory

We build a model that borrows from the electoral cycles literature (Rogoff and Sibert 1988; Shi and Svensson 2006; Drazen and Eslava 2010). The details of the model are in the Appendix. Briefly, the model shows that incumbents would like to signal their competence to voters by manipulating the expenditure on roads in election periods. The key assumption is that competence is a shock that the incumbent observes only after decisions on roads have been made. The shock itself is a moving average of time t and $t-1$ shocks. This process implies that only shocks that happen one period before are informative of the next period competence. Moreover elections happen only every other period. Voters would like a "competent" politician in the next non election period as that ensures more roads are completed for any fixed allocation. Politicians have incentives to increase road budgets (sanctioned roads) in election periods to improve the competence signal but not in non election periods. Therefore when the incumbent is making decisions on how much to allocate to roads in election periods, they will either go over the socially optimal budget (given the opportunity costs of roads) or they will increase the proportion spent on roads with lower stipulated time to complete. Voters are rational and anticipate such manipulation but party competition ensures that such misallocation takes place in equilibrium even though election results are unaffected. Secondly there is a difference between voters who are informed and, therefore can work out the exact manipulation and voters who are uninformed and have to guess the extent of manipulation. It is only the latter that matter for the probability of winning. We therefore get two main predictions:

(1) Sanctions and completions will be higher in the years just before election relative to other years. Moreover sanctions will be higher for roads which have shorter stipulated times.

(2) ACs with a higher share of uninformed voters display larger electoral cycles.

4.4 Data

4.4.1 Program Data

The PMGSY data set covers the years 2000-01 to 2012-13 financial years[21]. We have data on 18 major states under this program.[22] Program outcomes are observed at the road level. The census data, the source of our control variables, are reported at the village level, and the election data are at the pre-2008 delimitation assembly constituency level.[23]

To conduct our analysis at the assembly constituency level, we need to aggregate up the village level census data and the road level program data to the assembly constituency level which we accomplish through the following steps. First, we map the roads to census villages by using the administrative data sets available from the government website (http://omms.nic.in/)[24]. Then using Geographic Information Systems (GIS)[25], we map this data (road-census village matched data) to assembly constituencies.[26]

A brief summary of our main outcome variables is presented in Panel I of Table 4.1. The outcomes are separated into three distinct phases, each one indicating a separate stage of road construction[27]. The first phase is sanctioning, where we consider the total number of roads sanctioned, the total sanctioned length (in kms) and the amount sanctioned (in INR millions)[28] in a financial year in an assembly constituency. On an average, we find that about 4.8 roads are

[21]Financial years run from April to March of next calendar year. Program activities in PMGSY follow this financial year system.

[22]The states included in this study are Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Maharashtra, Madhya Pradesh, Odisha, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. We do not consider Uttarakhand, which split off from Uttar Pradesh in 2000, since the state had a delimitation in 2002 which makes matching of constituencies difficult.

[23]Delimitation refers to the redrawing of boundaries of various parliamentary and assembly constituencies. The last delimitation was carried out in 2008, on the basis of the 2001 census. The main objective of delimitation was to equalize the population across constituencies. This exercise makes the pre and post delimitation constituencies incomparable. Hence we focus on the pre-delimitation period so that we have consistent constituency boundaries which lets us use constituency fixed effects. The PMGSY program was launched in 2000, and the major part of the program was executed during politicians' terms who were elected during the pre-2008 delimitation period. From Figure 4.B.1, we observe that indeed, the pre-2008 delimitation politicians were responsible for getting the majority of the roads sanctioned in most states.

[24]This website is the online repository of all road level information on PMGSY.

[25]We thank Raphael Susewind for providing us with the shapefiles.

[26]For matching the road data with the village shape-files, we compare state, district and block names between the two data sets and manually verify that they are consistent. Next, we employ a fuzzy string-matching process to match villages between census shape files and PMGSY administrative data set. This gives us high quality merging, with 93 percent exact match in village names.We then aggregate the program outcomes at the constituency level, by intersecting the village level shape-files (2001 census villages) with assembly constituency shape files. We find that close to 93% roads do not cross constituency boundaries. Therefore, we retain only the roads that can be matched to a single constituency.

[27]Please refer to the steps marked in bold, from Figure 4.2.

[28]INR stands for Indian Rupee. For comparison, 1 USD is roughly equal to INR 79.10 as of 5th August, 2022.

sanctioned in a financial year, with a total sanctioned amount of INR. 13.45 million and with a total length of 19.87 kms. The second stage is award of sanctioned roads to contractors. From Table 4.1, we see that on an average, about 4.35 roads are awarded to contractors every year with a total length of about 18.04 kms. The third and final stage is the completion of awarded roads. We see from Panel I of Table 4.1 that on an average, about 3.54 roads are completed each year, with a yearly average total expenditure amount of INR 7.65 million.

We use the next set of variables as measures of program efficiency in PMGSY. In our sample, the per kilometre expenditure is about INR 0.57 million.[29] The quality variable (proportion of satisfactory roads) is a measure for the proportion of roads that received "satisfactory" rating in national quality inspection, out of the total number of completed roads that were subject to quality inspection in that constituency.[30] From Table 4.1, we see that on an average, about 48 percent of the roads subject to national quality inspection pass the quality check. As a measure of delay in completion, we look at the the average time overrun which calculates the average difference in days between the actual and the pre-designated date of completion (as specified in the contract) of a road in an assembly constituency. We also consider the stipulated construction time which measures the average number of days between the road award date and the pre-designated end date of construction (as specified in the contract) of a road in an assembly constituency. We find that a road typically should take 336.16 days or close to 1 year to complete, from award to completion. However, the actual construction time is much higher with the time overrun being about 258.46 days on average.

4.4.2 Election Data

We use state legislative assembly election data from Election Commission of India (ECI) covering elections between 1996 and 2007. This data set records the name, age, sex, total votes received of the candidates, the election year and the total number of voters and electors base for all constituencies. We merge the election data set (follows calendar year) with the PMGSY data (follows financial year)[31]. Next, we generate the year-wise election cycle dummies, that

[29]Note that amount sanctioned and expenditure are two distinct variables. Recall that roads are first drawn up, approved by various authorities and then sanctioned from the federal government. After that, roads are allocated to contractors via a tendering process, and then the contractors start building. The expenditure variable is generated in this latter stage.

[30]The designation of "satisfactory road" is assigned by a National Quality Monitor, if the road meets the standards of materials and execution of work. Otherwise, it is designated as "unsatisfactory" or "required improvement".

[31]We use the following process: if an incumbent starts her term from October or earlier in a financial year, then she has at least six months or more of that year to execute the program and hence that year is counted as the first

corresponding to each of the five years of a typical term of an MLA. These year-wise dummies account for our main set of regressors.

4.4.3 Controls

We use the 2001 census data to obtain information on demographic and socio-economic variables at the AC level, which could potentially be correlated with program implementation. We use the total population of constituency and the share of population belonging to marginalized caste groups (Scheduled Castes and Scheduled Tribes) in the constituency population as demographic controls.[32] To measure development at the constituency level, we also include share of the proportion of villages with a school in the AC. Finally, information on terrain at the 2001 census district level is taken from Iyer (2010).[33] From Panel II of Table 4.1 we find that the average constituency population stands at about 223,660, the proportion of reserved population is about 18%, while in a typical constituency, about 81% of villages have a primary school, as per the 2001 census. In our sample at the district level, the proportion of barren/rocky area is 0.7% on an average.

4.5 Empirical Strategy

4.5.1 Impact of Electoral Cycle

To capture the presence of electoral cycles, we employ a regression model similar to Cole (2009). We create the following dummy variables: S_{st}^{-k}, $k = 0, ..., 4$ that take the value 1 if the next *scheduled* election is k years away for state s in time t. The following regression gives the estimate of the entire cycle:

$$Y_{idst} = \gamma_i + \psi_t + \beta_0 S_{st}^{0} + \beta_1 S_{st}^{-1} + \beta_2 S_{st}^{-2} + \beta_3 S_{st}^{-3} + \tau Z_{ids} \times t + \epsilon_{idst} \tag{4.1}$$

year of her term. However, if she starts her term from November or later, then she has less than six months of the financial year left to do any work, and consequently the next financial year is counted as the first year of her term.

[32]Indian society has traditionally been stratified into a number of castes which are hereditary, endogamous groups and were originally based on occupation. Scheduled Caste (SC) is an administrative category, which consists of a number of castes which are economically and socially backward and have been historically subjected to discrimination. Similarly, Scheduled Tribe (ST) is another administrative category which comprises of a group of indigenous tribes who are economically and socially backward (Deshpande 2011).

[33]We use the proportion of barren/rocky area at the district level from the data-set of Iyer (2010), who extracted the district level geographical information from India Agriculture and Climate Data Set, World Bank (`https://ipl.econ.duke.edu/dthomas/dev_data/datafiles/india_agric_climate.htm`). This information is given for 1991 district boundaries, which we then mapped on to 2001 district boundaries, using Kumar and Somanathan (2009).

where Y_{idst} denotes program outcome in assembly constituency (AC) i of district d in state s in time t. The first year of an incumbent's term (i.e. S^{-4}) is taken as the reference group. The coefficients β_i, $i = 0, ..., 3$ measure the effect of election timing with respect to this reference group. We include AC fixed effects (γ_i) and year fixed effects (ψ_t). The vector Z_{ids} consists of time invariant base level characteristics from the 2001 census, at AC level i of district d in state s, such as the total population, the proportion of reserved population, and presence of schools. We interact these socio-economic and demographic variables with a linear time trend ($Z_{ids} \times t$) and include that as a set of control variables. Standard errors are clustered at the state level[34].

It is mandated by the constitution, that state elections are scheduled every five years. In order to claim causality, the state election cycles must be exogenous to the program outcomes we study. The claim of exogeneity of election timing will be valid if the elections were in fact held in every quinquennial year during the period of our study. Sometimes, however, actual elections are held one, two, three or four years after the last election, i.e. before their scheduled time owing to various reasons, such as a change in coalition leadership in the state government (Cole 2009) or other political developments such as changes in the ruling coalition. These elections are known as midterm elections. Midterm elections can pose a threat to identification if the timing of their occurrence is endogenous. For example, program outcomes can affect the decision to call for early elections, in which case, the timing of such midterm elections can be correlated with unobservable factors which affect program outcomes. Since we use *scheduled* election cycle dummies (rather than actual) as our main set of regressors, it circumvents the issue of incumbents strategically choosing the time of election, as the midterm election years are still counted as middle of term (Khemani 2004). Figure 4.3 illustrates an example of how the scheduled and the actual election cycle dummies can diverge from one another in the case of a midterm election. Additionally, midterm elections were very infrequent during our period of study, 2000-01 to 2012-13 with only three midterm elections occurring during this period[35].

In order to affirm our main results, we use two alternative empirical strategies as robustness checks for our main results. In the first check, we only consider the sample of elections where scheduled and actual elections coincide. Thus, we drop from the sample all the term years leading up to a midterm election, so that the remaining years correspond to only years leading up to a scheduled elections, and re-estimate equation (4.1). By dropping observations corresponding

[34]Since there are only 18 states in our sample, we have a small number of clusters. Hence we use the wild cluster-bootstrap method (Roodman et al. 2019.)

[35]Midterm elections have become increasingly less frequent over time in India. Cole (2009) shows that the presence of midterm elections was low, and not a concern even in the previous decade of 1992-1999.

to midterm election years, we ensure that the timing of election in the analysis sample is exogenously determined through scheduled election timing and is not strategically manipulated by politicians.

In the second alternative empirical strategy, we employ an instrumental variable strategy, using the scheduled election dummies S_{st}^{-k} as instruments for *actual* election dummies to indicate if an election is k years away, $k = 0, ..., 4$ (Cole, 2009). The scheduled election dummies follow the cycle illustrated in Figure 4.3, resetting after every midterm election. Hence, the scheduled election cycle dummies are closely correlated with the actual election cycle dummies, yet do not suffer from the same problem as actual election cycle dummies, in that these are not vulnerable to incumbents strategically choosing the timing of the elections when economic conditions are advantageous. Hence, these dummies are a natural choice of instruments for the actual election cycle (Khemani 2004).

4.6 Main Results

Do elections affect road building? To answer this question, we look at the temporal variation in road building outcomes across the incumbent's term by estimating equation (4.1). We focus on the sanctioning stage since politicians have the maximum scope to affect outcomes at this stage through formal channels. From Table 4.2, we observe a clear spike in sanctioning activities, such as, total sanctioned roads, total length sanctioned and total amount sanctioned on the fourth year of an incumbent's term (see Table 4.2). These increases are statistically significant, and sizeable. For example, from the column 1 of Table 4.2, we find that on the fourth year of an incumbent's term, 1.586 extra roads are sanctioned as compared to the base, which is the first year of the term. Given that the average number of sanctioned roads is 4.8 (from summary stats Table 4.1), this increase translates to a 33 percent increase over the mean in the fourth year of the electoral term. Similarly, the total sanctioned road length shows an approximately 29.2 percent rise over the mean (an increase of 5.808 km of total sanctioned road length on the fourth year, from column 2 of Table 4.2; the mean sanctioned road length is 19.87 km), and the annual total sanctioned amount displays almost a 21.6 percent rise over mean (an increase of about 2.911 million INR of total sanctioned amount on the fourth year, from column 3 of Table 4.2; the annual average is at 13.45 million INR).

As an alternative empirical strategy, we estimate equation 4.1, but by restricting the sample to only scheduled elections, i.e. by excluding the years leading up to midterm elections. The results, reported in Table 4.3 confirm our main findings. From column 1 of Table 4.3, we find that the coefficient of 1 year till next election is 2.205 for number of sanctioned roads, this increase translates to a 45.9 percent increase over mean. Similarly, the total sanctioned road length shows a 40.3 percent rise over the mean (an increase of 8.001 km of total sanctioned road length on the fourth year, from column 2), and the annual total sanctioned amount displays a 34.2 percent rise over mean (an increase of 4.604 million INR), from column 3 of the same table. Hence, from these tables we find that the impact of electoral cycle on sanctioning outcomes is, if anything, marginally bigger when we drop all mid-term elections.

In our second alternative empirical strategy, we instrument the four actual election cycle dummies with scheduled election cycle dummies. Similar to the scheduled election dummies, the actual election dummies indicate if the actual election was 0, 1, 2, 3, or 4 years away, with the first year of an incumbent's term (i.e. dummy to indicate the actual election is 4 years away) taken as the reference group. The results from the instrumental variable regression for sanctioning outcomes are reported in Table 4.4. These estimates are similar to our main results in Table 4.2 with the same sign and higher magnitude, thus lending confidence in our main empirical strategy.

To understand the efficiency and cost implications of electoral cycles in road building, we test for electoral cycles in measures such as quality, delay, expenditure per kilometre and stipulated construction time. The results are presented in Table 4.5. We do not find any statistically significant impact of election timing on quality of roads, time overrun and per kilometre expenditure. However, the roads that are built on the last year of the term have about 18.673 days shorter stipulated construction time (5.5 percent reduction over its mean), indicating that during the last year of their term incumbent state legislators are more likely to choose roads that can be built quickly. The statistically insignificant impact on quality, time overrun and cost are consistent with a major feature of PMGSY since its inception, which is the presence of a centralised monitoring system. This monitoring system was put in place to limit corruption Lehne et al. (2018). Time overrun and per kilometre cost are more easily observable in the central monitoring database, and hence incumbent politicians will be wary of engaging in activities which lead to their increase right before elections. Instead, we show that they sanction roads in such a manner that roads which take less time to build are completed right before elections.

Finally, we test for electoral cycles in the next two stages of PMGSY after sanctioning;

awards and completion. This is necessary to test so that we can check if legislator effort which results in electoral cycles in sanctioning translates into electoral cycles in more visible road building outcomes such as awards and completion. Table 4.6 and Table 4.7 demonstrate that the sanctioning spike is followed by an increase in award and completion activities on the fourth and fifth year of an incumbent's term. The number of awards increases by 1.546 on the fourth year of incumbent's term, which is a 35.5 percent rise over the mean of 4.35. It also increases on the year of next election as well, by 0.662, which is a 15.2 percent increase over the mean of 4.35. Similarly, total road length of awarded roads also show a significant increase of 4.31 (approximately 23.8 percent over the mean of 18.04) on the fourth year of the incumbent's term. Completion outcomes show a similar pattern of increase in road completion and total road length of completed roads on the fifth year of the term. The number of completed roads in a constituency increases by 0.961 on the fifth year of incumbent's term (27.1 percent increase over mean of 3.54), and total completed length of sanctioned roads increases by about 2.782 km (approximately 20.6 percent increase over mean, which is 13.49 km), all statistically significant increases. The total expenditure on completed roads also increases on the fifth year, but is not statistically significant.

Our results indicate that sanctioning outcomes peak on the fourth year of the incumbent's term while the corresponding award and completion outcomes peak respectively on the fourth and fifth year of the term. This pattern of sanctioning outcomes peaking in the fourth year of the incumbent's term while completion outcomes peaking in the year of the elections is interesting since it suggests strategic timing of effort by politicians to get a boost in outcomes right before elections even for outcomes like roads which have a relatively high gestation period. Since the mean time taken for road completion (award to completion) is 1.6 years, we expect incumbent politicians to already take this into account so that they are able to influence the real outcomes right before elections. Hence we should see a spike in sanctioning outcomes in the fourth year of an incumbent's term while the corresponding spike in completion outcomes would show in the final year of the term.

4.7 Mechanisms

In this section, we provide some suggestive evidence on two counts- first, we discuss how politicians bring about electoral cycles, and then we try to understand why electoral cycles exist.

One possible way in which politicians are able to induce electoral cycles in road building is through choosing to build relatively easier to build roads before elections. We had provided some evidence of this mechanism earlier in Section 4.6 where we saw that roads completed right before elections have significantly shorter stipulated construction time (column 4, Table main-quality). To provide additional evidence on this channel, we now look at the variation of cycle magnitude across different geographical terrain. Barren and rocky areas without vegetation can be more prone to issues such as soil erosion, slope stability, earthwork cost etc.[36] This, in turn, makes road construction in such areas 'difficult'. In Table 4.9, we use the proportion of barren/rocky areas in a district at the baseline (2001), and interact it with our main election dummies. We find that indeed, prior to elections, sanctioning activities for all three outcomes (number of sanctioned roads, sanctioned length and amount sanctioned) become lower in constituencies belonging to districts with more difficult terrain.

Next, we provide some suggestive evidence on mechanisms of why electoral cycle exists. Our model in Section 4.3 highlights that in presence of electoral incentives, incumbents generate increases in road building activity right before elections, possibly in greater amounts in areas with high information asymmetries. In line with our model's prediction, we find some suggestive evidence of the presence of information asymmetry (Rogoff 1990; Shi and Svensson 2006), as our leading explanation for electoral cycles in rural road building under PMGSY. Information asymmetry typically manifests as a lack of voter awareness, which hinders them from holding politicians accountable and therefore, increases the magnitude of electoral cycle. We use the proportion of illiterate population in an assembly constituency as a measure of the share of uninformed voters. We interact this variable with the dummies for electoral cycle, with a focus on the road sanctioning activities (number of sanctioned roads, sanctioned length and amount sanctioned) as a measure of politician effort. The results are presented in Table 4.10. The results indicate that the magnitude of electoral cycle in road sanction is significantly higher in constituencies having a larger share of illiterate population.

There could also be other possible explanations of electoral cycles in rural road-building. One possibility is that electoral cycles are generated through the presence of a learning effect; incumbents become more experienced in executing the program as their term progresses, thus giving rise to electoral cycles. The findings from our sanctioning outcomes, however, indicate otherwise. According to the results in Table 4.2, the peak in sanctioning outcomes occur not

[36] For example, F.A.O. (1992) provides an overview of different types of costs associated with roadwork.

on the fifth year of incumbent's term, but on the years before the fifth year. If electoral cycle is generated through a learning process, then we should expect it to increase monotonically over the years of the term, and consequently the peak should be in the fifth year.

Secondly, learning over the course of one's term should be more salient for first-time MLAs who have little experience, compared to MLAs with experience. To test for this, we interact a dummy (called first-time MLAs) that takes the value 1 if the incumbent is a first-time MLA and 0 otherwise. When interacting this dummy with the cycle dummies, we find no significant effect of the interaction of this variable with the cycle dummies for the sanctioning outcomes (Table 4.8), which likely indicates the absence of any learning effect.[37] Taken together, the results in this section seem to indicate that information asymmetry is a leading reason behind pre-electoral increases in rural road building outcomes under PMGSY, rather than politicians learning to better implement the program in the course of their electoral term.

4.8 Conclusion

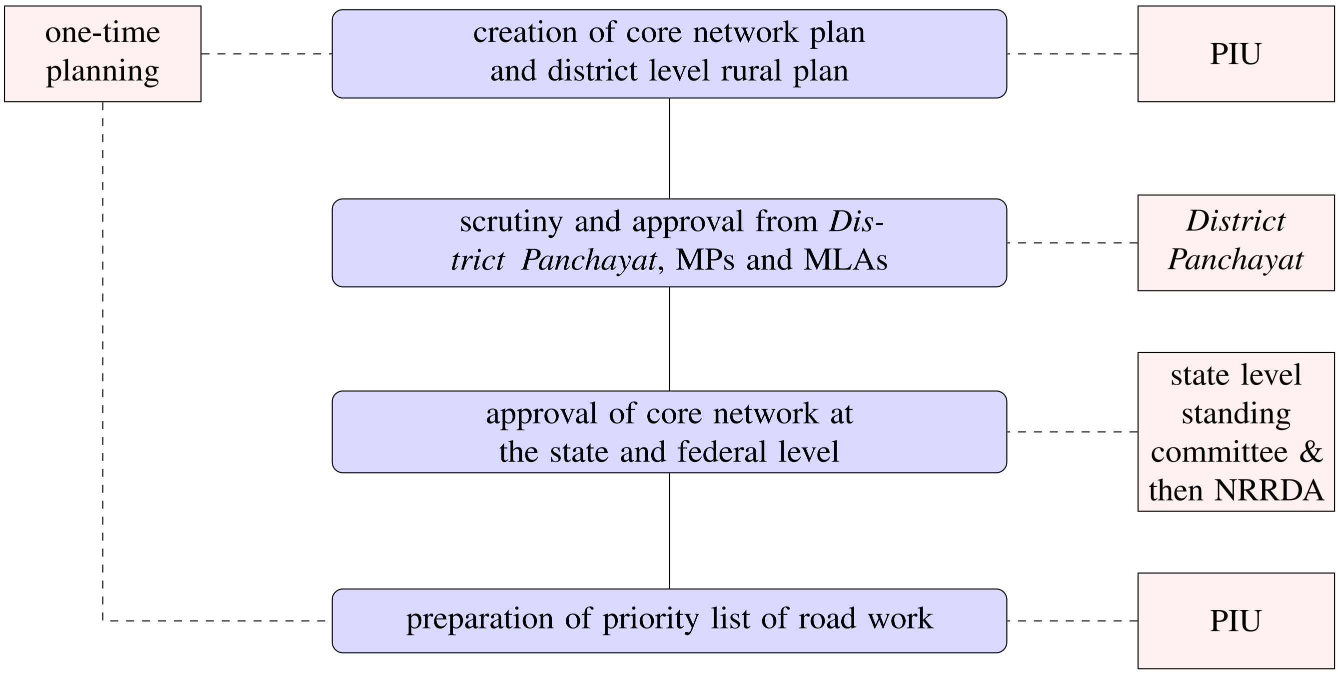
In this paper, we provide evidence of electoral cycle in a nationwide road program in India, through multiple successive stages of road building. Using road level data from eighteen states of India spread over a decade, we capture an increase in road sanctioning activities, followed by increase in road delivery prior to state elections. PMGSY is a scheme that is supposed to be rules based and local politicians cannot change roads once approved in the core network. Moreover

[37] We also examine if road delivery varies with the level of electoral competition faced by an incumbent MLA. In general, it is plausible that incumbents will focus on increasing program delivery in highly competitive areas right before elections, for effectively targeting swing voters (Baskaran et al., 2015; Cole, 2009). We use a dummy variable to identify constituencies that exhibit lower than the median of margin of victory in MLA elections, to measure the level of political competition in a constituency. Margin of victory is measured as the gap between of the winner's vote share from the share of the runner-up in the last election. The results (reported in Table 4.B.1) show that road sanctioning is not significantly larger in constituencies with higher levels of electoral competition. To analyze the impact of partisan vertical affinities between multiple tiers of government on the presence of electoral cycle in the sanctioning outcomes, we also constructed an alignment variable, which is a dummy that takes value one if an incumbent belongs to the same political party as the state Chief Minister and the Prime Minister. We call this type of alignment "seamless alignment". We interact this dummy with the electoral cycle dummies, and present the regression results in Table 4.B.2. We find that seamless alignment does not have a significant effect on the magnitude of electoral cycle likely because of the accuracy in attribution of credit for roads to the different levels (see Goyal (2019)). Finally, we also capture the correlation of the magnitude of pre-electoral spike in sanctioned roads, by estimating the equation $Re - election_{idst} = \gamma_i + \psi_t + \beta_1 \overline{C}_{idst} + \beta_2 \overline{dev\text{-}C}_{idst} + \tau Z_{ids} \times t + \epsilon_{idst}$, where the dependent variable $Re - election_{idst}$ is a dummy equal to 1, if the incumbent was re-elected in the next election in AC i of district d in state s in electoral term t. The total road outcome from the electoral term is split into two parts; the term $\overline{C}_{idst}$ captures the average PMGSY outcome, for all years in the current term except the peak year. Our main regressor of interest is the second part, $\overline{dev\text{-}C}_{idst}$, which measures the deviation of the average PMGSY outcome of the peak year from rest of the years of current term (i.e. measurement of the magnitude of electoral cycle). As reported in columns 1, 2 and 3 of Table 4.B.3, we do not find any statistically significant results for sanctioning outcomes.

the central government monitors performance closely and funds are released only conditional on successful performance. Therefore it is surprising that even in this context we find evidence of manipulation. We find that politicians target easier to build roads right before elections in the sense that roads with lower stipulated construction time get built more before elections. However we do not find any significant impact on various efficiency measures related to quality, cost and delay due to electoral cycles.

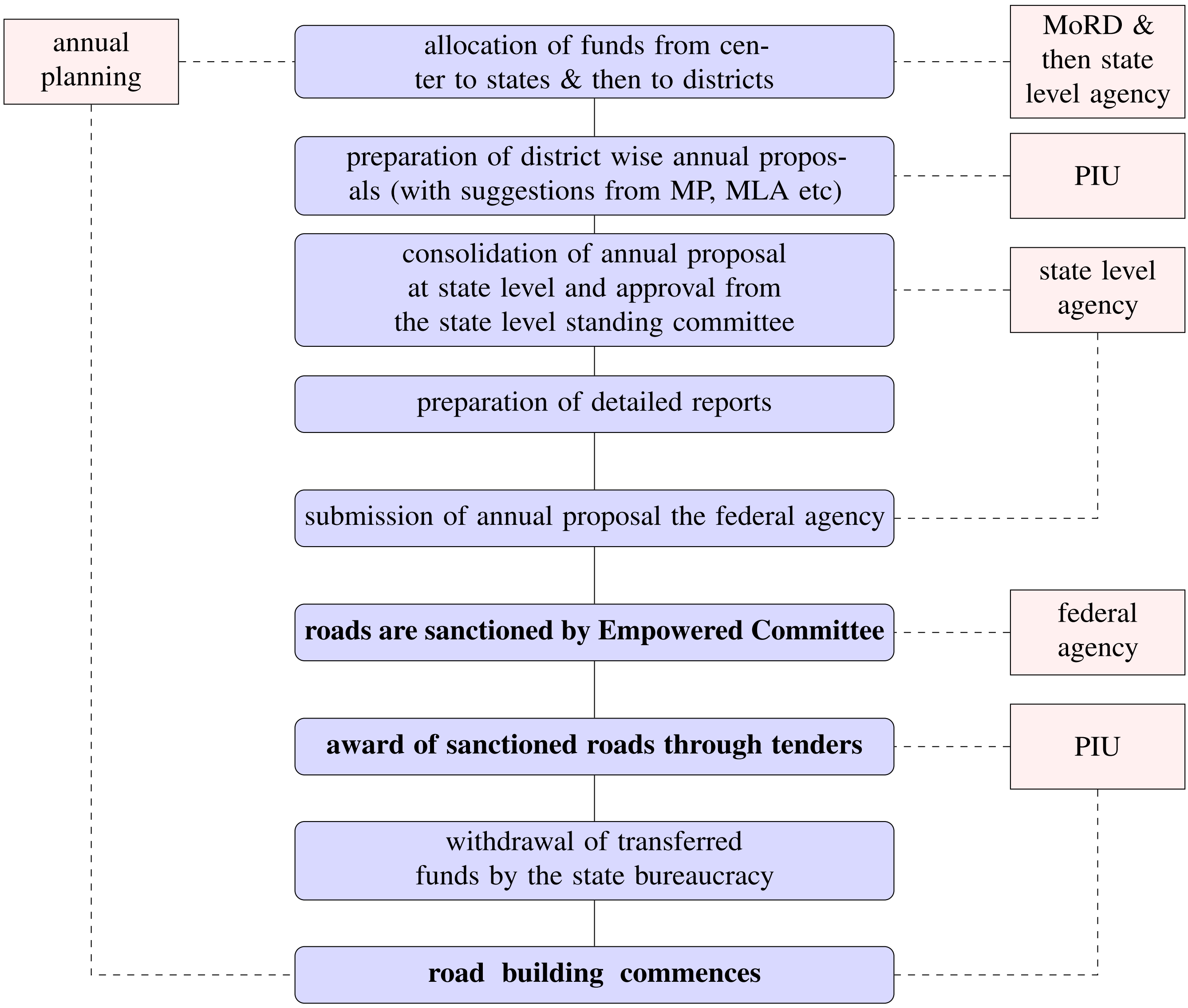
We also provide suggestive evidence on possible mechanisms. In line with our model's predictions, we show that assembly constituencies with a larger share of uninformed voters, as measured by the fraction of illiterate population, display larger electoral cycles. We also rule out competing explanations behind our results such as the presence of a learning effect leading to electoral cycles.

Figure 4.1: Preliminary Stages of PMGSY Road Planning (One Time Design)



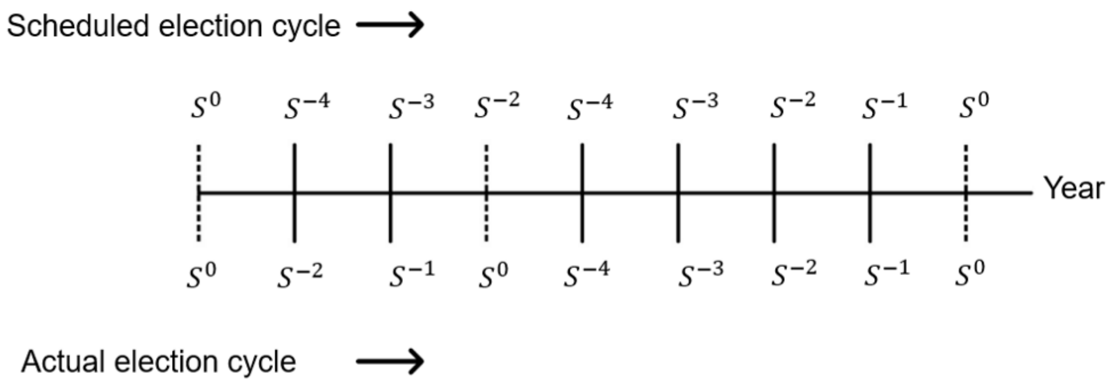
Notes: Flow chart showing a simplified overview of the initial road planning and approval activity (a one-time process). The relevant authority for each step is given in the right-hand side. The Program Implementation Units (PIU) are set up at the district level for implementing the program at state level. The National Rural Road Development Agency (NRRDA) is the federal level agency, set up under the chairmanship of the Minister of Rural Department (MoRD) to manage overall implementation. MP and MLA, respectively, are the Members of Parliaments and Legislative Assembly of the state. The *District Panchayat* or District Council is the third tier of the rural local government (*Panchayati Raj*) system and functions at the district levels in all states.

Figure 4.2: Annual Flow of PMGSY Work



Notes: Flow chart showing a simplified overview of the annual PMGSY activity. The boxes with bold phrases indicate that the corresponding steps are observed in the program data. The relevant authority for each step is given in the right-hand side. The Program Implementation Units (PIU) are set up at the district level for implementing the program at state level. The National Rural Road Development Agency (NRRDA) is the federal level agency, set up under the chairmanship of the Minister of Rural Department (MoRD) to manage overall implementation. MP and MLA, respectively, are the Members of Parliaments and Legislative Assembly of the state. The *District Panchayat* or District Council is the third tier of the rural local government (*Panchayati Raj*) system and functions at the district levels in all states. The Empowered Committee is chaired by a senior level bureaucrat from the Department of Rural Development for dealing with PMGSY proposals.

Figure 4.3: Scheduled and Actual Election Cycle



Notes: In this figure, the dotted lines indicate election years in a typical state. In the top panel, the dummies S_{st}^{-k}, $k = 0, ..., 4$ indicate if a *scheduled* election is k years away in state s in time t. In the bottom panel, the dummies S_{st}^{-k}, $k = 0, ..., 4$ indicate if the *actual* election was k years away in state s in time t. For the first and third dotted line, the elections are held in their scheduled time, hence the election dummies are identical for scheduled and actual election cycle leading up to these years. The second dotted line indicates an instance of midterm election, and the corresponding cycle dummies leading up to the midterm election diverge for the two cases.

Table 4.1: Descriptive Statistics

	Mean	Std. Dev
Panel I. Assembly Constituency Level Road Outcomes		
Outcomes Related to Road Sanctioning		
number of roads sanctioned	4.80	6.47
total length (km) of roads	19.87	27.98
amount sanctioned (INR millions)	13.45	21.11
Outcomes Related to Road Award		
number of roads awarded	4.35	5.59
total length (km) for awarded roads	18.04	25.09
Outcomes Related to Road Completion		
number of roads completed	3.54	4.40
total length (km) for completed roads	13.49	18.43
expenditure for completed roads (INR millions)	7.65	10.61
Quality and Efficiency Measures		
proportion of satisfactory roads	0.48	0.48
average time overrun (days) for a completed road in the AC	258.46	371.01
expenditure per km of completed roads (INR millions)	0.57	0.38
average stipulated construction time (days) for a completed road in the AC	336.16	187.19
Panel II. Assembly Constituency Demographic and Socio-Economic Characteristics		
proportion of reserved population in AC	0.18	0.10
total population in AC ('1000)	223.66	121.11
proportion of villages with primary school in AC	0.81	0.17
proportion of barren/rocky area in district	.007	.015
No of ACs	2999	

Notes: Unit of observation is assembly constituency-financial year for road outcomes, and assembly constituency-election year for election outcomes. Sample contains data for 18 states over the years FY 2000-01 to FY 2012-13. Amount sanctioned and total expenditure are adjusted for inflation using CPI-AL. The proportion of satisfactory roads indicates roads that meet the standards of materials and execution of work, when inspected by a National Quality Monitor. Otherwise, roads are designated as "unsatisfactory" or "required improvement".The time overrun (in days) is the gap between actual and pre-designated date of completion (as specified in the contract) or the delay. The gap between award and pre-designated construction date is called the stipulated construction time.

Table 4.2: Impact of Electoral Cycle on Sanctioning

	number of sanctioned roads	sanctioned length (km)	amount sanctioned (INR millions)
	(1)	(2)	(3)
year of next election (S^0)	-0.680	-1.044	-1.170
	[0.235]	[0.618]	[0.559]
1 year till next election (S^{-1})	1.586*	5.808**	2.911*
	[0.080]	[0.035]	[0.084]
2 years till next election (S^{-2})	1.663	2.709	3.763
	[0.118]	[0.368]	[0.251]
3 years till next election (S^{-3})	0.403	-1.538	-1.330
	[0.408]	[0.281]	[0.195]
observations	14040	14040	14040
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^{0}) respectively. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * $p< .10$, ** $p< .05$, *** $p< .01$

Table 4.3: Impact of Electoral Cycle on Sanctioning (Dropping Midterm Elections)

	number of sanctioned roads	sanctioned length (km)	amount sanctioned (INR millions)
	(1)	(2)	(3)
year of next election (S^0)	-0.408	0.151	-0.202
	[0.422]	[0.934]	[0.902]
1 year till next election (S^{-1})	2.205***	8.001***	4.604***
	[0.002]	[0.003]	[0.008]
2 years till next election (S^{-2})	2.110**	4.174	5.087
	[0.047]	[0.154]	[0.106]
3 years till next election (S^{-3})	0.571	-1.139	-0.954
	[0.323]	[0.515]	[0.479]
observations	12728	12728	12728
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^{0}) respectively. The analysis sample consists of observations where scheduled and actual election dummies coincide. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4.4: Impact of Electoral Cycle on Sanctioning (2SLS)

	number of sanctioned roads	sanctioned length (km)	amount sanctioned (INR millions)
	(1)	(2)	(3)
year of next election (S^0)	-0.750	-1.772	-1.751
	[0.249]	[0.499]	[0.468]
1 year till next election (S^{-1})	2.116**	6.801**	3.306
	[0.027]	[0.031]	[0.159]
2 years till next election (S^{-2})	1.645	2.035	3.463
	[0.158]	[0.559]	[0.357]
3 years till next election (S^{-3})	0.186	-2.924	-2.726
	[0.775]	[0.183]	[0.129]
observations	14040	14040	14040
Cragg Donald F stat	3273.736	3273.736	3273.736
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes

Notes: Each column represents a separate instrumental variable regression specification, computed using the following election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. The relevant instruments are the equivalent scheduled election dummies. Expenditure are measured in INR millions. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * p$<$ .10, ** p$<$ .05, *** p$<$ .01

Table 4.5: Impact of Electoral Cycle on Quality, Delay and Cost

	proportion of satisfactory roads	time overrun (days)	expenditure per km (INR millions)	stipulated construction time (days)
	(1)	(2)	(3)	(4)
year of next election (S^0)	0.382	-4.205	-0.014	-18.673**
	[0.105]	[0.875]	[0.431]	[0.024]
1 year of till next election (S^{-1})	0.328	-39.592	-0.002	-4.422
	[0.103]	[0.378]	[0.946]	[0.838]
2 years of till next election (S^{-2})	0.109	-10.932	0.010	-6.574
	[0.714]	[0.751]	[0.718]	[0.689]
3 years of till next election (S^{-3})	0.235	-14.670	0.032	9.464
	[0.613]	[0.725]	[0.393]	[0.432]
observations	711	11860	11834	11747
year fixed effects	yes	yes	yes	yes
year x AC characteristics	yes	yes	yes	yes
AC fixed effects	yes	yes	yes	yes

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. Proportion of satisfactory roads a measure for the proportion of "satisfactory road" as designated by a National Quality Monitor. The time overrun (in days) is the gap between actual and pre-designated date of completion (as specified in the contract) or the delay. The gap between project award and pre-designated construction date is called the stipulated construction time. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * $p< .10$, ** $p< .05$, *** $p< .01$

Table 4.6: Impact of Electoral Cycle on Award

	number of roads awarded	length (km)
	(1)	(2)
year of next election (S^0)	0.662*	2.968
	[0.096]	[0.110]
1 year till next election (S^{-1})	1.546***	4.310**
	[0.004]	[0.020]
2 years till next election (S^{-2})	0.481	0.345
	[0.225]	[0.801]
3 years till next election (S^{-3})	0.349	1.593
	[0.416]	[0.114]
observations	13148	13148
year fixed effects	yes	yes
year x AC characteristics	yes	yes
AC fixed effects	yes	yes

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. For columns 2-4, analysis sample consists of observations where scheduled and actual election dummies coincide. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4.7: Impact of Electoral Cycle on Completion

	number of completed roads	length (km)	expenditure (INR millions)
	(1)	(2)	(3)
year of next election (S^0)	0.961***	2.782**	1.089
	[0.008]	[0.024]	[0.183]
1 year till next election (S^{-1})	0.337	0.909	0.462
	[0.372]	[0.289]	[0.535]
2 years till next election (S^{-2})	-0.097	0.448	0.942
	[0.572]	[0.709]	[0.367]
3 years till next election (S^{-3})	-0.193	0.132	0.374
	[0.576]	[0.884]	[0.462]
observations	11860	11860	11860
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. For columns 4-6, analysis sample consists of observations where scheduled and actual election dummies coincide. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * p$<$ .10, ** p$<$ .05, *** p$<$ .01

Table 4.8: Persistence of Electoral Cycle (First-time MLAs)

	number of sanctioned roads	sanctioned length (km)	amount sanctioned (INR millions)
	(1)	(2)	(3)
S^0 x first-time MLA	0.087	1.963	1.877
	[0.838]	[0.334]	[0.187]
S^{-1} x first-time MLA	-0.038	-1.367	-1.764
	[0.952]	[0.560]	[0.242]
S^{-2} x first-time MLA	-0.381	1.091	-0.570
	[0.852]	[0.745]	[0.913]
S^{-3} x first-time MLA	-0.099	0.040	-0.431
	[0.838]	[0.981]	[0.745]
year of next election (S^0)	-0.614	-1.894	-1.935
	[0.258]	[0.401]	[0.388]
1 year till next election (S^{-1})	1.638*	6.651**	3.985*
	[0.094]	[0.028]	[0.056]
2 years till next election (S^{-2})	1.899	2.215	4.139
	[0.262]	[0.764]	[0.495]
3 years till next election (S^{-3})	0.425	-1.678	-1.192
	[0.346]	[0.398]	[0.334]
first-time MLA	-0.528	-2.155**	-2.091***
	[0.127]	[0.017]	[0.007]
observations	13974	13974	13974
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes

Note: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. The variable first-time MLA is a dummy that takes the value 1 if the incumbent is a first time MLA, 0 if she is not. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 4.9: Heterogeneity of Electoral Cycle in Sanctioning Outcome by Barren or Rocky Terrain Districts

	number of sanctioned roads	sanctioned length (km)	amount sanctioned (INR millions)
	(1)	(2)	(3)
S^0 x barren or rocky terrain	-36.731*	-145.699**	-116.729**
	[0.075]	[0.032]	[0.043]
S^{-1} x barren or rocky terrain	-43.665*	-90.431	-58.503*
	[0.072]	[0.209]	[0.089]
S^{-2} x barren or rocky terrain	-22.235	-100.664	-108.508
	[0.423]	[0.226]	[0.233]
S^{-3} x barren or rocky terrain	-15.410	-13.599	41.390
	[0.260]	[0.644]	[0.413]
year of next election (S^0)	-0.511	-0.364	-0.572
	[0.355]	[0.860]	[0.758]
1 year till next election (S^{-1})	1.829**	6.221**	3.194*
	[0.038]	[0.026]	[0.059]
2 years till next election (S^{-2})	1.733*	3.053	4.253
	[0.095]	[0.327]	[0.232]
3 years till next election (S^{-3})	0.453	-1.667	-1.795
	[0.384]	[0.254]	[0.106]
observations	13832	13832	13832
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. The variable 'barren or rocky terrain' is measured at district level, & sourced from Iyer (2010). This variable captures proportion of the district that is barren or rocky. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Prop illiterate indicates the proportion of illiterate population in a constituency, according to 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4.10: Heterogeneity of Electoral Cycle by Baseline (2001) Illiterate Population

	number of sanctioned roads	sanctioned length (km)	amount sanctioned (INR millions)
	(1)	(2)	(3)
S^0 x prop illiterate	5.662***	16.153**	15.573**
	[0.005]	[0.018]	[0.017]
S^{-1} x prop illiterate	6.593*	19.349	8.085
	[0.081]	[0.128]	[0.331]
S^{-2} x prop illiterate	10.935*	22.776	24.628
	[0.093]	[0.275]	[0.388]
S^{-3} x prop illiterate	-0.593	-6.049	-5.483
	[0.795]	[0.396]	[0.407]
year of next election (S^0)	-3.667**	-9.477*	-9.495*
	[0.014]	[0.051]	[0.058]
1 year till next election (S^{-1})	-1.917	-4.410	-1.343
	[0.229]	[0.472]	[0.774]
2 years till next election (S^{-2})	-4.221	-9.523	-9.539
	[0.119]	[0.224]	[0.360]
3 years till next election (S^{-3})	0.660	1.641	1.415
	[0.623]	[0.693]	[0.670]
observations	14040	14040	14040
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Prop illiterate indicates the proportion of illiterate population in a constituency, according to 2001 census. Standard errors are clustered at the state level, using wildcluster bootstrapping. *p* values are reported below coefficients: * $p < .10$, ** $p < .05$, *** $p < .01$

Appendix

4.A Model

Before getting into the model we describe some of the institutional features used in setting it up. First, consider the process of sanctioning of roads: The states after consultations with various levels including local government representatives, MLAs and MPs send a list of proposals to the centre that details the road length needed (based on the core network) for new connectivity and upgradation and this leads to the states annual allocation across districts (80% for new works, 20% for upgrades). The proposals are clubbed into Annual proposals for each state and sent to the Ministry of Rural Development (MoRD) which has an empowered committee to sanction these proposals. Although all three levels, federal, state and local are involved in the sanctioning decision, our model assumes a unitary actor: the MLA or state representative at the AC level. The reason is that for the PMGSY roads credit accrues to all three levels of government and there is little ambiguity because of the signs posted along the road, the inauguration ceremonies carried out by the state government and the active involvement of the MLA (Goyal (2019)).

We adapt the model in Shi and Svensson (2006) to our setting. There are 2 parties, L and R competing for state level elections and a continuum of voters in each AC. Voters' utility in a representative AC is given by:

$$U_{i,t} = \sum_{t}^{T}(r_t + \delta_i z_t) \tag{4.2}$$

where z is a binary variable taking the value $-\frac{1}{2}$ if L is elected and $\frac{1}{2}$ if R is elected. All voters are alike in their preferences over the public good r_t - the number of new roads at time t but they differ in the parameter δ_i which captures the effect of candidates' other policies or valence on voters' utility. Voters with $\delta_i < 0$ are biased in favor of party L and voters with $\delta_i > 0$ prefer party R all else equal. We assume that δ_i is distributed uniformly on $[-\frac{1}{2}, \frac{1}{2}]$. We assume discount factor to be 1.

We denote the type of roads in an AC by those that are easy (E) and those that are harder (H) to build. Type E roads are completed within period t. However type H roads can be completed only in the next period-harder roads require more time to complete. Voters observe only total roads built in period t. Sanctioned expenditure on roads of type θ is denoted by $g_t(\theta)$ where $\theta \in \{E, H\}$. θ is observed by the MLA but not by voters.

We consider decisions of the MLA/ state government representative in each AC. Each MLA influences the road building process. For simplicity we assume the state government and MLA belong to party L. As discussed earlier, the MLA is involved along with the state and central government in the sanctioning of roads. The PMGSY funds for a set of roads is allocated by the centre to the state, the state does not finance roads except in case of cost overruns, therefore the state government or the MLA do not internalize the cost of taxes on consumption, as in the original Shi and Svensson (2006) model.[38]

The role of the MLA in sanctioning is to present the roads that they deem to be high priority for each tranche at the beginning of the sanctioning process. This would involve costing of the roads, so in effect, sanctioning implies that the MLA affects the total amount and allocation of funds on roads for the year for his AC. This informs the modelling choice below.

Politician utility for a representative party and representative AC at time t in an AC is given by: $U_t = \sum_t^T \gamma(g_t(E) + g_t(H)) - c(g_t(E)) - c(g_t(H)) + X$ where $\gamma(\cdot)$ denotes per capita welfare due to type E and H roads sanctioned, $c(g_t(\theta))$ denotes the costs of type θ roads and X denotes the per period ego rents from office.

The timing of events is as follows: At the beginning of period t, the MLA chooses $g_t^i(\theta)$. The shock happens after the decisions have been made (in the middle of the period t) and elections happen at end of period t. There is no election in periods $t-1$ and $t+1$. The next election is in period $t+2$.

While $g_t(\theta)$ affects the number of roads built, the actual sanctions, construction and road completion depends on the competence of the local MLA. Thus, the number of roads completed and observed by voters at the end of time t is given by: $r_t = g_t(L) + \eta_t$, where $\eta_t = \mu_t + \mu_{t-1}$

[38]The funds provided by the centre via taxes on diesel are distributed across districts by the state government and finally across roads by the MLA.

is a competence shock that consist of a Moving Average of time t and $t-1$ shocks. This process implies that only shocks that happen one period before are informative of the next period competence. Each μ is an i.i.d random variable with mean 0, finite variance and distribution function $F(\mu)$ and pdf $f(\mu)$ with $f(0)=0$. We also assume that $f(x)<f(0)$ for all $x>0$. E.g. a normal distribution would satisfy these requirements. Note that the completed roads in period t do not include H type roads. $B_t(\theta)=\sum_\theta g_t(\theta)$ is the total sanctioned budget for roads of all types. The expenditure allocation on roads and the total budget is chosen by the incumbent to maximize the social welfare and ego rents across all periods of the election term.

4.A.1 Equilibrium without elections

Note that X is guaranteed to the incumbent across all periods in this case. Therefore there is no gain to be had from strategically choosing the timing and the type of roads to get sanctioned as there is no link between periods. This is a series of one period problems which we can solve by backward induction. Maximize $U_t=\gamma(g_t(E)+g_t(H)))-c(g_t(E))-c(g_t(H))$.

We assume $\gamma'(\cdot)>0$, $\gamma''(\cdot)<0$ to guarantee a unique interior solution. Cost functions are assumed to be quasi convex in g_t.

In this case the optimal allocation is $\gamma'(g_t(\theta))=c'(g_t(\theta))$ for each θ for each time period. Therefore allocations are stationary across time between H and E roads. Assuming there are enough unconnected roads remaining, the budget across all periods is also constant. Denote these optimized levels as $g^*(E), g^*(H)$ and B^*.[39] Note that these are independent of t. Although these are the optimal levels, we assumed that E roads can be built faster in the same period than H. Therefore by increasing spending on E roads the total roads that voters observe will be higher. Total roads built in realisation in period t are given by $\sum_\theta r_t(\theta)=g^*(L)+\eta_t$ which is less than the sanctioned roads $g^*(L)+g^*(H)+\eta_t$, given that H roads are not observed in period t. For simplicity denote $\sum_\theta r_t(\theta)=r_t$

4.A.2 Equilibrium with elections

In the post election period, $t+1$ the incumbent does not face an election until period $t+3$ so he has no incentive to manipulate the allocation as the incumbent's competence in period

[39] The argument does not depend on having different costs or benefits for H and L roads- only the time taken to build roads is important. However there is a cost to building more E roads compared to the optimal allocation if the benefits of H roads are higher- in this case the benefit function should be different to ensure that the optimal allocation of E and H roads is not symmetric.

$t+3$ is unrelated to his competence in period $t+1$. Since voters ignore the information from observed roads r_{t+1} for competence in period $t+3$, there is no incentive to manipulate B_{t+1} or the allocation across E and H roads. However r_{t+1} does depend on μ_t, so voters care about μ_t since they care about roads in period $t+1$.

So the incumbent's objective function is a series of two period problems t and $t+1$. The incumbent has a two period maximization problem: $U^i = \gamma(g_t(E) + g_t(H)) - c(g_t(E)) - c(g_t(H)) + X + P_{win}\left(\gamma(g_{t+1}(E) + g_{t+1}(H)) - c(g_{t+1}(E)) - c(g_{t+1}(H)) + X\right)$. The link between periods comes from the voters utility which affects the probability of winning for the incumbent, P_{win}.

Denote any extra expenditure on roads in period t over and above B^* by d_t. If the incumbent exceeds the optimal sanction B^* i.e. $d_t > 0$ for some period t then the cost of this extra expenditure is felt in period $t+1$ - it may affect the total state budget - i.e. some works that have been sanctioned in period t cannot be carried out, and as a result this may delay the next set of sanctions for the state government (see PMGSY rules). It is also possible that the budget remains at B^* but the allocation changes so that d_t represents the extra E roads that are built at the expense of H roads relative to the optimal benchmark without elections.

The cost to the MLA of over spending (or misallocating) in period t by d_t is denoted as $R(d_t)$, is felt in period $t+1$ and is increasing and convex. For example it may represent a cut in the budget for the next period from B^* to $B^* - R(d_t)$. Fewer roads are sanctioned in the next period for the AC that is not following the optimal road allocations/budget for each period.[40] Alternately it can be interpreted as the opportunity cost induced by the misallocation of H and E roads- the loss in income due to lack of connectivity of remote areas.

Working backwards, in period $t+1$ the choice of $g_{t+1}(\theta)$ does not affect ego rents as these are guaranteed until the next election period, $t+3$. Therefore $d_{t+1} = 0$. Therefore in period $t+1$ the (endogenous) budget is $B^* - R(d_t)$. $R(d)$ is a continuous function with $R(0) = 0$, $R'(0) = 1$, and $R''(d) > 0$ for all $d > 0$. The optimal choice of total roads is therefore lower than the socially optimal level by $R(d_t)$. $r_{t+1} = B^* - R(d_t) + \eta_{t+1}$ (alternately the allocation of the stock of E and H roads is not optimal).

In period t, the incumbent can increase expenditure on E roads by d_t to increase his chances

[40]If $d_t > 0$ the costs of that will be carried over into $t+1$ in the form of fewer roads being sanctioned (the rules for PMGSY are such that sanctions are conditioned on state performance- thus if some H roads are in the core network but have been delayed then either the cost of such roads might increase or the next period sanctioned budget maybe reduced- we capture these costs by $R(d)$. Alternately, if the sanctioned budget in period t is suboptimally high, then this would be discovered by the state and central level bodies that approve the budget and would have repercussions of $R(d)$ for the next budget.

of re-election: either by over spending on the socially optimal budget or under spending on $g_t(H)$. In either case, the cost next period is $R(d_t)$. Below we assume that there is excess spending over the socially optimal budget for ease of exposition, but the analysis is the same for allocation of roads. Note too, that in each period the total roads observed under this assumption are E roads sanctioned in period t and H roads sanctioned in period $t-1$. The only difference between election and non election periods are the terms $d_t, R(d_t)$. Therefore $\sum_\theta r_t(\theta) = B^* + d_t + \eta_t$.[41]

In period t voters vote for the incumbent vs the challenger. W.l.o.g we assume that the incumbent is the L party so we now denote the incumbent by superscript L and the challenger by superscript R.

Given symmetry once in office, the two parties choose exactly the same policies. However the challenger's competence is not known, while for the incumbent -voters can deduce the competence level in period t. Utility of voters in period $t+1$ with challenger is $= B^* - E_t(R(d_t^*)) + E_t(\eta_{t+1}^R) + \delta_i z$. Note that $E_t(\eta_{t+1}^R) = E_t(\mu_t^R) + E_t(\mu_{t+1}^R) = 0$. Utility of voters with incumbent in period $t+1$ is $= B^* - E_t(R(d_t^*)) + E_t(\eta_{t+1}^L) + \delta_i z$. But $E_t(\eta_{t+1}^L) = E_t(\mu_t^L)$, which can be deduced from g_t^* and μ_{t-1}^L. Therefore the difference between incumbent and challenger, conditional on the same δ_i is $= E_t(\mu_t^L)$. Note that $\delta_i < 0$ for an L party supporter. Therefore, a voter will vote for the incumbent iff $E_t(\mu_t^L) - \delta_i \geq 0$. The share of votes for the incumbent using the distribution of δ_i is $E_t(\mu_t^L) + \frac{1}{2}$.

We assume that a share σ (informed) of voters observe d_t, while $1-\sigma$ (uninformed) fraction only observe total roads. All agents observe μ_{t-1}. Informed voters observe d_t, therefore they can deduce μ_t^L using the equation $r_t = B^* + d_t + \mu_{t-1}^L + \mu_t^L$, where μ_{t-1}^L is observed by everyone and d_t is observed by informed voters only. So informed voters vote for the incumbent iff $\mu_t^L - \delta_i \geq 0$. The share of informed votes for the incumbent is $\mu_t^L + \frac{1}{2}$.

Uninformed voters do not observe d_t. However they anticipate the equilibrium strategy of the incumbent, and estimate d_t by $\hat{d}_t$. Thus, $r_t = B^* + \hat{d}_t + \mu_{t-1}^L + \hat{\mu}_t^L$. Using the expression for $\hat{\mu}_t^L = r_t - B^* - \hat{d}_t - \mu_{t-1}^L$ and substituting for $B^* = r_t - d_t = \mu_{t-1}^L = \mu_t^L$ we have $\hat{\mu}_t^L = d_t - \hat{d}_t + \mu_t^L$. Therefore the share of votes for the incumbent from uninformed voters is given by: $d_t - \hat{d}_t + \mu_t^L + \frac{1}{2}$. The probability of winning is the probability that the total vote share is bigger than $\frac{1}{2}$.

Then the probability of winning is given by:

[41] Since d_t enters as an additive term it does not affect B^* when we assume d_t is an excess over budget term.

$$P_t = Pr\left(\sigma\left(\mu_t^L + \frac{1}{2}\right) + (1-\sigma)\left(d_t - \hat{d}_t + \mu_t^L + \frac{1}{2}\right) \geq \frac{1}{2}\right) = Pr(\mu_t^L \geq (1-\sigma)(\hat{d}_t - d_t)) \tag{4.3}$$

Using the distribution function for μ_t we have $Pr(\mu_t^L \geq (1-\sigma)(\hat{d}_t - d_t)) = 1 - F\left((1-\sigma)(\hat{d}_t - d_t)\right)$

At the beginning of period t therefore the incumbent chooses d_t, to maximize two period utility given by:

$$\begin{aligned} & B^* + d_t + X \\ + & \left(1 - F\left((1-\sigma)(\hat{d}_t - d_t)\right)\right)(B^* - R(d_t) + X) \\ + & F\left((1-\sigma)(\hat{d}_t - d_t)\right)(B^* - R(d_t)) \end{aligned} \tag{4.4}$$

The FOCs are:

$1 + (1-\sigma)F'((1-\sigma)(\hat{d}_t - d_t))X - R'(d_t) = 0$. In equilibrium, rational expectations imply that $\hat{d}_t = d_t$. Therefore we have $1 + (1-\sigma)f(0)X - R'(d_t) = 0$ It follows from Shi and Svensson (2006) that the electoral cycle is more pronounced when X is higher or when σ is lower, i.e. the share of uninformed voters is higher. Moreover since the cycle is anticipated by voters it has no effect on re-election probability in equilibrium.

If the only distortion is a misallocation between L and H roads but no over spending, d_t cancels out but we still have $R'(d) > 0$ and the FOCs change to:

$(1-\sigma)F'((1-\sigma)(\hat{d}_t - d_t))X - R'(d_t) = 0$. The comparative statics remain the same.

Therefore we get the following predictions:

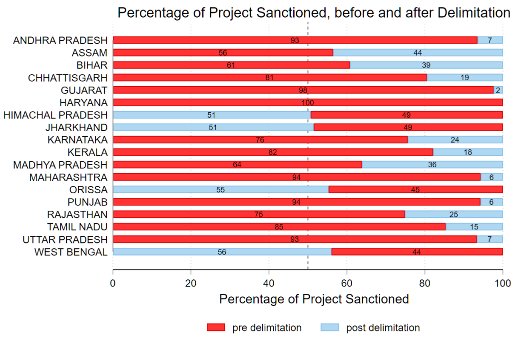
(1) Sanctions and Road completions will be higher in the years just before election relative to other years

(2) ACs with a higher share of uninformed voters display larger electoral cycles.

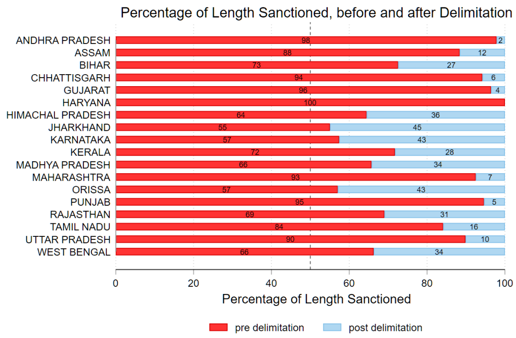
4.B Additional Analysis

Figure 4.B.1: Program Delivery By Pre and Post 2008 Delimitation MLAs, Statewise

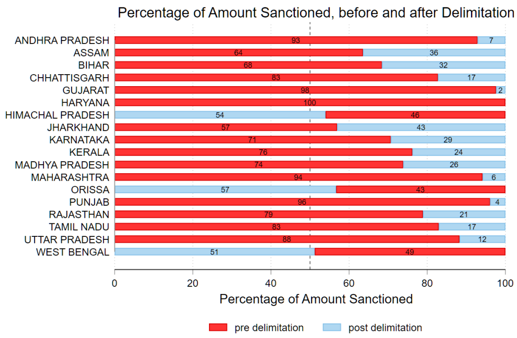
1(a): Number of Sanctioned Roads



1(b): Total Length Sanctioned (km)



1(c): Total Amount Sanctioned (million INRs)



Notes: The data covers the years 2000-01 to 2012-13. The three figures show the percentages of sanctioned roads (1a), percentage of length sanctioned (1b), and percentage of amount sanctioned (1c) for each state in our sample for the pre and post 2008 delimitation period.

Table 4.B.1: Heterogeneity of Electoral Cycle in Sanctioning Outcome by Electoral Competition

	number of sanctioned roads	sanctioned length (km)	amount sanctioned (INR millions)
	(1)	(2)	(3)
S^0 x high comp	0.161	0.093	-0.599
	[0.618]	[0.948]	[0.579]
S^{-1} x high comp	0.304	0.726	-0.248
	[0.583]	[0.743]	[0.895]
S^{-2} x high comp	0.343	-0.623	-0.430
	[0.615]	[0.824]	[0.796]
S^{-3} x high comp	0.596*	2.296	0.902
	[0.077]	[0.128]	[0.496]
high comp	-0.203	-0.449	0.428
	[0.618]	[0.772]	[0.768]
year of next election(S^0)	-0.753	-1.056	-0.854
	[0.182]	[0.622]	[0.634]
1 year till next election(S^{-1})	1.444	5.492*	3.067
	[0.122]	[0.077]	[0.125]
2 years till next election(S^{-2})	1.490	3.039	3.979
	[0.169]	[0.347]	[0.191]
3 years till next election(S^{-3})	0.109	-2.658	-1.779
	[0.841]	[0.146]	[0.130]
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes
observations	14040	14040	14040
R^2	0.157	0.198	0.268

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. Amount sanctioned is measured in INR millions. highcomp is a dummy for constituencies with lower than median level of margin of victory. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wild cluster bootstrapping. *p* values are reported below coefficients: * p< .10, ** p< .05, *** p< .01

Table 4.B.2: Heterogeneity of Electoral Cycle in Sanctioned Projects by Political Alignment of Incumbent

	number of sanctioned roads	sanctioned length (km)	amount sanctioned (INR millions)
	(1)	(2)	(3)
S^0 x aligned (both)	-0.095	-0.313	-4.596
	[0.960]	[0.967]	[0.332]
S^{-1} x aligned (both)	1.757	6.964	0.459
	[0.346]	[0.324]	[0.912]
S^{-2} x aligned (both)	2.563	7.943	1.356
	[0.326]	[0.416]	[0.772]
S^{-3} x aligned (both)	-0.458	-1.382	-3.263
	[0.439]	[0.608]	[0.124]
aligned (both)	1.052	3.002	4.096
	[0.376]	[0.449]	[0.160]
year of next election (S^0)	-0.770	-1.327	-0.666
	[0.269]	[0.578]	[0.726]
1 year till next election (S^{-1})	1.159	4.129**	2.488
	[0.195]	[0.050]	[0.174]
2 years till next election (S^{-2})	1.185	1.233	3.370
	[0.431]	[0.737]	[0.445]
3 years till next election (S^{-3})	0.447	-1.373	-0.904
	[0.395]	[0.377]	[0.369]
year fixed effects	yes	yes	yes
year x AC characteristics	yes	yes	yes
AC fixed effects	yes	yes	yes
observations	14040	14040	14040
R^2	0.169	0.205	0.272

Notes: Each column represents a separate regression specification, computed using the following scheduled election dummy variables for each year of incumbent's term, named: 4 years till next election (base category, omitted), 3 years till next election (i.e. S^{-3}), 2 years till next election (i.e. S^{-2}), 1 year till next election (i.e. S^{-1}) and year of next election (i.e. S^0) respectively. Aligned (both) is a dummy indicating that the incumbent belongs to the same party as the Chief Minister of state and to the party of the Prime Minister. Amount sanctioned is measured in INR millions. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wild cluster bootstrapping. *p* values are reported below coefficients: * $p < .10$, ** $p < .05$, *** $p < .01$

Table 4.B.3: Persistence of Electoral Cycle

dependent variable: Re-election dummy	(1)	(2)
deviation from project sanctioned on year of spike	0.003	
	[0.593]	
project sanctioned on years except year of spike	0.003	
	[0.635]	
average projects sanctioned (full mandate)		0.000
		[0.859]
year fixed effects	yes	yes
year x AC characteristics	yes	yes
AC fixed effects	yes	yes
observations	5915	5915
R^2	0.023	0.023

Notes: Each column represents a separate regression specification. The panel data is collapsed at election year-assembly constituency level. The deviation variables are a measurement of the magnitude of electoral cycle, i.e. it's the deviation of the average outcome of the peak year from rest of the years of current term. Number of sanctioned projects peaked on the fourth year of incumbent's term. The regressions control for AC (assembly constituency) level demographic and amenities information such as AC population, proportion of SC & ST population and proportion of villages with a school in the AC which are obtained from the 2001 census. Standard errors are clustered at the state level, using wild cluster bootstrapping. p values are reported in parentheses: * $p < .10$, ** $p < .05$, *** $p < .01$

Chapter 5

Conclusion

Through this thesis we broadly attempt to understand why corruption persists in different forms and in different public spaces, and what measures can motivate citizens to increase their participation in the fight against corruption. Though we have restricted our analysis to only the Indian context, the broader conclusions reached in this thesis can be extended to other similar developing countries, as well.

The survey data used in this thesis are unique and innovative in itself. To the best of my knowledge, this data set is among the first in India to capture citizens' anti-corruption effort in healthcare at a time when the entire sector was under tremendous focus. Additionally, by capturing their willingness to act both through a number of actual and self-reported measures of anti-corruption activism, we are able to provide a well-rounded view of 'activism' in general, whereas the literature mostly focuses on only one type of activism at a time. In this context, we highlight the importance of two channels- providing information and facilitating co-ordination by correcting misaligned beliefs about others' decision to act against corruption. The exercise was carried out through an online survey for a sample that was most likely to be exposed to the colossal demand of healthcare support during the COVID times, and therefore more likely to have experienced corruption related to this sector. In this context, we are able to highlight a significantly large positive effect of both channels on anti-corruption activism.

Further, we extend our analysis by broadening the choice of actions presented to our subjects, and contrast the findings with a scenario where subjects are offered actions in isolation. This exercise is also innovative, but resembles the real-life choices that a citizen faces when they decide to take action. This additional exercise yields interesting policy implications for civil society groups or other non-governmental organizations who very often have to decide what mode of presentation would maximize engagement from the general public, given the current low levels of participation in anti-corruption efforts.

Finally, we also assess the incentives of politicians to deliver important public goods when elections are near, by assembling a large scale data-set on a road program. By mapping administrative data on road delivery, to villages to electoral districts, we are able to compare changes in the behavior of incumbent politicians between each year of their term. We add to this literature by analyzing pre-electoral changes, in not just the quantity but also potentially qualitative, public good provision.

These essays contribute to the growing body of lab-in-the-field experiments on corruption, as well as speak to the set of evidence on public service delivery.

Bibliography

Abbink, K., E. Freidin, L. Gangadharan, and R. Moro (2018). The Effect of Social Norms on Bribe Offers. The Journal of Law, Economics, and Organization 34(3), 457–474.

Adida, C., J. Gottlieb, E. Kramon, and G. McClendon (2020). When does information influence voters? the joint importance of salience and coordination. Comparative Political Studies 53(6), 851–891.

Adukia, A., S. Asher, and P. Novosad (2020). Educational Investment Responses to Economic Opportunity: Evidence from Indian Road Construction. American Economic Journal: Applied Economics 12(1), 348–76.

Afridi, F. (2017). Governance and public service delivery in india.

Afridi, F., B. Barooah, and R. Somanathan (2020). Improving learning outcomes through information provision: Experimental evidence from indian villages. Journal of Development Economics 146(September).

Afridi, F., K. Mahajan, and N. Sangwan (2022). Employment Guaranteed? Social Protection during a Pandemic. Oxford Open Economics 1.

Aggarwal, S. (2018). Do Rural Roads Create Pathways Out of Poverty? Evidence from India. Journal of Development Economics 133, 375–395.

Aggarwal, S. (2021). The Long Road to Health: Healthcare Utilization Impacts of a Road Pavement Policy in Rural India. Journal of Development Economics 151, 102667.

Aidt, T. S. and D. S. Eterovic (2011). Political Competition, Electoral Participation and Public Finance in 20th Century Latin America. European Journal of Political Economy 27(1), 181–200.

Aidt, T. S. and G. Mooney (2014). Voting Suffrage and the Political Budget Cycle: Evidence from the London Metropolitan Boroughs 1902–1937. Journal of Public Economics 112, 53–71.

Aidt, T. S., F. J. Veiga, and L. G. Veiga (2011). Election Results and Opportunistic Policies: A New Test of the Rational Political Business Cycle Model. Public Choice 148(1-2), 21–44.

Aker, J. C., P. Collier, and P. C. Vicente (2017). Is information power? using mobile phones and free newspapers during an election in mozambique. Review of Economics and Statistics 99(2), 185–200.

Akhmedov, A. and E. Zhuravskaya (2004). Opportunistic Political Cycles: Test in a Young Democracy Setting. The Quarterly Journal of Economics 119(4), 1301–1338.

Aksoy, C. G., B. Eichengreen, and O. Saka (2020). The Political Scar of Epidemics. Available at SSRN 3625190.

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

Alesina, A., N. Roubini, and G. D. Cohen (1997). Political Cycles and the Macroeconomy. MIT press.

Amat, F., A. Arenas, A. Falcó-Gimeno, and J. Muñoz (2020). Pandemics Meet Democracy. Experimental Evidence from the COVID-19 Crisis in Spain.

Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. Journal of the American statistical Association 103(484), 1481–1495.

Andrabi, T., J. Das, and A. I. Khwaja (2017). Report cards: The impact of providing school and child test scores on educational markets. American Economic Review 107(6), 1535–63.

Andres, L. A., L. Andres, D. Biller, and M. Herrera Dappe (2014). Infrastructure Gap in South Asia: Infrastructure Needs, Prioritization, and Financing. World Bank Policy Research Working Paper (7032).

AP (2020). Thousands Protest in Jerusalem Against Netanyahu over COVID-19 Corruption. Business Standard India.

Asher, S. and P. Novosad (2020). Rural Roads and Local Economic Development. American Economic Review 110(3), 797–823.

Asrani, P., M. S. Eapen, M. I. Hassan, and S. S. Sohal (2021, September). Implications of the Second Wave Of COVID-19 in India. The Lancet Respiratory Medicine 9(9), e93–e94. Publisher: Elsevier.

Banerjee, A., E. Duflo, C. Imbert, S. Mathew, and R. Pande (2020). E-governance, accountability, and leakage in public programs: Experimental evidence from a financial management reform in india. American Economic Journal: Applied Economics 12(4), 39–72.

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

Banerjee, A. V., R. Banerji, E. Duflo, R. Glennerster, and S. Khemani (2010). Pitfalls of participatory programs: Evidence from a randomized evaluation in education in india. American Economic Journal: Economic Policy 2(1), 1–30.

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

Banerjee, S. G., J. M. Oetzel, and R. Ranganathan (2006). Private Provision of Infrastructure in Emerging Markets: Do Institutions Matter? Development Policy Review 24(2), 175–202.

Barbera, S., M. O. Jackson, et al. (2016). A model of protests, revolution, and information. Unpublished workingpaper.

Barbera, S., M. O. Jackson, et al. (2020). A model of protests, revolution, and information. Quarterly Journal of Political Science 15(3), 297–335.

Barnwal, P. (2014). Curbing leakage in public programs with direct benefit transfers. Technical report, Working Paper.

Barr, A. and D. Serra (2010). Corruption and Culture: An Experimental Analysis. Journal of Public Economics 94(11-12), 862–869.

Baskaran, T., B. Min, and Y. Uppal (2015). Election Cycles and Electricity Provision: Evidence from a Quasi-experiment with Indian Special Elections. Journal of Public Economics 126, 64–73.

BBC (2021). COVID: Thousands Protest in Brazil Against Bolsonaro over Pandemic Handling - BBC News.

Belloni, A., V. Chernozhukov, and C. Hansen (2014). Inference on treatment effects after selection among high-dimensional controls. The Review of Economic Studies 81(2), 608–650.

Benjamini, Y., A. M. Krieger, and D. Yekutieli (2006). Adaptive linear step-up procedures that control the false discovery rate. Biometrika 93(3), 491–507.

Berger, H. and U. Woitek (1997). Searching for Political Business Cycles in Germany. Public Choice 91(2), 179–197.

Beyer, R., T. Jain, and S. Sinha (2021). Lights Out? COVID-19 Containment Policies and Economic Activity. COVID-19 Containment Policies and Economic Activity (May 29, 2021).

Bhattacharjee, S. (2022). The Timing of Elections and Neonatal Mortality: Evidence from India. The World Bank Economic Review 36(4), 972–998.

Bhogale, S., S. Hangal, F. R. Jensenius, M. Kumar, C. Narayan, B. U. Nissa, and G. Verniers (2019). TCPD Indian Elections Data v1. Trivedi Centre for Political Data, Ashoka University.

Björkman, M. and J. Svensson (2009). Power to the people: evidence from a randomized field experiment on community-based monitoring in uganda. The Quarterly Journal of Economics 124(2), 735–769.

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

Bove, V., G. Efthyvoulou, and A. Navas (2017). Political Cycles in Public Expenditure: Butter Vs Guns. Journal of Comparative Economics 45(3), 582–604.

Brender, A. and A. Drazen (2005). Political Budget Cycles in New Versus Established Democracies. Journal of Monetary Economics 52(7), 1271–1295.

Bursztyn, L., D. Cantoni, D. Y. Yang, N. Yuchtman, and Y. J. Zhang (2021). Persistent political engagement: Social interactions and the dynamics of protest movements. American Economic Review: Insights 3(2), 233–50.

Bursztyn, L., G. Egorov, and S. Fiorin (2020). From extreme to mainstream: The erosion of social norms. American economic review 110(11), 3522–48.

Bursztyn, L., A. L. González, and D. Yanagizawa-Drott (2020). Misperceived social norms: Women working outside the home in saudi arabia. American Economic Review 110(10), 2997–3029.

Bursztyn, L. and D. Y. Yang (2021). Misperceptions about others. Annual Review of Economics 14.

Bussell, J. (2019). Clients and Constituents: Political Responsiveness in Patronage Democracies. Modern South Asia.

Cameron, L., A. Chaudhuri, N. Erkal, and L. Gangadharan (2009). Propensities to Engage In and Punish Corrupt Behavior: Experimental Evidence from Australia, India, Indonesia and Singapore. Journal of Public Economics 93(7-8), 843–851.

Cantoni, D., D. Y. Yang, N. Yuchtman, and Y. J. Zhang (2019). Protests as strategic games: experimental evidence from hong kong's antiauthoritarian movement. The Quarterly Journal of Economics 134(2), 1021–1077.

Carnegie Endowment for International Peace (2023). Global Protest Tracker. `https://carnegieendowment.org/publications/interactive/protest-tracker#`. Online; accessed 14 February 2023.

Chang, E. C. and Y.-h. Chu (2006). Corruption and Trust: Exceptionalism in Asian Democracies? The Journal of Politics 68(2), 259–271.

Chiplunkar, G. and S. Das (2021). Political Institutions and Policy Responses During a Crisis. Journal of Economic Behavior & Organization 185, 647–670.

Chong, A., A. L. De La O, D. Karlan, and L. Wantchekon (2015). Does Corruption Information Inspire the Fight or Quash the Hope? A Field Experiment in Mexico on Voter Turnout, Choice, and Party Identification. The Journal of Politics 77(1), 55–71.

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

Chuang, Y. and L. Schechter (2015). Stability of Experimental and Survey Measures of Risk, Time, and Social Preferences: A Review and Some New Results. Journal of Development Economics 117, 151–170.

Clark, D. and P. Regan (2016). Mass Mobilization Protest Data.

Cole, S. (2009). Fixing Market Failures or Fixing Elections? Agricultural Credit in India. American Economic Journal: Applied Economics 1(1), 219–50.

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

De Haan, J. and J. Klomp (2013). Conditional Political Budget Cycles: A Review of Recent Evidence. Public Choice 157(3-4), 387–410.

Deshpande, A. (2011). The Grammar of Caste: Economic Discrimination in Contemporary India. Oxford University Press.

Dhingra, S. and S. J. Machin (2020). The Crisis and Job Guarantees in Urban India.

Di Maro, V., S. Leeffers, D. Serra, and P. C. Vicente (2021). Mobilizing parents at home and at school: An african experiment on primary education.

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

Drazen, A. and M. Eslava (2010). Electoral Manipulation via Voter-friendly Spending: Theory and Evidence. Journal of Development Economics 92(1), 39–52.

Dubois, E. (2016). Political Business Cycles 40 Years after Nordhaus. Public Choice 166(1-2), 235–259.

Eckel, C. C. and P. J. Grossman (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. Journal of Economic Behavior & Organization 68(1), 1–17.

Economic Times (2021). Economic Times. https://economictimes.indiatimes.com/news/india/india-warns-against-mass-farmers-protest-citing-covid-super-spreader-risk/articleshow/82906842.cms?from=mdr. Online; accessed 17 April 2022.

Efthyvoulou, G. (2012). Political Budget Cycles in the European Union and the Impact of Political Pressures. Public Choice 153(3), 295–327.

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

Elias, J. J., N. Lacetera, and M. Macis (2019). Paying for kidneys? a randomized survey and choice experiment. American Economic Review 109(8), 2855–88.

Enikolopov, R., A. Makarin, and M. Petrova (2020). Social media and protest participation: Evidence from russia. Econometrica 88(4), 1479–1514.

Facchini, G., Y. Margalit, and H. Nakata (2016). Countering public opposition to immigration: The impact of information campaigns.

Fagernäs, S. and P. Pelkonen (2020). Teachers, electoral cycles, and learning in India. Journal of Human Resources 55(2), 699–732.

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

F.A.O. (1992). Cost Control in Forest Harvesting and Road Construction. https://www.fao.org/3/t0579e/t0579e06.htm#4.1%20introduction. Online; accessed 2 November 2022.

Ferraz, C. and F. Finan (2008). Exposing corrupt politicians: the effects of brazil's publicly released audits on electoral outcomes. The Quarterly Journal of Economics 123(2), 703–745.

Galli, E. and S. P. Rossi (2002). Political Budget Cycles: The Case of the Western German Länder. Public Choice 110(3), 283–303.

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

George, S., S. Gupta, and Y. Neggers (2018). Coordinating voters against criminal politicians: Evidence from a mobile experiment in india. Technical report, Working paper.

Giuliano, P. and A. Spilimbergo (2014). Growing up in a Recession. Review of Economic Studies 81(2), 787–817.

González, F. (2020). Collective action in networks: Evidence from the chilean student movement. Journal of Public Economics 188, 104220.

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

Goyal, T. (2019). Do Citizens Enforce Accountability for Public Goods Provision? Evidence from India's Rural Roads Program. Available at SSRN: `https://ssrn.com/abstract=3378451`.

Grier, K. (2008). US Presidential Elections and Real GDP Growth, 1961–2004. Public Choice 135(3), 337–352.

Grigorieff, A., C. Roth, and D. Ubfal (2020). Does information change attitudes toward immigrants? Demography 57(3), 1117–1143.

Gualtieri, G., M. Nicolini, F. Sabatini, and L. Zamparelli (2018). Natural Disasters and Demand for Redistribution: Lessons from an Earthquake.

Haaland, I. and C. Roth (2020). Labor market concerns and support for immigration. Journal of Public Economics 191, 104256.

Haaland, I. and C. Roth (2021). Beliefs about racial discrimination and support for pro-black policies. The Review of Economics and Statistics, 1–38.

Haaland, I., C. Roth, and J. Wohlfart (2020). Designing Information Provision Experiments.

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

Hardoon, D. (2011). Daily Lives and Corruption: Public Opinion in South Asia. Transparency Internat., Internat. Secretariat.

Hindustan Times (2021a). Hindustan Times. `https://www.hindustantimes.com/india-news/second-wave-spreading-much-faster-in-rural-india-than-first-101620416984127.html`. Online; accessed 19 April 2022.

Hindustan Times (2021b). Hindustan Times. `https://www.hindustantimes.com/india-news/indias-78-of-covid-19-cases-emerging-from-5-states-amid-fears-of-second-wave-101615801439550.html`. Online; accessed 19 April 2022.

India Today (2021a). India Today. `https://www.indiatoday.in/coronavirus-outbreak/story/explained-why-india-is-facing-oxygen-shortage-during-2nd-covid-wave-1793435-2021-04-21`. Online; accessed 19 April 2022.

India Today (2021b). India Today. `https://www.indiatoday.in/coronavirus-outbreak/story/just-before-2nd-covid-wave-hit-india-icu-beds-decreased-by-46-oxygen-ones-by-36-1796830-2021-05-03`. Online; accessed 19 April 2022.

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

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

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

Iyer, L. (2010). Direct versus Indirect Colonial Rule in India: Long-term Consequences. The Review of Economics and Statistics 92(4), 693–713.

Jensen, N. M., M. G. Findley, and D. L. Nielson (2020). Electoral Institutions and Electoral Cycles in Investment Incentives: A Field Experiment on over 3,000 US Municipalities. American Journal of Political Science 64(4), 807–822.

Jensenius, F. R. and P. Suryanarayan (2015). Fragmentation and Decline in India's State Assemblies: A Review, 1967–2007. Asian Survey 55(5), 862–881.

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

Kapoor, G., S. Hauck, A. Sriram, J. Joshi, E. Schueller, I. Frost, R. Balasubramanian, R. Laxminarayan, and A. Nandi (2020). State-wise estimates of current hospital beds, intensive care unit (icu) beds and ventilators in india: Are we prepared for a surge in covid-19 hospitalizations? MedRxiv.

Katsimi, M. and V. Sarantides (2012). Do Elections Affect the Composition of Fiscal Policy in Developed, Established Democracies? Public Choice 151(1), 325–362.

Khemani, S. (2004). Political Cycles in a Developing Economy: Effect of Elections in the Indian States. Journal of Development Economics 73(1), 125–154.

Klein, M. W. (1996). Timing Is All: Elections and the Duration of United States Business Cycles. Journal of Money, Credit, and Banking 28(1), 84.

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

Klomp, J. and J. de Haan (2016). Election Cycles in Natural Resource Rents: Empirical Evidence. Journal of Development Economics 121, 79–93.

Kovaleva, A. (2012). The IE-4: Construction and validation of a short scale for the assessment of locus of control, Volume 9. DEU.

Kumar, H. and R. Somanathan (2009). Mapping Indian Districts across Census Years, 1971-2001. Economic and Political Weekly, 69–73.

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

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

Leeson, P. T. and R. S. Sobel (2008). Weathering corruption. The Journal of Law and Economics 51(4), 667–681.

Lehne, J., J. N. Shapiro, and O. V. Eynde (2018). Building Connections: Political Corruption and Road Construction in India. Journal of Development Economics 131, 62–78.

Lindbeck, A. (1976). Stabilization Policy in Open Economies with Endogenous Politicians. The American Economic Review 66(2), 1–19.

Maffioli, E. M. (2021). The political economy of health epidemics: evidence from the ebola outbreak. Journal of Development Economics 151, 102651.

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

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

Manacorda, M. and A. Tesei (2020). Liberation technology: Mobile phones and political mobilization in africa. Econometrica 88(2), 533–567.

McCallum, B. T. (1978). The Political Business Cycle: An Empirical Test. Southern Economic Journal, 504–515.

Mechtel, M. and N. Potrafke (2013). Electoral Cycles in Active Labor Market Policies. Public Choice 156(1-2), 181–194.

Michelitch, K. and S. Utych (2018). Electoral cycle fluctuations in partisanship: Global evidence from eighty-six countries. The Journal of Politics 80(2), 412–427.

Min, B. and M. Golden (2014). Electoral Cycles in Electricity Losses in India. Energy Policy 65, 619–625.

Mironov, M. and E. Zhuravskaya (2016). Corruption in procurement and the political cycle in tunneling: Evidence from financial transactions data. American Economic Journal: Economic Policy 8(2), 287–321.

Mishra, A. (2021). COVID-19 Treatment: At Least 38 Complaints of Overcharging for Treatment Filed. Hindustan Times.

Mohanan, M., A. Malani, K. Krishnan, and A. Acharya (2021). Prevalence of COVID-19 In Rural Versus Urban Areas in a Low-Income Country: Findings from a State-Wide Study in Karnataka, India. University of Chicago, Becker Friedman Institute for Economics Working Paper (2021-92).

Moore, C. T. and R. Sabherwal (2017). Addressing the Gender Gap in Mobile Phone Access | Harvard Evidence for Policy Design. `https://epod.cid.harvard.edu/news/addressing-gender-gap-mobile-phone-access`. Online; accessed 24 February 2022.

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

Muralidharan, K., P. Niehaus, and S. Sukhtankar (2016). Building state capacity: Evidence from biometric smartcards in india. American Economic Review 106(10), 2895–2929.

Nikolova, E. and N. Marinov (2017). Do public fund windfalls increase corruption? evidence from a natural disaster. Comparative Political Studies 50(11), 1455–1488.

Nordhaus, W. D. (1975). The Political Business Cycle. The Review of Economic Studies 42(2), 169–190.

N.R.R.D.A (2005). PMGSY Operations Manual. `https://pmgsy.nic.in/sites/default/files/pdf/opman_feb.pdf`. Accessed: 2021-08-23.

N.R.R.D.A (2012). PMGSY Guidelines. `http://omms.nic.in/ReferenceDocs/PMGSY_Guidelines.pdf`. Online; accessed 5 August 2022.

Olken, B. A. (2007). Monitoring corruption: evidence from a field experiment in indonesia. Journal of political Economy 115(2), 200–249.

Olken, B. A. (2009). Corruption Perceptions vs. Corruption Reality. Journal of Public Economics 93(7-8), 950–964.

Olken, B. A. and R. Pande (2012). Corruption in developing countries. Annu. Rev. Econ. 4(1), 479–509.

Oppenheimer, D. M., T. Meyvis, and N. Davidenko (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. Journal of experimental social psychology 45(4), 867–872.

Ortiz, I., S. Burke, M. Berrada, and H. Saenz Cortés (2022). World Protests: A Study of Key protest Issues in the 21st Century. Springer Nature.

Pandey, P., S. Goyal, and V. Sundararaman (2009). Community participation in public schools: impact of information campaigns in three indian states. Education economics 17(3), 355–375.

Panneer, S., L. Bhat, L. Rice, K. Kantamaneni, et al. (2022). The Second Wave of COVID-19 and Beyond. Economic and Political Weekly 57(2).

Passarelli, F. and G. Tabellini (2017). Emotions and political unrest. Journal of Political Economy 125(3), 903–946.

Patel, V., R. Parikh, S. Nandraj, P. Balasubramaniam, K. Narayan, V. K. Paul, A. S. Kumar, M. Chatterjee, and K. S. Reddy (2015). Assuring Health Coverage for All in India. The Lancet 386(10011), 2422–2435.

Persson, T. and G. Tabellini (1990). Macroeconomic Policy, Credibility and Politics. Chur:Harwood Academic Publishers.

Persson, T., G. E. Tabellini, et al. (2003). Do Electoral Cycles Differ Across Political Systems? Innocenzo Gasparini Institute for Economic Research.

Potrafke, N. (2010). The Growth of Public Health Expenditures in OECD Countries: Do Government Ideology and Electoral Motives Matter? Journal of Health Economics 29(6), 797–810.

Potrafke, N. (2012). Political Cycles and Economic Performance in OECD Countries: Empirical Evidence from 1951–2006. Public Choice 150(1), 155–179.

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

Pulla, P. (2014). Medical Council of India Is Corrupt, Says Health Minister. `https://www.bmj.com/content/349/bmj.g4762/rapid-responses`. Online; accessed 19 April 2022.

Reddy, K. S., V. Patel, P. Jha, V. K. Paul, A. S. Kumar, L. Dandona, L. I. G. for Universal Healthcare, et al. (2011). Towards Achievement of Universal Health Care in India by 2020: A Call to Action. The Lancet 377(9767), 760–768.

Reinikka, R. and J. Svensson (2005). Fighting corruption to improve schooling: Evidence from a newspaper campaign in uganda. Journal of the European economic association 3(2-3), 259–267.

Reuters (2021a). Reuters. `https://www.reuters.com/article/us-health-coronavirus-india-surge-idUSKBN2BV129`. Online; accessed 16 April 2022.

Reuters (2021b). Reuters. `https://www.reuters.com/article/us-health-coronavirus-india-maharashtra-idUSKBN2BT15V`. Online; accessed 19 April 2022.

Rogoff, K. and A. Sibert (1988). Elections and Macroeconomic Policy Cycles. The Review of Economic Studies 55(1), 1–16.

Rogoff, K. S. (1990). Equilibrium Political Budget Cycles. American Economic Review (80), 21–36.

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

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

Roth, C. and J. Wohlfart (2020). How Do Expectations About the Aggregate Economy Affect Personal Expectations and Behavior? Experimental Evidence. Review of Economics and Statistics 102.

Saikia, N. and J. K. Bora (2016). Gender Difference in Health-Care Expenditure: Evidence from India Human Development Survey. PloS One 11(7), e0158332.

Selvaraj, S. and A. K. Karan (2009). Deepening Health Insecurity in India: Evidence from National Sample Surveys since 1980s. Economic and Political Weekly, 55–60.

Settele, S. (2019). How do beliefs about the gender wage gap affect the demand for public policy? Available at SSRN 3382325.

Shamdasani, Y. (2021). Rural Road Infrastructure & Agricultural Production: Evidence from India. Journal of Development Economics 152, 102686.

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

Shi, M. and J. Svensson (2006). Political Budget Cycles: Do They Differ Across Countries and Why? Journal of Public Economics 90(8-9), 1367–1389.

Shresth, S. and S. Verma (2020). How India Gives (2020-2021), Centre for Social Impact and Philanthropy, Ashoka University. https://csip.ashoka.edu.in/wp-content/uploads/2022/09/How_India_Gives_2020_21.pdf. Online; accessed 12 February 2023.

Singhal, P. (2021). Overcharging for COVID Treatment: Panchkula Private Hospitals to Return Rs 20 Lakh, Most Refunds Processed, Say Authorities. The Indian Express.

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

Stolfi, F. and M. Hallerberg (2016). Clientelistic Budget Cycles: Evidence from Health Policy in the Italian Regions. Journal of European Public Policy 23(6), 833–850.

Streb, J. M., D. Lema, and G. Torrens (2009). Checks and Balances on Political Budget Cycles: Cross-country Evidence. Kyklos 62(3), 426–447.

The Hindu (2021). The Hindu. https://www.thehindu.com/opinion/editorial/saving-lives-on-health-facilities-in-india/article34361865.ece. Online; accessed 19 April 2022.

Times of India (2021a). Times of India. `https://timesofindia.indiatimes.com/india/indias-covid-tsunami-did-election-rallies-lead-to-perfect-storm/articleshow/82290041.cms`. Online; accessed 17 April 2022.

Times of India (2021b). Times of India. `https://timesofindia.indiatimes.com/city/kolkata/hosps-stare-at-cov-bed-shortage-as-second-wave-sweeps-state/articleshow/81994665.cms`. Online; accessed 19 April 2022.

Transparency International India (2005). India Corruption Survey. `https://transparencyindia.org/wp-content/uploads/2019/04/India-Corruption-Study-2005.pdf`. Online; accessed 13 February 2023.

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

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

Vaishnav, M. (2017). When Crime Pays: Money and Muscle in Indian Politics. Yale University Press.

Veiga, L. G. and F. J. Veiga (2007). Does Opportunism Pay Off? Economics Letters 96(2), 177–182.

Vergne, C. (2009). Democracy, Elections and Allocation of Public Expenditures in Developing Countries. European Journal of Political Economy 25(1), 63–77.

Voors, M. J., E. E. Nillesen, P. Verwimp, E. H. Bulte, R. Lensink, and D. P. Van Soest (2012). Violent Conflict and Behavior: A Field Experiment in Burundi. American Economic Review 102(2), 941–64.

Withnall, A. (2020). Thousands of Migrant Workers Gather Together in India to Protest Lockdown Extension. The Independent.

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

Appendix I: Online Survey Questionnaire (Chapter 2 and 3)

Questionnaire for Online Survey in Qualtrics

INFORMATION SHEET FOR THE PARTICIPANTS [Consent Form (all)]*Ethical Clearance Reference Number: MRM-20/21-20739*

CLICK HERE TO DOWNLOAD A COPY OF THIS INFORMATION SHEET.

The title of our project is "Understanding Individual Attitudes and Behaviors During COVID-19".
We would like to invite you to participate in this original research project, conducted by Dr. Farzana Afridi, Dr. Amrita Dhillon, Dr. Danila Serra and Ahana Basistha from Kings College London, Texas A&M University and Indian Statistical Institute, Delhi. Before you decide whether you want to take part, it is important for you to understand why the research is being done and what your participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information.

What is the purpose of the project?

The purpose of the project is to learn more about how people view their current situation in the society during the ongoing COVID-19 pandemic.

Why have I been invited to take part?

You are being invited to participate in this project by completing an online survey hosted at Qualtrics, as someone who is a research respondent recruited via the Qualtrics online panels.

What will happen if I take part?

If you choose to be in the study, you will be asked to complete a survey. The survey will be approximately 15 to 20 minutes long. The questions in the survey will be about your household characteristics and on how you view your current situation in the society during the ongoing Covid-19 pandemic. You can stop the survey at any time without penalty. Your survey answers will be sent to a link at Qualtrics where data will be stored in a password protected electronic format. No one will be able to identify you or your answers, and no one will know whether or not you participated in the study.

Many survey takers do not like answering open-ended questions and tend to quit a survey once they see such questions. If a sizable number of people quit a survey halfway, the data quality of that survey would be compromised. However, our research depends on good quality data. Thus, please make sure you do not mind open-ended questions before taking this survey.

Do I have to take part?

Participation is completely voluntary. You should only take part if you want to and choosing not to take part will not disadvantage you in anyway. Once you have read the information sheet, please contact us if you have any questions that will help you make a decision about taking part. If you decide to take part, we will ask you to sign a consent form and you will be given a copy of the consent form to keep.

Incentives

Each participant will be compensated the pre-specified amount they agreed upon before entering the survey.

What are the possible risks of taking part?

There are no foreseeable risks involved in participating in this study.

What are the possible benefits of taking part?

You will receive no direct benefits from participating in this research study. However, your responses may help us learn more about how people view their current situation in the society during the ongoing COVID-19 pandemic.

Data handling and confidentiality

Your data will be processed in accordance with the General Data Protection Regulation 2016 (GDPR). Your survey answers will be sent to a link at Qualtrics where data will be stored in a password protected electronic format. Your personal information will not be shared outside the research team with any third-party.

Data Protection Statement

Your data will be processed in accordance with the General Data Protection Regulation 2016 (GDPR). If you would like more information about how your data will be processed in accordance with GDPR please visit the link below: https://www.kcl.ac.uk/research/support/research-ethics/kings-college-london-statement-on-use-of-personal-data-in-research

What if I change my mind about taking part?

You are free to withdraw at any point of the project, by exiting the survey without having to give a reason, up until the survey has been submitted. Withdrawing from the project will not affect you in any way.

How is the project being funded?

This project is being funded by UKAID.

What will happen to the results of the project?

A copy of the project's final report, and offprints of any academic articles arising from the study, will be sent to you on request.

Who should I contact for further information?

If you have any questions or require more information about this project, please contact me using the following contact details:

Dr. Amrita Dhillon: amrita.dhillon@kcl.ac.uk

Office phone number: +44 207 848 2907

What if I have further questions, or if something goes wrong?

If this project has harmed you in any way or if you wish to make a complaint about the conduct of the project you can contact King's College London using the details below for further advice and information: The College Research Ethics Committee, rec@kcl.ac.uk
The project has been registered with the Research Ethics Committee under the reference number MRM-20/21-20739.

Thank you for reading this information sheet and for considering taking part in this research.

1. If you want to participate in this study, select "AGREE, START THE SURVEY" below. Clicking on the "Agree" button indicates that—

- You have read the above information.
- You voluntarily agree to participate.
- You are 18 years of age or older

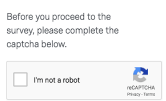
Please click on "DISAGREE, END THE SURVEY" button and press the arrow button (down right corner) if you do not wish to proceed with the survey.

☐ AGREE, START THE SURVEY

☐ DISAGREE, END THE SURVEY <-{cannot continue}

<page break>

2. Please complete the reCAPTCHA check to proceed.



<page break>

3. How often do you take online surveys?

☐ one or more times a day
☐ a few times a week
☐ one or more times a month
☐ a few times a year
☐ never

4. Are you participating in this survey using a computer, a phone or a tablet?

☐ computer
☐ phone
☐ tablet

<page break>

SECTION A: This section has questions about you and your family

5. How old are you?

☐ 18-24
☐ 25-34
☐ 35-44
☐ 45-54
☐ 55-64
☐ 65 and above

6. What is your gender?

☐ male
☐ female <-{cannot continue}

7. What is your religion?

☐ Hindu
☐ Muslim
☐ Christian
☐ Sikh
☐ Buddhist
☐ Jain
☐ Tribal
☐ other (please specify)
☐ none

8. What caste group do you belong to?

☐ Scheduled caste
☐ Scheduled tribe
☐ Other backward classes (OBC)
☐ others

9. Do you have any children?

☐ no
☐ yes, please write the number of children below—-

10. What is your current marital status?

☐ married ☐ widow(er)

☐ unmarried/ single ☐ divorced

11. What is the highest level of education that you have completed?

☐ 10th to 12th standard ☐ M.A/ M.S.c/ M.Com ☐ other (please specify)—-

☐ B.A/ B.S.c/ B.Com ☐ vocational training

12. Which state do you currently live in? {drop down list }

☐ Andaman & Nicobar ☐ Jammu & Kashmir ☐ NCT of Delhi

☐ Andhra Pradesh ☐ Jharkhand ☐ Orissa

☐ Arunachal Pradesh ☐ Karnataka ☐ Puducherry

☐ Assam ☐ Kerala ☐ Punjab

☐ Bihar ☐ Ladakh ☐ Rajasthan

☐ Chandigarh ☐ Lakshadweep ☐ Sikkim

☐ Chhattisgarh ☐ Madhya Pradesh ☐ Tamil Nadu

☐ Dadra & Nagar Haveli ☐ Maharashtra ☐ Telangana

☐ Goa ☐ Manipur ☐ Tripura

☐ Gujarat ☐ Meghalaya ☐ Uttar Pradesh

☐ Haryana ☐ Mizoram ☐ Uttarakhand

☐ Himachal Pradesh ☐ Nagaland ☐ West Bengal

13. In your household, do you have elderly (above 60 years) living with you?

☐ yes ☐ no

14. What is your occupation?

☐ student

☐ engineer

☐ doctor

☐ teacher

☐ legal field

☐ health and paramedical services

☐ catering OR nutrition OR hotel related work

☐ creative art

☐ office/business work

☐ beauty industry

☐ journalism OR mass communication related work

☐ driving or motor related work

☐ work related to child-care, nutrition, pre-school or creche

☐ other (please specify)—

15. Which of these best describe your personal earnings (in rupees) in the last month?

☐ Less than Rs 10000

☐ Rs 10000-30000

☐ Rs 30000-60000

☐ Rs 60000-100000

☐ More than Rs 100000

16. And which of these best describe your household income (in rupees) in the last month? *Household income is the total income earned by you and by every working member of the household.*

☐ Less than Rs 10000

☐ Rs 10000-30000

☐ Rs 30000-60000

☐ Rs 60000-100000 {cannot continue }

☐ More than Rs 100000 {cannot continue }

17. Which of these items do you own? (Select all that apply)

☐ washing machine

☐ flat screen TV

☐ bike / scooter

☐ air conditioner

☐ car

☐ fridge

☐ computer

☐ power backup

☐ smart phone

☐ gym/pool membership

18. Which of the following people currently live and take meals with you? (Click all that apply).

☐ wife
☐ father
☐ father-in-law
☐ sons, enter how many—
☐ mother
☐ mother-in-law
☐ daughters, enter how many—
☐ siblings, enter how many—
☐ others, enter how many—

19. Which of the following best describes your current living situation?

☐ I own a house or apartment

☐ I rent a house or apartment

☐ I live with parents or other relatives without paying rent

☐ I live with parents or other relatives and I contribute to their rent/ mortgage expenses

20. The following 6 statements apply to different attitudes towards life and the future. To what extent do you think these statements apply to you?

I like taking responsibility

☐ applies to me to a very great extent

☐ applies to me to a great extent

☐ applies to me to some extent

☐ hardly applies to me at all

☐ does not apply to me at all

I find it best to make decisions myself, rather than to rely on fate

☐ applies to me to a very great extent

☐ applies to me to a great extent

☐ applies to me to some extent

☐ hardly applies to me at all

☐ does not apply to me at all

When I encounter problems or opposition, I usually find ways and means to overcome them

☐ applies to me to a very great extent

☐ applies to me to a great extent

☐ applies to me to some extent

☐ hardly applies to me at all

☐ does not apply to me at all

Success often depends more on luck than on effort

☐ applies to me to a very great extent

☐ applies to me to a great extent

☐ applies to me to some extent

☐ hardly applies to me at all

☐ does not apply to me at all

I often have the feeling that I have little influence over what happens to me

☐ applies to me to a very great extent

☐ applies to me to a great extent

☐ applies to me to some extent

☐ hardly applies to me at all

☐ does not apply to me at all

When I make important decisions, I often look at what others have done

☐ applies to me to a very great extent

☐ applies to me to a great extent

☐ applies to me to some extent

☐ hardly applies to me at all

☐ does not apply to me at all

21. Please tell us, in general, **how willing or unwilling are you to take risks**, using a scale of 0 to 10 below. 0 indicates you are completely unwilling to take risks, and 10 indicates you are very willing to take risks.

☐ 0

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

22. 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, and 10 indicates you are very willing to give.

☐ 0

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

23. 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 doing so**, using a scale of 0 to 10 below. <u>0 indicates that you are completely unwilling to take revenge, and 10 indicates that the you are very willing to take revenge.</u>

☐ 0

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

24. 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. <u>0 indicates that the statement does not describe you at all, and 10 indicates that the statement describes you perfectly.</u>

☐ 0

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

25. 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, and 10 indicates you are very willing to do so.

☐ 0

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

26. 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, and 10 indicates you are very willing to do so.

☐ 0

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

27. We will like to ask you how much you trust people from various groups or organizations.

Could you tell us for each of the groups, whether you trust people from that group completely, somewhat, not very much or not at all?

people you personally know

☐ trust completely

☐ trust somewhat

☐ do not trust very much

☐ do not trust at all

people you don't know personally

☐ trust completely

☐ trust somewhat

☐ do not trust very much

☐ do not trust at all

government officials

☐ trust completely

☐ trust somewhat

☐ do not trust very much

☐ do not trust at all

healthcare professionals

☐ trust completely

☐ trust somewhat

☐ do not trust very much

☐ do not trust at all

<page break>

SECTION B: This section has questions on your experience with respect to the COVID-19 pandemic

28. Are you or a member of your household considered “high-risk” with respect to the COVID-19 pandemic?

☐ no ☐ yes, specify who—

☐ yes, me ☐ don’t know/ can’t say

29. Since April 2020 till date, did you or anyone from your household or immediate social environment test positive for COVID-19? (tick all that apply)

☐ no ☐ yes, me ☐ yes, but not me (specify who)—

30. If yes, what was the per head cost of treatment for COVID-19? Please type the amount below (in Rs).

☐ doesn't apply ☐ amount (Rs)—

31. What are your chances of getting infected with COVID-19?

☐ very unlikely ☐ somewhat unlikely

☐ somewhat unlikely ☐ very likely

32. In your opinion, during the COVID 19 pandemic, has the quality of health care in your state

☐ decreased ☐ increased

☐ remained the same ☐ don't know

33. Since April 2020 till date, how many times did you or a member of your household require to seek care from health worker/ visit a clinic or hospital?

The visits may or may not be related to COVID-19

☐ never

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

☐ more than 10 times

34. **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 give them a gift**, or **have to do a favor** or **have to pay extra money** to obtain a medical service?

give them a gift

☐ never

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

☐ more than 10 times

do a favor

☐ never

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

☐ more than 10 times

pay extra money

☐ never

☐ 1

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10

☐ more than 10 times

35. If you had to pay extra money one or more times, how much did you pay (in Rs) on average? Please type the amount in the text box below.

☐ does not apply ☐ enter the amount (in Rs) below—

36. Do you know what is the rate you would have to p**ay per day for an ICU bed** at your local hospital?

☐ don’t know ☐ yes, enter the amount per day (Rs)—

37. Did you or a member of your household have to spend 1 or more night at the hospital since April 2020? The visits may or may not be related to COVID-19, and may be for you or a member of your household.

☐ yes ☐ no

38. {display if answer=yes to Q.37} How much did you or a member of your household have to pay for every night of hospital stay?

☐ 0 ☐ positive amount per day, enter amount (Rs)— ☐ don’t know/ can’t say

39. {display if answer=yes to Q.37} Do you think you or a member of your household were **illegally overcharged** by the healthcare professionals for the hospital stay?

☐ yes ☐ no ☐ don’t know/ can’t say

40. 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?

☐ option A

☐ option B

☐ option C

☐ option D

41. According to your experience, the current level of corruption in the health sector is

☐ not a problem at all ☐ a moderate problem

☐ a small problem ☐ a major problem

42. In your opinion, has the level of corruption in the health sector during the COVID-19 pandemic (since April 2020 till date)

☐ increased a lot ☐ stayed the same ☐ decreased a lot

☐ increased somewhat ☐ decreased somewhat ☐ don't know

43. 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 the scale of 1 to 10 below (where 1 denotes that the action is never justifiable, 10 denotes it is always justifiable).

avoiding a fare on public transport

☐ 1 (never justifiable)

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10 (always justifiable)

doctors overcharging for a hospital bed during COVID-19 pandemic

☐ 1 (never justifiable)

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10 (always justifiable)

someone accepting a bribe in the course of their duties

☐ 1 (never justifiable)

☐ 2

☐ 3

☐ 4

☐ 5

☐ 6

☐ 7

☐ 8

☐ 9

☐ 10 (always justifiable)

44. How many people in your community do you think expect you to complain if you are overcharged or asked to pay a bribe by a doctor?

☐ nobody ☐ many people ☐ everybody

☐ a few people ☐ most people

<page break>

45. 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. ———————-

<page break>

SECTION C: This section has questions about issues that are important to you

46. Do you agree or disagree with the following statements?

you play an active role in one or more voluntary organizations

☐ strongly disagree

☐ somewhat agree

☐ neither agree nor disagree

☐ somewhat agree

☐ strongly agree

you don't like to discuss politics with other people

☐ strongly disagree

☐ somewhat agree

☐ neither agree nor disagree

☐ somewhat agree

☐ strongly agree

being involved in your neighborhood is important to you

☐ strongly disagree

☐ somewhat agree

☐ neither agree nor disagree

☐ somewhat agree

☐ strongly agree

you don’t get involved in political protests

☐ strongly disagree

☐ somewhat agree

☐ neither agree nor disagree

☐ somewhat agree

☐ strongly agree

you generally vote in elections

☐ strongly disagree

☐ somewhat agree

☐ neither agree nor disagree

☐ somewhat agree

☐ strongly agree

47. Prior to the COVID-19 pandemic (since April 2020 till date), have you ever been involved in any of the following actions to help solve a problem that mattered to you?

protest

☐ never

☐ yes, 1-3 times

☐ yes, 4-6 times

☐ yes, 7-10 times

☐ more than 10 times

walkouts or strike

☐ never

☐ yes, 1-3 times

☐ yes, 4-6 times

☐ yes, 7-10 times

☐ more than 10 times

boycott

☐ never

☐ yes, 1-3 times

☐ yes, 4-6 times

☐ yes, 7-10 times

☐ more than 10 times

petition

☐ never

☐ yes, 1-3 times

☐ yes, 4-6 times

☐ yes, 7-10 times

☐ more than 10 times

lodging complaints

☐ never

☐ yes, 1-3 times

☐ yes, 4-6 times

☐ yes, 7-10 times

☐ more than 10 times

marching

☐ never

☐ yes, 1-3 times

☐ yes, 4-6 times

☐ yes, 7-10 times

☐ more than 10 times

donation to an organization

☐ never

☐ yes, 1-3 times

☐ yes, 4-6 times

☐ yes, 7-10 times

☐ more than 10 times

48. During the last year, how much did you donate to charity?

☐ didn't donate ☐ Rs (1000 - 5000) ☐ don't know/ can't say

☐ less than Rs 1000 ☐ more than Rs 5000

<page break>

SECTION D: In this section you will answer some questions that will allow you to earn bonus money. You will have a chance to earn between 0 and Rs 198 as a bonus.

49. On each of the following pages, you will be presented with a statement. We have asked previous study participants whether they agree or disagree with each of these statements. The respondents were all men based in India.

First, you will be asked whether you personally agree with each statement. You will then be asked to guess what percentage of previous participants agreed with each statement. You will have to state whether you agree or disagree with 3 statements, and guess the percentages of previous participants who agreed with the same statements. **For each statement, if your guess is correct, you earn Rs 50.**

In order to make sure you understand what will happen in this section of the survey, we ask you to first answer the 3 questions below.

If *TWO* of your guesses are correct, how much will you receive as a bonus from this part of the study?

☐ 0

☐ 50

☐ 250

☐ 100

If *NONE* of your guesses are correct, how much will you receive as a bonus from this part of the study?

☐ 0

☐ 50

☐ 250

☐ 100

If *THREE* of your guesses are correct, how much will you receive as a bonus from this part of the study?

☐ 0

☐ 50

☐ 250

☐ 100

<page break>

We can now proceed with the 3 statements. Recall that a large number of Indian men have participated in the study already. You will have to state whether you agree or disagree with each of the 3 statements, and guess the percentages of previous participants who agreed with each statement. You will earn Rs 50 of bonus money for each correct guess.

<page break>

50. **In order to contain the spreading of COVID-19, people should wear face masks when they are in public spaces.**

Do you **agree** or **disagree** with the statement above?

☐ agree

☐ disagree

51. What percentage of previous participants in this study do you think agreed with the statement above?

If your guess is correct, you will receive Rs 50.

☐ 0-10%

☐ 10-20%

☐ 20-30%

☐ 30-40%

☐ 40-50%

☐ 50-60%

☐ 60-70%

☐ 70-80%

☐ 80-90%

☐ 90-100%

<page break>

52. **I believe that citizens should demand that the usage of relief funds set up during the pandemic should be audited by independent third-party organizations.**

Do you **agree** or **disagree** with the statement above?

☐ agree

☐ disagree

53. What percentage of previous participants in this study do you think agreed with the statement above?

If your guess is correct, you will receive Rs 50.

☐ 0-10%

☐ 10-20%

☐ 20-30%

☐ 30-40%

☐ 40-50%

☐ 50-60%

☐ 60-70%

☐ 70-80%

☐ 80-90%

☐ 90-100%

<page break>

54. **I am willing to raise my voice and participate in a protest against corruption in the provision of health service.**

Do you **agree** or **disagree** with the statement above?

☐ agree

☐ disagree

55. What percentage of previous participants in this study do you think agreed with the statement above?

If your guess is correct, you will receive Rs 50.

☐ 0-10%

☐ 10-20%

☐ 20-30%

☐ 30-40%

☐ 40-50%

☐ 50-60%

☐ 60-70%

☐ 70-80%

☐ 80-90%

☐ 90-100%

<page break>

55. Please rate how confident you are about the opinions of the other participants. (1 means not confident at all, 5 means very confident.)

☐ 1 (not confident at all)

☐ 2

☐ 3

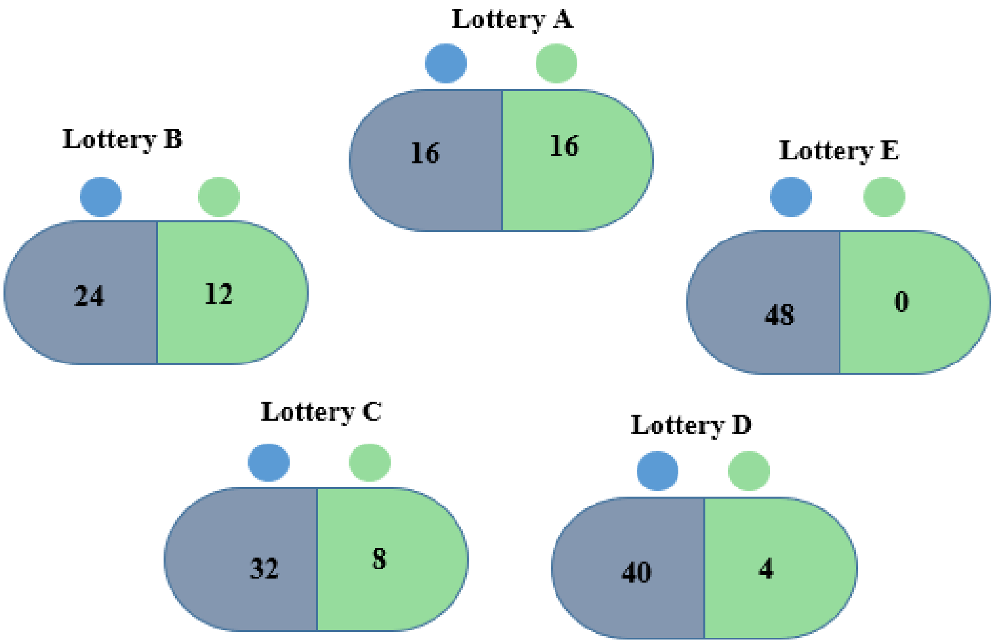
☐ 4

☐ 5 (very confident)

<page break>

56. We are going to ask you to choose between 5 lotteries.
Each lottery has **two possible outcomes**, one that would earn you a **small amount of money** and one that would earn you a **larger amount of money**. That is **real money** that you could earn in this section.
In each of the 5 lotteries, there is a 50% chance that you earn the small amount of money, and a 50% chance that you earn the large amount of money.
Think of an urn with two balls, a blue ball and a green ball. If the blue ball comes out, you earn the small amount of money. If the green ball comes out, you earn the large amount of money. The **figure below** shows the **5 lotteries** and the small and large amount of money

associated with each lottery.



There are 5 possible lotteries. You will have to **choose which lottery you would like to play. Each lottery** has a different **small** and **large** amounts of money that you could win if the **blue ball** or the **green ball** is selected.

*Here is an example. If you choose to play **Lottery C** and the **blue ball comes out**, you win **Rs 32**. If instead the green ball comes out, you win **Rs 8**.*

*Here is another example: If you choose to play **Lottery D** and the **blue ball comes out**, you win **Rs 40**. If instead the **green ball comes out**, you win **Rs 4**.*

*Remember that there is a **50% chance** that the **blue ball** will come up and a **50% chance** that the **green ball** will come out.*

Suppose that you choose Lottery B and the computer randomly draw the **green ball**, how much would you earn?

☐ 12

☐ 24

☐ 16

☐ 0

Suppose that you choose Lottery E and the computer randomly draw the **blue ball**, how much would you earn?

☐ 12

☐ 48

☐ 16

☐ 0

{display this question if previous two answers are correct}**Please choose which lottery you would like to play**. Remember that the amounts you see in the lotteries, are **real money.**

☐ lottery A

☐ lottery B

☐ lottery C

☐ lottery D

☐ lottery E

<page break>

57. As you know, in addition to your compensation for participating in the survey, you may have earned a bonus amount of up to Rs 198 from the lottery and from correctly guessing the answers of previous participants. You will be paid the additional amount with 3 weeks.

How much do you think you earned as bonus today? Please indicate a Rs. amount in the slider below.

Rs 0–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–|–Rs 198

<page break>

You have reached the end of the survey, thank you for your participation!

Please move to the next page

<page break>

{**Randomly Assign Subjects into 4 Anti-corruption Groups (*Information, Belief Correction, Combined* and *Control*)**}

———CONTROL BLOCK———

{**Randomly Assign Control Group Subjects into 4 Action Groups (*Petition, Donation, Video* and *Choice*)**}

———PETITION SUB-BLOCK———

P1. Before you exit the survey, we would like you to think of the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic. The **"All India Drug Action Network" (A.I.D.A.N)** is a non-profit organization that has been pressuring local and central governments to better regulate health care in India, fostering transparency in hospitals and assisting patients who have been illegally overcharged.

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

☐ PETITION

☐ EXIT THE SURVEY {End survey here, if this button is clicked}

{Display petition text if "PETITION" IS SELECTED ABOVE}

P2. [PETITION TEXT]–>

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

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

1. Adoption of regulatory laws like the Clinical Establishment Act, 2010

2. Clear display of treatment protocol and prescription audit

3. District level grievance redressal system for patients

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

This petition is addressed to:

1. Union health minister: Dr. Harsh Vardhan (hfm[at]gov[dot]in)

2. health ministers of the states:

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

____

{Record timing (not visible to subjects)-

- First Click
- Last Click
- Page Submit
- Click Count}

———DONATION SUB-BLOCK———

D1. Before you exit the survey, we would like you to think of the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic. The **“All India Drug Action Network” (A.I.D.A.N)** is a non-profit organization that has been pressuring local and central governments to better regulate health care in India, fostering transparency in hospitals and assisting patients who have been illegally overcharged.

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

☐ DONATION

☐ EXIT THE SURVEY {End survey here, if this button is clicked}

{Display donation text if “DONATION” IS SELECTED ABOVE}

D2. You can support A.I.D.A.N. by donating part or all of your bonus earnings from Section D of the survey. You can donate any amount between 0 and 100% of your bonus earnings.
How much would you like to donate to A.I.D.A.N out of your bonus earnings from Section D?

☐ 0% of bonus

☐ 10% of bonus

☐ 20% of bonus

☐ 30% of bonus

☐ 40% of bonus

☐ 50% of bonus

☐ 60% of bonus

☐ 70% of bonus

☐ 80% of bonus

☐ 90% of bonus

☐ 100% of bonus

———VIDEO SUB-BLOCK———

V1. Before you exit the survey, we would like you to think of the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic. The **“All India Drug Action Network” (A.I.D.A.N)** is a non-profit organization that has been pressuring local and central governments to better regulate health care in India, fostering transparency in hospitals and assisting patients who have been illegally overcharged.

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

☐ VIDEO

☐ EXIT THE SURVEY {End survey here, if this button is clicked}

{Display donation text if "VIDEO" IS SELECTED ABOVE}

V2. We are now going to show you the video.

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

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

<page break>

<show video>

{Record timing (not visible to subjects)-

- First Click
- Last Click
- Page Submit
- Click Count}

———CHOICE SUB-BLOCK———

C1. Before you exit the survey, we would like you to think of the problem of corruption and overcharging in Indian hospitals during the COVID-19 pandemic. The **"All India Drug Action Network" (A.I.D.A.N)** is a non-profit organization that has been pressuring local and central governments to better regulate health care in India, fostering transparency in hospitals and assisting patients who have been illegally overcharged.

Would you like to support the A.I.D.A.N.'s activities? If so, you could sign **a petition** to the Health Ministry asking for more regulation and transparency in health care charges. Please click PETITION below, and you will be redirected to the page containing necessary instructions.

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

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

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

☐ PETITION {Repeat P2, if this button is clicked}

☐ DONATION {Repeat D2, if this button is clicked}

☐ VIDEO {Repeat V2, if this button is clicked}

☐ EXIT THE SURVEY {End survey here, if this button is clicked}

. . . . *THE END* . . . .

——INFORMATION BLOCK——

{**Randomly Assign Information Group Subjects into 4 Action Groups (*Petition, Donation, Video* and *Choice*)**}

We are now going to show you a short informational video (3 minutes long approximately) on the state of healthcare during the COVID-19 pandemic information on illegal behavior and overcharging by hospitals.

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

Please do not forward the video. You will not be able to proceed with the survey until you watch this 3-minute video. If you forward the video, you will still have to wait until the 3 minutes have passed before being able to continue with the survey.

<*page break*>

If you exit the video before it reaches the end (before 3 minutes have passed), you will have to wait to be able to proceed with the survey. When 3 minutes have passed, a next button in the bottom right corner will appear and you will be able to move forward.

<*video*>

{Record timing (not visible to subjects)-

- First Click
- Last Click
- Page Submit
- Click Count}

<*page break*>

{**Randomly Assign Information Group Subjects into 4 Action Groups (*Petition, Donation, Video* and *Choice*)**}

———PETITION SUB-BLOCK———

Repeat P1 and P2.

———DONATION SUB-BLOCK———

Repeat D1 and D2.

———VIDEO SUB-BLOCK———

Repeat V1 and V2.

———CHOICE SUB-BLOCK———

Repeat C1.

. . . . *THE END* . . . .

——BELIEF CORRECTION BLOCK——

We previously asked to guess the percentage of previous survey respondents who agreed with 3 statements. The table shows you the actual percentages of respondents who agreed with each statement.

In order to contain the spreading of COVID-19, people should wear face masks when they are in public spaces.	$90-100\%$ agree
I believe that citizens should demand that the usage of relief funds set up during the pandemic should be audited by independent third-party organizations	$80-90\%$ agree
I am willing to raise my voice and participate in a protest against corruption in the provision of health service.	$80-90\%$ agree

Please take the next ten seconds to go over this table. The next button will appear after ten seconds have passed.

<page break>

{**Randomly Assign Belief Correction Group Subjects into 4 Action Groups (*Petition, Donation, Video* and *Choice*)**}

——PETITION SUB-BLOCK——

Repeat P1 and P2.

——DONATION SUB-BLOCK——

Repeat D1 and D2.

——VIDEO SUB-BLOCK——

Repeat V1 and V2.

——CHOICE SUB-BLOCK——

Repeat C1.

. . . . *THE END* . . . .

———COMBINED BLOCK———

We are now going to show you a short informational video (3 minutes long approximately) on the state of healthcare during the COVID-19 pandemic information on illegal behavior and overcharging by hospitals.

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

Please do not forward the video. You will not be able to proceed with the survey until you watch this 3-minute video. If you forward the video, you will still have to wait until the 3 minutes have passed before being able to continue with the survey.

<page break>

If you exit the video before it reaches the end (before 3 minutes have passed), you will have to wait to be able to proceed with the survey. When 3 minutes have passed, a next button in the bottom right corner will appear and you will be able to move forward.

<video>

{Record timing (not visible to subjects)-

- First Click
- Last Click
- Page Submit
- Click Count}

<page break>

We previously asked to guess the percentage of previous survey respondents who agreed with 3 statements. The table shows you the actual percentages of respondents who agreed with each statement.

Please take the next ten seconds to go over this table. The next button will appear after ten seconds have passed.

In order to contain the spreading of COVID-19, people should wear face masks when they are in public spaces.	$90 - 100\%$ agree
I believe that citizens should demand that the usage of relief funds set up during the pandemic should be audited by independent third-party organizations	$80 - 90\%$ agree
I am willing to raise my voice and participate in a protest against corruption in the provision of health service.	$80 - 90\%$ agree

<page break>

{**Randomly Assign Combined Group Subjects into 4 Action Groups (*Petition, Donation, Video* and *Choice*)**}

———PETITION SUB-BLOCK———

Repeat P1 and P2.

———DONATION SUB-BLOCK———

Repeat D1 and D2.

———VIDEO SUB-BLOCK———

Repeat V1 and V2.

———CHOICE SUB-BLOCK———

Repeat C1.

. . . . *THE END* . . . .