Aggregate health shocks have long-lasting mental health effects: Evidence from Covid-19 surges in India*

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ⓡRandomized author order

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Abstract

We examine the mental health costs of higher Covid-19 incidence in India, leveraging the quasi-random timing of India's statewide elections—typically accompanied by large gatherings—which coincided with the rise of the delta variant. Using a difference-in-differences strategy, we find additional time away from home in election states, alongside a doubling of Covid incidence in the months following the election. These changes are accompanied by a roughly 30% decline in mental health, as measured by a scale capturing anxiety and depression (PHQ-4). These effects are durable, with declines persisting up to a year after elections.

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1 Introduction

Health shocks — especially when they affect entire communities through events like pandemics, natural disasters, and climate change — can impose massive costs on societies, with profound implications for well-being extending beyond the direct effects of illness. At the individual level, these shocks are likely to cause anxiety and worry. At the community level, coping strategies like disease containment policies can slow economic activity, exacerbating poverty and inequality; and illness itself can augur economic harm (Egger et al., 2021). In both scenarios, mental health may suffer, imposing direct welfare costs and attendant productivity losses (The Lancet Global Health, 2020; Trautmann and Wittchen, 2016). To the extent such mental health effects persist, they can have lasting implications for welfare. Yet these costs are often difficult to quantify as mass shocks are almost always non-random.

In this paper, we leverage an exogenous shock to the incidence of Covid-19 in India to capture the effects of increased disease burden on population mental health from one month to one year following the shock. The staggered timing of state-level elections, which drive additional movement and social interaction during campaigning, provide a natural experiment to causally identify the effect of increased Covid-19 disease burden.

Specifically, state-level elections in India take place every 5 years with different states holding elections on different years. These cycles were determined by political events that predominately occurred in the 1980s and 1990s. The 2021 election season coincided with the rise of the delta variant. Indian elections are accompanied by rallies attended by thousands of individuals, many of whom must travel to attend (Khan, 2019). This process results in significantly more time spent outside of the household, as we show using a difference-in-differences approach and Google mobility data. We find that this increased movement is accompanied by increased disease incidence in election states, with roughly twice as many cases recorded in both survey and administrative data.

The bulk of our analysis leverages the Real Time Insights of Covid-19 in India (RTI) panel survey, which tracks over 1,700 households originally enrolled in a nationally-representative study of households with older adults. RTI conducted bi-monthly phone surveys with enrollees for two years, starting in May 2020 and ending after India's omicron wave in May 2022. These rich data track respondents' experiences with Covid, mental health, and economic well-being multiple times both before and after the elections we study.

The mental health effects we observe are large; people in election states experienced a 54% increase in their PHQ-4 scores, corresponding to an 18 percentage point increase in the likelihood of showing signs of psychological distress[1]. These mental health effects

[1]This corresponds to a score of 3 and above on the PHQ-4, a validated screening tool for anxiety and

are persistent, lasting for up to a year after the initial election-induced shock. They also exacerbate existing inequalities, with significantly larger negative impacts on mental health among poorer households. Importantly, these effects do not appear to be driven by elections themselves. A placebo test with a previous round of elections finds no impact on mental health.

There are multiple reasons why the election-induced surge in Covid caseloads may have negatively impacted mental health. Covid and associated morbidity and mortality in the household or one's extended network was likely emotionally difficult. Increased caseloads and/or lockdown policies may have worsened individuals' economic situations, their sense of social isolation, or general pessimism regarding future effects of the pandemic. While we cannot fully parse these possibilities, we provide suggestive evidence on the relative contributions of these channels. The effects do not appear to be solely driven by household disease burdens — while high and low socioeconomic status (SES) households experienced similarly elevated caseloads, mental health effects were larger among low SES households. Moreover, impacts persist when dropping all households who ever report a Covid-19 infection, pointing to spillover effects of the aggregate shock. In terms of economic channels, we find no significant overall impacts on household income or the likelihood of having any income, but we do find some suggestive evidence that the surge worsened perceived financial health, especially among lower-SES households. We also find evidence consistent with the idea that exposure to the pandemic created a persistent, elevated sense of unease and worry, with respondents in election states reporting significantly more fear of infection/death in the family and increased stress among household members one year after the election-induced Covid shock.

This paper contributes to two broad literatures. First, research studying the downstream effects of health shocks, which has typically focused on economic well-being (Beegle et al., 2008; Cochrane, 1991; Dercon and Krishnan, 2000; Gertler and Gruber, 2002; Wagstaff, 2007). We contribute by expanding to another critical aspect of well-being, mental health. Further, we build upon the more limited literature studying the mental health consequences of individual health shocks to consider aggregate health shocks, whose causal effects are typically harder to identify cleanly (Alem and Tato, 2023; Valle et al., 2013).

Second, we contribute to an extensive literature studying the downstream effects of Covid by making three advances. First, in contrast to much of the literature reporting correlations, we leverage an exogenous source of variation in Covid-19 incidence to provide credible identification.[2] Second, our rich panel data allow us to track impacts on mental health over time,

depression (Löwe et al., 2010). A score of 3 is the threshold for 'mild' distress.

[2]Researchers have estimated the effect of plausibly exogenous political gatherings and elections on Covid

documenting the notable durability of the caseload-induced decrement in mental health, well after lockdown-style restrictions on movement were phased out.[3] Third, our broadly representative data speak to population-level patterns in low-income settings, allowing us to extend previous work on more targeted groups including households with job losses in Pakistan, mothers of young children in India, and the elderly in Turkey (Baranov et al., 2022; Bau et al., 2022; Altindag et al., 2022). Our data also allow us to examine heterogeneity in the impacts across key demographics to shed light on distributional impacts of increased Covid spread.

The remainder of the paper begins with background on Covid and elections in India in Section 2. The data sources are described in Section 3 followed by the empirical specification in Section 4. Results are described in Section 5 and we conclude in Section 6.

2 Background

2.1 Covid-19 in India

Figure A.1 graphs RTI survey waves against India's pandemic trajectory. Grey shading represents the election period, yellow shading survey waves, and total caseload and policy stringency in our sample states — as measured by the policy stringency index from (Hale et al., 2021) — are red and black dashed lines, respectively.

India initially responded to Covid-19 with an abrupt, restrictive national lockdown, which lasted from March 25-May 31 2020. The first major wave of Covid-19 infection occurred in fall 2020, after the lockdown lifted and before vaccinations. The second and largest wave, driven by the delta variant, peaked between March-June 2021. This wave was coincident with the country's vaccination drive. While vaccine distribution was restricted to the elderly (60+) and individuals 45 and older with qualifying comorbidities in March, in April it was opened to all above 45, and then expanded to all the adults in May. However, supply shortages limited overall vaccination rates during the delta wave.[4] This period was marked by

caseloads in high-income settings (Bernheim et al., 2020; Palguta et al., 2022), while others have used (non-exogenous) variation in Covid-protective measures to estimate their efficacy at slowing disease spread (Friedson et al., 2021; Dave et al., 2021; Hsiang et al., 2020). Underscoring the challenges inherent to endogenous adoption of protective measures, Berry et al. (2021) argues that earlier estimates are often sensitive empirical specifications and overstate the benefits of protective measures.

[3] A number of papers in higher income settings consider the effects of strict lockdowns on mental health (Brodeur et al., 2021; Tubadji et al., 2022; Adams-Prassl et al., 2022; Thomas et al., 2021). However, as evidenced by the large rallies held during the elections, restrictions of this type were limited in India during our period of interest.

[4] At the peak of this wave, only 9.5% of the total population had received at least one dose of the Covid-19 vaccine; this rose to 60% at the end of 2021 (Our World in Data, 2022).

high morbidity and mortality, alongside severe healthcare shortages, with many individuals in need of care unable to secure admission to hospitals or find necessary support such as oxygen (BBC, 2021). Many states instituted restrictions on movement and/or gatherings during this period. Non-election states reacted a few weeks earlier than election states, but election states instituted more restrictions post-elections — potentially in reaction to higher caseloads (see Figure A.2).

Finally, a third wave driven by the omicron variant occurred in January 2022. Pandemic restrictions did not shift as much during this wave, and dropped noticeably afterwards.

2.2 Elections in India

Timing. State assembly elections are scheduled to occur every five years. Importantly for our purposes, states are on different five year cycles due to historical political events such as formation or reorganization of states. Following the established cycle, assembly elections were scheduled for four states — Assam, Kerala, West Bengal, and Tamil Nadu — and one union territory — Puducherry — in March-April 2021. Elections took place as scheduled, with Kerala, Tamil Nadu and Puducherry voting on a single day (April 6). Elections in Assam were spread over three days (March 27, April 4 and 6) and elections in West Bengal took place in phases between March 27 and April 29.

Centrality of Rallies. State Assembly elections are heavily contested in India, with extensive campaigning beginning 1-2 months beforehand. Political rallies are used to motivate the base and demonstrate support for candidates (Wyatt, 2021). Rallies are often very large, with attendance in the thousands (Kumar, 2022). While frequently outdoors, the events are often densely packed and many individuals travel on public transportation to attend (Khan, 2019).

Rallies occurred in March and early April 2021 for the states contesting elections. These events were coincident with the rise of the delta variant and raised safety concerns, leading to calls to cancel or restrict campaigning (Indian Express, 2021). The elections went forward as planned, but public pressure to stop large scale rallies did result in a 500-person cap (Firstpost, 2021). However, this policy was imposed on April 22, 2021, after nearly all campaigning and voting had taken place.

3 Data

Our analysis uses five data sets.

Real Time Insights of COVID-19 in India (RTI). Our most important data source is a unique panel survey spanning the first two years of the pandemic (May 2020 to May 2022): the Real Time Insights of COVID-19 in India (RTI) survey (Petrosyan et al., 2022). This survey is an extension of the Longitudinal Aging Study in India Diagnostic Assessment of Dementia (LASI-DAD), a nationally representative panel survey of households with at least one individual over the age of 60, which was first fielded in 2017 (Lee et al., 2020).

The RTI was designed as a high-frequency phone survey tracking well-being during the pandemic. Figure A.1 plots the 9 waves of RTI surveys against India's official Covid-19 caseload counts. 2,704 of the original 3,224 LASI-DAD households had valid phone numbers and were targeted for enrollment into RTI; 1,766 households participated in at least one round. The survey enrolled both LASI-DAD respondents (who were all 60+), and two randomly selected adults, one male and one female, per household.[5] The RTI survey covers 18 states and union territories, including all election states with the exception of the small union territory Puducherry.

The RTI data over-represent older (60+) and higher socioeconomic status (SES) individuals, given the nature of the sampling frame and that surveys were conducted over the phone.[6] Recontact rates were high across the panel — 76% of households completed at least 5 of the 9 waves. A typical wave contained roughly 2,000 individuals from 1,000 households. Response rates are detailed in Appendix Table A.1. These rates did not differentially change in response to the election "treatment" (Appendix Table A.2). Further, we find no evidence that elections altered the sample's demographic composition (Appendix Table A.3).

The RTI surveys covered topics including Covid-19 in the household (symptoms, cases, knowledge, attitudes and behavior), health care utilization, economic indicators, and mental health. Mental health data collection began in wave 2 — we therefore drop wave 1 throughout our analysis. The high frequency of the data collection and long coverage window allow us to track outcomes across a fast-changing disease environment in the year following the elections.

Administrative Data on Covid-19. Indian state governments reported data on Covid-19 tests, cases, test positivity, and Covid-related deaths. Our analysis uses administrative data from July 2020 to May 2022, paralleling the timing of the RTI survey (Datakind Belgaluru

[5]The Data Appendix provides additional sampling details.

[6]Even so, given high rates of phone ownership in India and the fact that 31% of households have at least one individual aged 60 and older, the survey achieves relatively wide representation (Nagarajan, 2014).

and Development Data Lab, 2022). We adjust all statistics except test positivity to per capita rates using the 2011 Census of India. States likely under-reported to some degree, and data quality varies widely (Vasudevan et al., 2021; Jha et al., 2022). Because we cannot assess whether reporting quality is differential across time and location we consider these data a secondary source.

CMIE's CPHS. The Centre for Monitoring Indian Economy (CMIE) has produced the Consumer Pyramids Household Survey (CPHS), a nationally-representative survey of over 170,000 households, three times annually since 2014 (CMIE, 2022). Given the relatively limited economic variables in the RTI survey, we rely on the CMIE CPHS data to provide additional insight on the economic effects of the election-induced Covid surge. In 2020, CMIE shifted rapidly to telephone interviews during lockdowns, facilitating continuous data throughout the pandemic. The CPHS focuses on household economic outcomes, and includes data on labor supply, earnings, consumption, and economic outlook.

Google Mobility Data. We use cell phone mobility data to verify that elections caused individuals to spend more time out of their homes. Specifically, we access data from users who opted into Google's location history. While these data are not representative, they are attractive in that sample selection is unlikely to change as a result of the elections.

To preserve anonymity, Google pre-processes the data and only releases Indian state-level aggregates. The data (Google LLC, 2022) are represented by a relative change in time spent in different categories of locations (e.g. home, transit) relative to a five-week pre-pandemic period. So, for example, a value of 5 would mean that 5% more time is spent in that location category relative to the baseline period.

Because rallies could increase time spent at a range of locations and it is not obvious which location(s) should be most affected, we focus on time spent away from home to proxy changes in social interactions.

Oxford University's Covid-19 Government Response Tracker. In order to examine the role of governmental Covid policy responses in mediating election effects, we draw on data from Oxford University's Covid-19 Government Response Tracker (Hale et al., 2021). We use the Government Response Index, which is calculated at the state level and aggregates indicators of containment and health policy (school and workplace closings, restrictions on movement), economic policy (income support and debt relief) and health system policy (including facial covering policy and contact tracing). The index ranges from 0 to 100, with higher values indicating more stringent policies.

4 Empirical Strategy

We leverage the quasi-random timing of elections to study the impact of a higher Covid-19 caseload on mental health via a differences-in-differences approach:

$$y_{ist} = \beta_0 + \beta_1 Treat_s \times Post_t + \beta_2 Post_t + \delta_s + \lambda_t + \gamma \mathbf{X}_{ist} + \varepsilon_{ist}, \tag{1}$$

where y_{ist} is the outcome of interest for individual i in state s at time t, δ_s are state fixed effects, and λ_t are survey wave (for RTI and CMIE data) or month fixed effects (for other data). $Treat_s$ identifies election states, and $Post_t$ marks the beginning of the election period (March 15 2021) onwards.[7] When available, we also control for a small number of individual-level covariates, $\mathbf{X}_{ist}$, namely age, gender, education, whether the household belongs to a scheduled caste/tribe, and pre-pandemic household assets. Estimates are robust to dropping these controls.

We must make the standard parallel trends assumption to interpret β_1 as the causal effect of elections. This is well-supported by pre-trends (see Figures A.5-A.6), in line with the facts that (a) years in which different Indian states hold elections are idiosyncratic and (b) Covid was a sudden, unexpected shock exogenous to pre-existing and unchanged election schedules. To interpret β_1 as the causal effect of increased Covid caseload on downstream outcomes like mental health, we must further assume that elections themselves do not directly influence these outcomes. We test (and find support for) this assumption via a placebo test, using an earlier round of elections *prior to Covid* in Section 5.6. For consistency, we limit the sample to the 17 states in the RTI dataset with clear treatment assignment.[8]

Conventional clustered standard errors are inappropriate in our setting for two reasons. First, the number of clusters (states) is small. A common solution is to implement a wild cluster bootstrap (Cameron et al., 2008). However, this can be biased when the number of treated clusters is very small (Conley and Taber, 2011). One solution is to implement a sub-cluster bootstrap, which can reduce bias (MacKinnon and Webb, 2018).[9] However, in differences-in-differences settings like ours, this approach is likely to under-reject and is therefore conservative.[10]

[7] Since the $Post_t$ indicator switches to 1 at the same time for all states, we avoid two-way fixed effects issues (de Chaisemartin and D'Haultfœuille, 2020).

[8] We drop Uttar Pradesh, since it held only local elections. However, results are robust to its inclusion (Tables A.4 and A.5).

[9] In the sub-cluster bootstrap, errors are permuted at a finer-grained (household) sub-cluster with the t-statistic for each replication calculated using standard errors clustered at the higher (state) level cluster.

[10] MacKinnon and Webb (2018) note that the sub-cluster bootstrap will tend to under-reject when the number of post-treatment observations per treated cluster is small relative to the number of untreated observations. Only 15% of our observations fall into the $Treat \times Post$ category.

An alternative approach is to calculate p-values for the sharp null hypothesis of no treatment effect for any unit using a Fisher Randomization Test. This is well-suited to our application, where "treatment" is arguably exogenous (Roth et al., 2022). We use these p-values (p_{RI} — in square brackets) as primary tests of statistical significance, and report sub-cluster wild bootstrap p-values (p_W — in curly braces) as a robustness check. We do not report conventional clustered standard errors, as they suffer significant downward bias.

5 Results

5.1 Elections and movement

We begin by using mobility data to show that elections increased time spent outside the home.[11].

To provide a fine-grained sense of temporal patterns, we interact the election state dummy with month dummies (the omitted time period is July 2020-November 2020, six months or more before the "main" [$t = 0$] campaign and election month of April 2021). Figure A.3 plots the relative difference in time spent at home between election and non-election states over time. Supporting our identification assumption, we find no evidence of significant pre-trends. During the election period, individuals spent roughly 4.7% ($p_{RI} = 0.02$) less time in their homes. Immediately after the election month, time spent at home reverts to baseline levels. Then, consistent with an election-induced increase in Covid, people in election states spend 4.0% *more* time at home two months after the election period ($p_{RI} = 0.08$) before mobility again reverts back to baseline levels.

The Google mobility data mirror patterns in official containment policy: Figure A.2 reports raw time trends in the Oxford Government Response Index, while Figure A.4 reports difference-in-difference impacts on the overall index (Panel A), and sub-indices capturing policies relevant to participating in election gatherings (Panel B) and policies unlikely to affect individuals' ability to attend gatherings (Panel C). Policy stringency is quite similar in election and non-election states in the months leading up to the elections. However, states in which elections were held experience a relative dip in stringency in the election/campaign month (16.4 units, $p_{RI} = 0.04$)) followed by a gradual rise in stringency over the following three months (peaking at 20.5 units, $p_{RI} = 0.01$), again mirroring Covid caseloads. As shown in Panel B, these effects are driven by policies that impact individuals' ability to attend large gatherings.

[11]We drop the state of Jammu and Kashmir from this analysis due to a ban on mobile Internet during much of the pre-election period (Wani and Sibal, 2021)

5.2 Covid-19 burdens

To track the progression of Covid cases over time, we begin with self-reported cases in the RTI data. For waves 2-8, participants were asked whether anyone in the household had *ever been diagnosed* with Covid-19 by a healthcare provider. For wave 9, the survey instrument changed to include not only confirmed, but also suspected Covid cases. As seen in Panel A of Table 1 column 1 and Figure A.5, despite very consistent pre-trends across election and non-election states, election states experienced a marked increase in reported Covid cases following the election. In fact, participants in these states are 7 percentage points more (nearly twice as) likely to report that someone in the household had been infected with Covid ($p_{RI} = 0.047$, $p_W = 0.061$).

State-level administrative data on Covid cases and test positivity rates show similar patterns (Table 1, columns 2-4). Beyond the assumption that elections did not influence individuals' desire or ability to receive a test, interpreting these results as indicative of overall caseload effects requires assuming that the elections did not alter state reporting of case counts.[12] Consistent with the survey-based results, the administrative data show an approximate doubling in reported Covid-19 caseload in election states. While estimates using the per capita caseload are imprecise, column 3 shows an increase of just over one log point ($p_{RI} = 0.017$, $p_W = 0.013$). Since election states may have a differential incentive to under-test, we also examine impacts on the test positivity rate — which may be more difficult to manipulate — in column 4. We find an over 40% increase in election states ($p_{RI} = 0.037$, $p_W = 0.053$). These findings align with other studies showing that mass gatherings accelerate Covid spread (Bernheim et al., 2020; Dave et al., 2021).

Panel B augments our main specification to study short- (pre-omicron) and long-term (post-omicron) treatment effects. We do this by replacing $Treat \times Post$ with two covariates: $Treat \times Post \times Wave2-8$ and $Treat \times Post \times Wave9$, where $Wave2-8$ is a dummy variable equal to one for waves 2 to 8 of the RTI survey (all pre-omicron) and $Wave9$ is a dummy variable equal to one for wave 9 (post-omicron). While not significant, the long-run point estimate on self-reported infection is stable, suggesting delta wave caseloads persistently increased (perceived) infection with the disease. We find no significant long-run effects on administrative case counts, with a negative point estimate on log caseloads, suggesting elections did not meaningfully affect the trajectory of caseloads beyond the delta wave.

[12]The main risk being election states would under-report cases due to political pressure generated by negative news coverage of the election rallies. This would result in an underestimate of the true effect.

5.3 Increased Covid spread harms mental health

Next, we study the mental health implications of increased Covid burdens. We proxy mental health via the Patient Health Questionnaire-4 (PHQ-4), a widely-used, validated brief screening survey designed to capture anxiety and depression (Löwe et al. (2010)).[13] The questionnaire asks participants "Over the last two weeks, how often have you been bothered by the following problems? 1) Feeling nervous, anxious or on edge, 2) Not being able to stop or control worrying, 3) Feeling down, depressed or hopeless, 4) Little interest or pleasure in doing things." The first two items capture anxiety while the second two capture depression. Higher scores indicate worse mental health, with typical recommended cut-points being 0-2 for normal mental health, 3-5 for mild psychological distress, 6-8 for moderate distress, and 9-12 for severe distress.

Table 2, column 1, shows that individuals in election states, who experienced increased Covid rates, experienced a corresponding decline in mental health. The increase of 0.93 points ($p_{RI} = 0.019$, $p_W = 0.034$) corresponds to roughly 8% of the overall range of the scale or a 54% increase in the score relative to the post period control mean. Column 2 shows this reflects an 18 percentage point increase in the likelihood of exhibiting any psychological distress (total score of 3 or higher), relative to a base rate of 28 percent ($p_{RI} = 0.049$, $p_W = 0.11$). Effect sizes are similar for the anxiety and depression sub-scales, at 0.51 ($p_{RI} = 0.009$, $p_W = 0.018$) and 0.42 ($p_{RI} = 0.070$, $p_W = 0.11$) points, respectively (columns 3 and 4).

5.4 Mental health effects are persistent

Panel B of Table 2 studies the time path of effects (also visible in Figure A.6). Post-election declines in mental health are remarkably persistent, with *larger* point estimates in the long run. We reject equality of short- and long-run treatment effects for the overall score ($p_{RI} = 0.057$, $p_W = 0.088$) and the depression sub-score ($p_{RI} = 0.024$, $p_W = 0.051$), suggesting that the psychological costs of more severe Covid waves can be long-lasting. It is also possible that successive waves of illness amplify initial mental health effects: the omicron wave may have heightened feelings of worry, anxiety, and stress for individuals who had experienced a more severe delta wave, driving growth in treatment effects over time.

[13] The PHQ-4 combines the GAD-2, which screens for anxiety and the PHQ-2, which screens for depression. Both have been independently validated as screening tools for anxiety and depression (Kroenke et al., 2009).

5.5 Lower-SES households are disproportionately affected

We next explore whether the election-induced surge in Covid caseload had disproportionate effects on vulnerable demographic groups. We focus on socioeconomic status (SES), proxied by two indicators: whether anyone in the household has postsecondary education, and whether the household was in the top tercile of the pre-Covid asset distribution (measured in the LASI survey). We also consider heterogeneity by age above/below 50 — because older individuals are more vulnerable, and gender — given previous research suggesting that women experienced greater reductions in mental health post-Covid (Adams-Prassl et al., 2022; Etheridge and Spantig, 2022). Table 3 presents results from equations that have been modified to include the specified heterogeneity trait, and its interactions with the $Treat \times Post$, $Treat$, and $Post$ indicators. The first column studies heterogeneous effects of the elections on reported Covid infection, while columns 2-5 focus on mental health effects. We find no significant heterogeneity in impact on Covid infection — differential effects are never statistically significant and generally small in magnitude. However, mental health effects differ importantly in the first two panels, where individuals in higher SES households are *less* negatively affected than their lower SES peers. In contrast, there is no significant heterogeneity with respect to age or gender.

5.6 Elections do not directly impact mental health

One concern with our interpretation that mental health effects reflect increased Covid burdens is that elections may directly impact mental health. To evaluate this possibility, we conduct a placebo test using state elections held between 2017 and 2020. During this period, 5 states (Telangana, Madhya Pradesh, Maharashtra, Gujarat, and Karnataka) (a) held elections and (b) had LASI surveys before elections and LASI-DAD surveys after elections.[14] To identify the effect of these earlier elections, we limit the sample to LASI-DAD states, build a panel with the LASI and LASI-DAD survey rounds, and regress outcomes on state and month fixed effects, as well as an election×post indicator and individual controls.[15]

We examine whether this round of elections produced a similar decline in mental health in Table A.6. Point estimates indicate a small improvement in mental health, though results

[14]Elections dates were 9 and 14 December 2017, December 7, 2018, November 28, 2018, October 21, 2019, and May 12, 2018 for Gujarat, Telengana, Madhya Pradesh, Maharashtra, and Karnataka respectively. India also held national elections April-May 2019, which we account for with time fixed effects. LASI and LASI-DAD capture mental health via the CESD-10, a ten-item validated scale that captures levels of depression (González et al., 2017). Other states had elections in between 2017 and 2020, but were not bookended by LASI and LASI-DAD surveys.

[15]For randomization inference, we permute dates of all state elections held between 2017 and 2020 at the state level, generating a permuted election×post indicator based on individual survey dates.

are not statistically significant. Thus it is unlikely that the negative effects we observe are being driven by elections per se.

5.7 Channels for mental health effects

There are multiple, potentially intersecting ways a greater disease burden could harm mental health. First, the effects could reflect direct impacts (i.e. the effect of an infection in the household) and/or indirect, spillover effects (i.e. due to containment policy or generalized fear). To assess indirect channels, Table A.8 and Figure A.8 drop all RTI households who ever reported a Covid infection and re-estimate effects of the state-level treatment focusing on the sample of spillover households. We find no evidence of pre-trends and impacts on mental health remain statistically significant — including in the long run — though are slightly smaller in magnitude. This suggests that the aggregate nature of the shock had important spillover effects on households who did not personally experience illness.

We can further disaggregate impacts by examining whether they operate via health- or economic channels. Regarding health, the unprecedented strain on India's healthcare system created near universal worry; and experiencing or witnessing Covid-related morbidity and mortality likely had negative psychological consequences for many. Beyond this, government- or self-imposed isolation may have increased loneliness and / or increased household conflict. In terms of economic impacts, households may have suffered financial shocks like medical expenses or income loss due to poor health or a broader economic slowdown. While our ability to precisely identify channels is limited by data constraints, we present a series of suggestive analyses intended to shed light on the extent to which mental health effects were driven by these factors.

First, the fact that we observe significantly worse mental health effects for lower SES individuals despite no differential effect on Covid caseloads (Table 3) points to a potential role for economic effects. To explore this further, Table 4 presents treatment effects on economic outcomes. Columns 1-4 use RTI data. We find no significant overall effects on monthly household income, the likelihood of having any income in the past month, subjective financial health, and an index of food security.[16] Columns 5-6 use CMIE data (which fields a more detailed income module) and finds similarly-small null effects on income-related outcomes.

Even so, the 0.19 unit (10 percent) reduction in the financial health score in column 3

[16]The financial health score ranges from 0-3, reflecting Likert responses to a question asking whether the pandemic had affected the household's ability to meet its financial obligations. Zero indicates a 'major impact' while 3 indicates 'no impact'. The food security score aggregates 5 dummy variables indicating *no* distress in the past week vis-a-vis 5 food security scenarios. See table notes for details.

is just shy of marginal significance ($p_{RI} = 0.15$, $p_W = 0.12$), and treatment effects are economically meaningful and significant in the long run ($p_{RI} = 0.060$, $p_W = 0.032$); this timing suggests households may have suffered general financial strain, possibly driven by a combination of income loss and debt. To explore this more deeply, Table 5 studies heterogeneity in results with respect to SES. While column 3 shows that negative financial health effects are indeed concentrated in the bottom part of the pre-Covid asset distribution, we are not able to reject equality of treatment effects by SES group. Taken together, we conclude that there is suggestive, though by no means conclusive, evidence that economic channels may have played a role in harming mental health among lower SES households.

Table A.7 and Figure A.7 use RTI data from a survey module asking about pandemic-related concerns to explore other channels. This module asked individuals to rate the extent to which they had been affected by (a) fear of infection/death in the family, (b) loneliness, and (c) elevated stress in the family. Responses are coded on a Likert scale, with a value of 1 corresponding to 'not at all concerned' and a value of 4 corresponding to 'extremely concerned'. Panel A shows similar-in-magnitude effects on all outcomes with relatively large point estimates — typically about one-third of the control mean or an increase of 0.75 standard deviation units in an index of all three measures. While large, the overall estimates are never significant at conventional levels (p-values range from 0.10 to 0.17). Panel B of Table A.7 shows that point estimates for impacts on loneliness are similar in magnitude over both the short- and long-run, while impacts on intra-household stress and especially fear of infection/death grow in magnitude in the long run (effects for the latter are significant with $p_{RI} = 0.010$ and $p_W = 0.022$). Given that omicron caseloads were similar in election and non-election states, these patterns are consistent with the idea that past distress from the delta wave was brought to the fore by the omicron surge.

Taken together, we find suggestive evidence that both Covid-associated health and economic factors likely contributed to election-induced decline in mental health, with a disproportionate burden being borne by low-SES households and substantial spillovers to uninfected households.

6 Conclusion

Our analysis provides some of the first causal estimates of the impact of an aggregate health shock on mental health in a low-income setting. To identify this effect, we leverage the exogenously set timing of India's 2021 elections, which induced increased mobility and social interaction during the deadly delta Covid-19 wave. Impacts are economically meaningful —- elections resulted in an approximate doubling in Covid-19 incidence according to both

survey and administrative data, which translates into a 65% increase in the likelihood of exhibiting psychological distress per the PHQ-4. These effects persist for at least a year, growing in magnitude following the 2022 omicron surge. Mental health impacts are equally apparent for young and old, men and women. While this suggests *within-household* effects of the election-induced surge were similarly felt, we find important heterogeneity *across households*: although the elections increased Covid incidence among both low- and high-SES households, only lower-SES households' mental health suffered. In light of suggestive evidence pointing to increased fear of infection/death alongside increased difficulty meeting financial obligations, we hypothesize that both the disease environment and economic effects of the surge played a role in harming well-being among the more vulnerable.

Our results also have practical implications. Policymakers must balance competing interests when deciding how to respond to a surge in infectious disease; while well-crafted containment measures may slow disease spread and prevent the overburdening of the health system, they also impose economic and psychological costs of their own, with some arguing that aggressive containment disproportionately harms the poor and vulnerable (Broadbent et al., 2020). The primary objective of such measures is to blunt a surge in disease; therefore, it is important to understand how exposure to surges affects both immediate and downstream health and well-being. Our estimates suggest that accounting for psychological costs when performing such calculations is important due to their magnitude, persistence, and socioeconomic regressivity.

When interpreting our results, one should keep in mind that the surge we study was especially deadly and occurred before most adults had been vaccinated. The mental health consequences of increased caseloads could be less severe in a setting where overall infection rates were lower or the health system were less overwhelmed. Additional research to better understand the relationship between large, unexpected health shocks and mental health in other contexts — and the extent to which this relationship is nonlinear or disproportionately impacts certain groups — is needed to provide a more comprehensive picture of the consequences of shocks like pandemics on mental health.

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7 Tables and Figures

Table 1: Impacts on Covid Cases

	RTI Covid	Administrative Data		
	Covid Infection in Household	Covid Cases per Capita	Log Covid Cases per Capita	Test Positivity Rate
	(1)	(2)	(3)	(4)
A. Overall Effect				
Treat × Post	0.070	56.1	1.03	0.042
	[0.047]	[0.44]	[0.017]	[0.037]
	{0.061}	{0.57}	{0.013}	{0.053}
Observations	17113	11458	11458	10861
B. Treatment Effects by Time Period				
Treat × Post × Short Run	0.067	63.3	1.55	0.040
	[0.029]	[0.51]	[0.0080]	[0.044]
	{0.039}	{0.55}	{0.011}	{0.053}
Treat × Post × Long Run	0.082	39.3	-0.18	0.045
	[0.25]	[0.38]	[0.73]	[0.16]
	{0.24}	{0.59}	{0.63}	{0.13}
Tests of Equality: Short vs. Long Run				
Randomization Inference P-value	0.77	0.59	0.014	0.77
Bootstrap P-value	0.78	0.46	0.011	0.68
Control Mean in Post Period	0.072	66.5	1.99	0.073
N	17113	11458	11458	10861

This table presents the difference-in-difference estimates of the effect of the 2021 state elections on Covid infections and test positivity rates. Panel A presents the overall treatment effect. Panel B presents the treatment effect split by short run (up to 9 months post-election) and long run (12 to 14 months post-election) effects. Covid Infection in the Household (column 1) is based on self-reports in the RTI survey data. Outcomes in columns 2-4 are from administrative data corresponding to the period covered by the RTI survey. Covid Cases per Capita (column 2) is the 14-day rolling average of state-level reported daily Covid cases per one million population. Log Covid Cases (column 3) is the logarithmic transformation of the variable in column 2. Test Positivity Rate (column 4) is the 14-day rolling average of the fraction of positive Covid tests in the state. For column 1, the regression is specified at the level of the individual and controls for state and wave fixed effects as well as the respondent's age, gender, pre-pandemic depression level (CESD-10 score), whether the household is in an urban region, the household's pre-pandemic total asset value (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). Control variables are from the LASI Wave 1 survey administered between 2017-19. All missing values for controls are recoded as zero and regressions include a dummy variable for variable-specific missing values. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 2,380 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level. For columns 2-4, the regressions are specified at the level of state, and include state and month fixed effects. For these variables, we report wild bootstrapped standard errors clustered at the state level.

Table 2: Impacts on Mental Health

	PHQ-4 Score	Any Psychological Distress	Anxiety Score	Depression Score
	(1)	(2)	(3)	(4)
A. Overall Effect				
Treat × Post	0.93	0.18	0.51	0.42
	[0.019]	[0.049]	[0.0088]	[0.070]
	{0.034}	{0.11}	{0.018}	{0.11}
Observations	17150	17150	17156	17152
B. Treatment Effects by Time Period				
Treat × Post × Short Run	0.76	0.16	0.43	0.32
	[0.046]	[0.065]	[0.018]	[0.16]
	{0.053}	{0.100}	{0.020}	{0.18}
Treat × Post × Long Run	1.59	0.27	0.78	0.82
	[0.013]	[0.089]	[0.021]	[0.015]
	{0.030}	{0.12}	{0.037}	{0.038}
Tests of Equality: Short vs. Long Run				
Randomization Inference P-value	0.057	0.25	0.17	0.024
Bootstrap P-value	0.088	0.25	0.17	0.051
Control Mean in Post Period	1.73	0.28	0.98	0.75
N	17150	17150	17156	17152

This table presents the difference-in-difference estimates of the effect of the 2021 state elections on the mental health outcomes reported in the RTI survey data. Panel A presents the overall treatment effect. Panel B presents the treatment effect split by short (up to 9 months post-election) and long run (12 to 14 months post-election) effects. Participants responded to the four-item Patient Health Questionnaire (PHQ-4) for anxiety and depression, reporting feelings of anxiety and depression on a 4 point scale, ranging from feeling the emotion 'not at all' (with a value of 0) to 'nearly every day' (value of 3). PHQ-4 Score (column 1) sums the scores of the four items; Any Psychological Distress (column 2) is an indicator variable equaling 1 if the respondent's total PHQ-4 score is 3 or above, signalling presence of at least mild psychological distress (Kroenke et al., 2009); Anxiety Score (column 3) is the sum of the two anxiety-related questions; Depression Score (column 4) is the sum of the two depression-related questions. All regressions are specified at the level of the individual and control for state and wave fixed effects as well as the respondent's age, gender, pre-pandemic depression level (CESD-10 score), whether the household is in an urban region, the household's pre-pandemic total asset value (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). All missing values for controls are recoded as zero and regressions include a dummy variable for variable-specific missing values. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 2,380 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Table 3: Heterogeneous Treatment Effects on Covid Exposure and Mental Health

	Covid Infection	PHQ-4 Score	Any Psychological Distress	Anxiety Score	Depression Score
	(1)	(2)	(3)	(4)	(5)
Heterogeneity by Edu: Any Postsecondary					
γ_1: Treat × Post × Edu: Any Postsecondary	0.0071	-0.60	-0.10	-0.30	-0.29
	[0.80]	[0.0071]	[0.018]	[0.0088]	[0.024]
	{0.80}	{0.0019}	{0.016}	{0.0030}	{0.010}
γ_2: Treat × Post	0.065	1.14	0.22	0.61	0.53
	[0.11]	[0.0080]	[0.033]	[0.0034]	[0.041]
	{0.12}	{0.020}	{0.081}	{0.011}	{0.063}
$\gamma_1 + \gamma_2 = 0$: Randomization Inference P-value	0.047	0.076	0.13	0.032	0.28
$\gamma_1 + \gamma_2 = 0$: Bootstrap P-value	0.018	0.12	0.17	0.062	0.29
Heterogeneity by HH in Top Asset Tercile					
γ_1: Treat × Post × HH in Top Asset Tercile	-0.0089	-0.83	-0.13	-0.41	-0.42
	[0.74]	[0.019]	[0.050]	[0.052]	[0.011]
	{0.75}	{0.022}	{0.065}	{0.048}	{0.017}
γ_2: Treat × Post	0.071	1.24	0.24	0.65	0.59
	[0.092]	[0.0076]	[0.032]	[0.0059]	[0.038]
	{0.080}	{0.0083}	{0.035}	{0.0099}	{0.033}
$\gamma_1 + \gamma_2 = 0$: Randomization Inference P-value	0.050	0.41	0.46	0.25	0.58
$\gamma_1 + \gamma_2 = 0$: Bootstrap P-value	0.044	0.41	0.48	0.28	0.56
Heterogeneity by Age>50					
γ_1: Treat × Post × Age>50	0.0078	0.28	0.039	0.11	0.17
	[0.79]	[0.54]	[0.66]	[0.67]	[0.44]
	{0.77}	{0.54}	{0.67}	{0.66}	{0.45}
γ_2: Treat × Post	0.064	0.75	0.16	0.43	0.31
	[0.14]	[0.15]	[0.20]	[0.12]	[0.28]
	{0.17}	{0.20}	{0.27}	{0.14}	{0.30}
$\gamma_1 + \gamma_2 = 0$: Randomization Inference P-value	0.059	0.017	0.050	0.013	0.055
$\gamma_1 + \gamma_2 = 0$: Bootstrap P-value	0.038	0.032	0.090	0.023	0.084
Heterogeneity by Female					
γ_1: Treat × Post × Female	0.0042	-0.16	-0.039	-0.069	-0.095
	[0.69]	[0.17]	[0.19]	[0.40]	[0.13]
	{0.69}	{0.18}	{0.22}	{0.40}	{0.13}
γ_2: Treat × Post	0.067	1.01	0.20	0.54	0.47
	[0.055]	[0.013]	[0.046]	[0.0076]	[0.052]
	{0.065}	{0.031}	{0.097}	{0.017}	{0.082}
$\gamma_1 + \gamma_2 = 0$: Randomization Inference P-value	0.053	0.030	0.072	0.015	0.100
$\gamma_1 + \gamma_2 = 0$: Bootstrap P-value	0.061	0.043	0.12	0.022	0.15
Control Mean in Post Period	0.072	1.73	0.28	0.98	0.75
N	17113	17150	17150	17156	17152

This table presents the heterogeneous treatment effects of the 2021 state elections on covid cases and mental health outcomes using RTI survey data. Each panel explores heterogenity by a different variable including: 1) Any Postsecondary, an indicator variable equaling 1 if at least one member of the respondent's household has postsecondary education; 2) HH in Top Asset Tercile, an indicator variable equaling 1 if the household was in the top asset tercile prior to the start of the pandemic (measured by LASI); 3) Age $>$ 50, an indicator variable equaling 1 if the respondent is above the age of 50 years; and 4) Female , taking the value 1 if the respondent is female. Covid Infection (column 1) is an indicator variable for a self-report of covid infection in the household. Participants responded to the four-item patient health questionnaire (PHQ-4) for anxiety and depression, reporting feelings of anxiety and depression on a 4 point scale, ranging from feeling the emotion 'not at all' (with a value of 0) to 'nearly every day' (value of 3). The PHQ-4 score (column 2) sums the scores of the four items; Any Psychological Distress (column 3) is an indicator variable equaling 1 if the respondent's total PHQ-4 score is 3 or above signalling the presence of at least mild psychological distress (Kroenke et al., 2009); Anxiety Score (column 4) is the sum of the two anxiety-related questions; Depression Score (column 5) is the sum of the two depression-related questions. All regressions are specified at the level of the individual and control for state and wave fixed effects as well as the respondent's age, gender, pre-pandemic depression level (CESD-10 score), whether the household is in an urban region, the household's pre-pandemic total asset value (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). All missing values for controls are recoded as zero and regressions include an indicator dummy variable for variable-specific missing values. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 2,380 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Table 4: Impacts on Economic Outcomes

	RTI Covid				CMIE	
	Income	Any Income	Financial Health Score	Food Security Score	Income	Any Income
	(1)	(2)	(3)	(4)	(5)	(6)
A. Overall Effect						
Treat × Post	-426.8	-0.067	-0.19	-0.18	-334.9	-0.018
	[0.67]	[0.41]	[0.15]	[0.47]	[0.57]	[0.39]
	{0.66}	{0.45}	{0.12}	{0.46}	{0.53}	{0.47}
Observations	14229	14229	15527	15925	2044331	2044331
B. Treatment Effects by Time Period						
Treat × Post × Short Run	-739.6	-0.067	-0.11	-0.19	-605.6	-0.014
	[0.37]	[0.40]	[0.28]	[0.45]	[0.32]	[0.39]
	{0.38}	{0.43}	{0.30}	{0.44}	{0.30}	{0.45}
Treat × Post × Long Run	764.7	-0.065	-0.51	-0.15	116.8	-0.023
	[0.68]	[0.51]	[0.060]	[0.63]	[0.85]	[0.42]
	{0.66}	{0.53}	{0.032}	{0.64}	{0.85}	{0.48}
Tests of Equality: Short vs. Long Run						
Randomization Inference P-value	0.24	0.94	0.050	0.86	0.24	0.52
Bootstrap P-value	0.24	0.95	0.023	0.86	0.20	0.57
Control Mean in Post Period	14898.7	0.90	1.97	4.50	24577.5	0.95
N	14229	14229	15527	15925	2044331	2044331

This table presents the difference-in-difference estimates of the effect of the 2021 state elections on economic outcomes. Panel A presents the overall treatment effect. Panel B presents the treatment effect split by short (up to 9 months post-election) and long run (12 to 14 months post-election) effects. Columns 1-4 use RTI survey data. Income (column 1) is the household income in the last month, including closed bracket imputations, and top-coded at the 99th percentile. Any Income (column 2) is an indicator variable which equals one if the household reported non-zero income in the past month and zero otherwise. Financial Health Score (column 3) is the self-reported impact of the pandemic on households' ability to meet financial obligations on a likert scale of 0 (major impact) to 3 (no impact). Food Security Score (column 4) counts the number of the following items the respondent answered *no* to, reflecting on the past week: worried would run out of food, ate less than wanted, ate differently due to cost, did not eat for a whole day, and could not eat usual food due to unavailability. Regressions using RTI survey data are specified at the level of the individual and control for state and wave fixed effects. Additional controls include respondent's age, gender and pre-pandemic depression level (CESD-10 score), whether the household belongs to an urban region, household's pre-pandemic value of total assets of household (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). Columns 5-6 use CMIE Consumer Pyramids Survey data from the same time period. Income (column 5) is the household income in the last month, top-coded at the 99th percentile. Any Income (column 6) is an indicator variable which equals one if the household reported non-zero income (excluding transfers) in the past month and zero otherwise. CMIE regressions are specified at the level of the household and control for state and month fixed effects as well as whether the household belongs to an urban region, whether at least one member of the household belongs to a lower caste (SC/ST), pre-pandemic wealth index and highest education level in the household. All missing values for controls are recoded as zero and regressions include an indicator dummy variable for variable-specific missing values. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 2,380 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Table 5: Heterogeneous Treatment Effects on Economic Outcomes

	RTI Covid				CMIE	
	Income	Any Income	Financial Health Score	Food Security Score	Income	Any Income
	(1)	(2)	(3)	(4)	(5)	(6)
Heterogeneity by Edu: Any Postsecondary						
γ_1: Treat × Post × Edu: Any Postsecondary	622.7	0.012	0.26	0.14	-1104.5	-0.0020
	[0.72]	[0.62]	[0.31]	[0.37]	[0.097]	[0.81]
	{0.72}	{0.64}	{0.26}	{0.38}	{0.11}	{0.79}
γ_2: Treat × Post	-677.9	-0.071	-0.28	-0.22	-27.4	-0.016
	[0.59]	[0.41]	[0.11]	[0.42]	[0.95]	[0.40]
	{0.58}	{0.45}	{0.076}	{0.41}	{0.94}	{0.48}
$\gamma_1 + \gamma_2 = 0$: Randomization Inference P-value	0.97	0.44	0.94	0.70	0.23	0.46
$\gamma_1 + \gamma_2 = 0$: Bootstrap P-value	0.97	0.43	0.94	0.68	0.21	0.50
Heterogeneity by HH in Top Asset Tercile						
γ_1: Treat × Post × HH in Top Asset Tercile	3038.2	0.11	0.20	0.21	-1326.7	-0.015
	[0.069]	[0.14]	[0.18]	[0.14]	[0.052]	[0.26]
	{0.062}	{0.15}	{0.16}	{0.15}	{0.038}	{0.36}
γ_2: Treat × Post	-1212.2	-0.095	-0.26	-0.25	28.3	-0.015
	[0.35]	[0.35]	[0.12]	[0.37]	[0.95]	[0.43]
	{0.29}	{0.37}	{0.068}	{0.34}	{0.95}	{0.49}
$\gamma_1 + \gamma_2 = 0$: Randomization Inference P-value	0.11	0.73	0.66	0.85	0.072	0.19
$\gamma_1 + \gamma_2 = 0$: Bootstrap P-value	0.11	0.76	0.66	0.83	0.065	0.38
Control Mean in Post Period	14898.7	0.90	1.97	4.50	24577.5	0.95
N	14229	14229	15527	15925	2044331	2044331

This table presents the heterogeneous treatment effects of the 2021 state elections on household finances. The top panel explores heterogeneity by education, where Any Postsecondary is an indicator variable equaling 1 if at least one member of the respondent's household has postsecondary education. The bottom panel explores heterogeneity by wealth, where HH in Top Asset Tercile is an indicator variable equaling 1 if the household was in the top asset tercile prior to the pandemic (measured by asset value in the LASI survey, asset index in CMIE). Outcomes in columns 1-4 are from the RTI survey. Income (column 1) is the household income in the previous month top-coded at the 99th percentile. Any Income (column 2) is an indicator variable which equals one if the household reported non-zero income in the past month and zero otherwise. Financial Health Score (column 3) records the self-reported impact of the coronavirus pandemic on households' ability to meet financial obligations on a likert scale of 1 (major impact) to 4 (no impact). Food Security Score (column 4) counts the number of the following items the respondent answered *no* to, reflecting on the past week: worried would run out of food, ate less than wanted, ate differently due to cost, did not eat for a whole day, and could not eat usual food due to unavailability. Regressions in columns 1-4 are specified at the level of the individual and control for state and wave fixed effects. Additional controls include respondent's age, gender, pre-pandemic depression level (CESD-10 score), whether the household belongs to an urban region, the household's pre-pandemic value of total assets of household (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). Columns 5-6 use CMIE Consumer Pyramids Survey data from the same time period. Income (column 5) is the household income in the previous month top-coded at the 99th percentile. Any Income (column 6) is an indicator variable which equals one if the household reported non-zero income (excluding transfers) in the past month and zero otherwise. Regressions in columns 5-6 are specified at the level of the household and control for state and wave fixed effects. Additional controls include whether the household belongs to an urban region, whether at least one member of the household belongs to a lower caste (SC/ST), and pre-pandemic wealth index and highest education level in the household. All missing values for controls are recoded as zero and regressions include an indicator dummy variable for variable-specific missing values. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 2,380 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

A Online Appendix: Supplementary Tables and Figures

Table A.1: Response Rate Across RTI Waves

RTI Wave	HH Response Rate		
	Full Sample	Control States (Non-Election)	Treatment States (Election)
	(1)	(2)	(3)
2	44.32	43.55	46.02
3	45.94	45.07	47.89
4	45.98	45.96	46.02
5	46.33	44.56	50.25
6	44.78	44.23	46.02
7	44.63	43.05	48.13
8	42.97	40.98	47.39
9	37.60	39.29	33.83
2-9	44.07	43.34	45.69

This table shows the raw statistics for household-level response rates across waves of the RTI survey. The household-level response rate is calculated based on the sub-sample of households with LASI-DAD respondents selected for participation in the first wave of the RTI survey. Full Sample (column 1) is the response rate for the full sample of the households; Control States (column 2) is the response rate in the non-election states; Treatment States (column 3) is the response rate in the election states.

Table A.2: Selection Test: Treatment Effects on Response Rate

	Household Responded	Number Household Members Responded
	(1)	(2)
Treat × Post	-0.0080	0.031
	[0.78]	[0.52]
	{0.79}	{0.54}
Control Mean in Post Period	0.42	0.79
N	20704	20704

This table presents the difference-in-difference estimates of the effect of the 2021 state elections on the RTI survey response rate. A sub-sample of households with LASI-DAD respondents were selected for participation in the RTI survey. Two randomly selected adults (one male, one female) and the LASI-DAD respondent (from wave 3 onwards) were enrolled in the survey. Additional details on sampling are provided in the data appendix. Household Responded (column 1) is an indicator variable equaling 1 if a household participated in a survey wave and 0 otherwise; Number Household Members Responding (column 2) is the number of household members who participated in a survey wave. All regressions are at the level of the household and control for state and wave fixed effects. Paralleling the main analysis sample, we drop the first round and Uttar Pradesh from the analysis. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 2,380 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Table A.3: Selection Test: Treatment Effects on Sample Composition

	Age	Female	Urban	Caste: SC/ST	Highest Education in HH	HH Assets (Rs 10,000s)	CESD-10 Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat × Post	0.14	-0.0048	0.00086	-0.010	-0.00077	18.7	-0.0083
	[0.78]	[0.72]	[0.94]	[0.22]	[0.96]	[0.34]	[0.91]
	{0.77}	{0.71}	{0.93}	{0.18}	{0.96}	{0.29}	{0.93}
Control Mean in Post Period	51.3	0.48	0.37	0.23	1.38	408.0	2.73
N	17172	17172	17172	17172	17172	15215	17172

This table presents the difference-in-difference estimates of the effect of the 2021 state elections on the household sample composition in the RTI survey data. Age (column 1) is the respondent's age in years; Female (column 2) is an indicator variable which equals 1 if the respondent is female, and 0 otherwise; Urban (column 3) is an indicator variable equaling 1 if the respondent belongs to a household in an urban region and 0 otherwise; Caste: SC/ST (column 4) is an indicator variable for whether at least one member of the household belongs to a lower caste (SC/ST); Highest HH Education (column 5) is the highest level of education achieved in the household, taking the value 0 if the highest level of education is less than primary, 1 if the highest level of education is primary to secondary, and 2 if the highest level of education is high school and above; Household Assets (column 6) is the total value of household assets net of debt in ten thousands of rupees recorded during the first wave of LASI survey (2017-19); CESD-10 Score (column 7) measures the severity of depressive symptoms during the first wave of LASI survey (2017-19) where higher values denotes worse symptoms. All regressions are specified are at the level of the individual and control for the state and wave fixed effects. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 2,380 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Table A.4: Impacts on Covid Cases – Uttar Pradesh Included as Election State

	RTI Covid	Administrative Data		
	Covid Infection in Household	Covid Cases per Capita	Log Covid Cases per Capita	Test Positivity Rate
	(1)	(2)	(3)	(4)
A. Overall Effect				
Treat × Post	0.055	40.9	0.66	0.037
	[0.12]	[0.59]	[0.18]	[0.041]
	{0.12}	{0.68}	{0.19}	{0.037}
Observations	18212	12132	12132	11347
B. Treatment Effects by Time Period				
Treat × Post × Short Run	0.053	46.1	0.98	0.035
	[0.10]	[0.66]	[0.16]	[0.053]
	{0.095}	{0.67}	{0.17}	{0.046}
Treat × Post × Long Run	0.063	28.8	-0.080	0.042
	[0.31]	[0.46]	[0.85]	[0.14]
	{0.28}	{0.70}	{0.83}	{0.090}
Tests of Equality: Short vs. Long Run				
Randomization Inference P-value	0.82	0.62	0.23	0.67
Bootstrap P-value	0.82	0.54	0.24	0.53
Control Mean in Post Period	0.072	66.5	1.99	0.073
N	18212	12132	12132	11347

This table mirrors Table 1 and presents the difference-in-difference estimates of the effect of the 2021 state elections on Covid infection outcomes, but includes Uttar Pradesh — which held only local elections, which are less heavily contested — in the sample coded as a treated state. Panel A presents the overall treatment effect. Panel B presents the treatment effect split by short (up to 9 months post-election) and long run (12 to 14 months post-election) effects. Covid Infection in the Household (column 1) is based on self-reports in the RTI survey data. Outcomes in columns 2-4 are from administrative data corresponding to the period covered by the RTI survey. Covid Cases per Capita (column 2) is the 14-day rolling average of state-level reported daily Covid cases per one million population. Log Covid Cases (column 3) is the logarithmic transformation of the variable in column 2. Test Positivity Rate (column 4) is the 14-day rolling average of the fraction of positive Covid tests in the state. For column 1, the regression is specified at the level of the individual and controls for state and wave fixed effects as well as the respondent's age, gender, pre-pandemic depression level (CESD-10 score), whether the household is in an urban region, the household's pre-pandemic total asset value (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). Control variables are from the LASI Wave 1 survey administered between 2017-19. All missing values for controls are recoded as zero and regressions include a dummy variable for variable-specific missing values. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 8,568 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level. For columns 2-4, the regressions are specified at the level of state, and include state and month fixed effects. For these variables, we report wild bootstrapped standard errors clustered at the state level.

Table A.5: Impacts on Mental Health – Uttar Pradesh Included as Election State

	PHQ-4 Score	Any Psychological Distress	Anxiety Score	Depression Score
	(1)	(2)	(3)	(4)
A. Overall Effect				
Treat × Post	0.79	0.15	0.41	0.37
	[0.025]	[0.054]	[0.039]	[0.049]
	{0.044}	{0.096}	{0.053}	{0.080}
Observations	18250	18250	18256	18252
B. Treatment Effects by Time Period				
Treat × Post × Short Run	0.65	0.14	0.36	0.30
	[0.042]	[0.055]	[0.050]	[0.11]
	{0.048}	{0.085}	{0.049}	{0.12}
Treat × Post × Long Run	1.27	0.21	0.62	0.65
	[0.054]	[0.13]	[0.076]	[0.054]
	{0.073}	{0.15}	{0.091}	{0.073}
Tests of Equality: Short vs. Long Run				
Randomization Inference P-value	0.22	0.40	0.28	0.20
Bootstrap P-value	0.23	0.39	0.29	0.20
Control Mean in Post Period	1.73	0.28	0.98	0.75
N	18250	18250	18256	18252

This table mirrors Table 2 and presents the difference-in-difference estimates of the effect of the 2021 state elections on the mental health outcomes reported in the RTI survey data, but includes Uttar Pradesh – which held only local elections which are less heavily contested – in the sample coded as a treated state. Panel A presents the overall treatment effect. Panel B presents the treatment effect split by short (up to 9 months post-election) and long run (12 to 14 months post-election) effects. Participants responded to the four-item Patient Health Questionnaire (PHQ-4) for anxiety and depression, reporting feelings of anxiety and depression on a 4 point scale, ranging from feeling the emotion 'not at all' (with a value of 0) to 'nearly every day' (value of 3). PHQ-4 Score (column 1) sums the scores of the four items; Any Psychological Distress (column 2) is an indicator variable equaling 1 if the respondent's total PHQ-4 score is 3 or above, signalling presence of at least mild psychological distress (Kroenke et al., 2009); Anxiety Score (column 3) is the sum of the two anxiety-related questions; Depression Score (column 4) is the sum of the two depression-related questions. All regressions are specified at the level of the individual and control for state and wave fixed effects as well as the respondent's age, gender, pre-pandemic depression level (CESD-10 score), whether the household is in an urban region, the household's pre-pandemic total asset value (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). All missing values for controls are recoded as zero and regressions include a dummy variable for variable-specific missing values. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 8,568 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Table A.6: Placebo Test: Impact of Pre-Covid Elections on Mental Health

	CESD-10 Score	At Risk for Depression
	(1)	(2)
Treat × Post	-0.63	-0.098
	[0.54]	[0.34]
	{0.42}	{0.22}
Control Mean	10.5	0.54
N	7878	7878

This table assesses impacts of the 2018-2019 election on mental health among respondents in the LASI and LASI-DAD survey. Treated states include all states holding elections during this period — Gujarat, Telengana, Madhya Pradesh, Maharashtra, and Karnataka. CESD-10 Score (column 1) is the respondent's score on the CESD-10 questionnaire and ranges from 0 to 30 with higher scores indicating that the respondent experienced more depressive symptoms during the week prior to the interview. Depression Diagnosis (column 2) is an indicator variable which equals 1 if a respondent's CESD-10 score is greater than 10 (Andresen et al., 1994). All regressions are specified are at the level of the individual and control for state and survey×year fixed effects. Additional controls include respondent's age, gender, whether the household belongs to an urban region, household's value of total assets of household (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST), all recorded during the LASI survey's first wave. Randomization inference p-values in square brackets are based on 5,000 permutations of state election dates observed between 2017 and 2020, when LASI and LASI-DAD were fielded. We permute dates at the state level and use the permuted date to assign Election×Post at the individual level. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Table A.7: Impacts on Pandemic Attitudes

	Fear Infection/ Death in Family	Feeling Lonely	Increased Stress in Family	Summary Index
	(1)	(2)	(3)	(4)
A. Overall Effect				
Treat × Post	0.62	0.58	0.50	0.75
	[0.17]	[0.13]	[0.17]	[0.16]
	{0.11}	{0.12}	{0.12}	{0.11}
Observations	11495	11498	11499	11488
B. Treatment Effects by Time Period				
Treat × Post × Short Run	0.51	0.57	0.44	0.67
	[0.19]	[0.11]	[0.16]	[0.16]
	{0.17}	{0.10}	{0.14}	{0.13}
Treat × Post × Long Run	1.03	0.64	0.73	1.04
	[0.010]	[0.21]	[0.11]	[0.095]
	{0.022}	{0.20}	{0.076}	{0.067}
Tests of Equality: Short vs. Long Run				
Randomization Inference P-value	0.0017	0.77	0.10	0.063
Bootstrap P-value	0.0018	0.78	0.12	0.098
Control Mean in Post Period	1.82	1.58	1.58	0.047
N	11495	11498	11499	11488

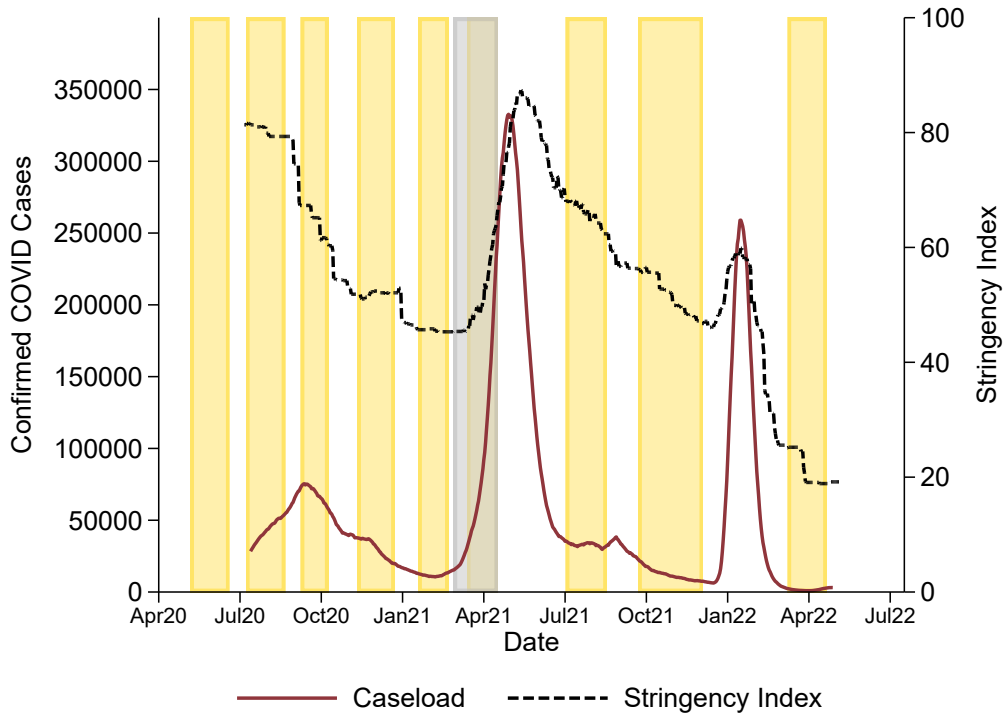
This table presents difference-in-difference estimates of the effect of the 2021 state elections on pandemic-related attitudes among respondents in the RTI survey. Panel A presents the overall treatment effect. Panel B presents the treatment effect split by short (up to 9 months post-election) and long run (12 to 14 months post-election) effects. Respondents are asked to report how concerned they are about the impacts of coronavirus a given dimension on a scale of 1 to 4, where 1 denotes 'not at all concerned' and 4 denotes 'extremely concerned.' Infection/Death in Family (column 1) captures concern about fear of infection or death in the family; Feeling Lonely (column 2) captures concern about feeling lonely or unable to meet relatives or friends; Increased Stress (column 3) captures concern about increased stress among household members; Summary Index (column 4) averages the standardized (using the control mean in the post-period) values of the items in columns 1-3. All regressions are specified at the level of the individual and control for state and wave fixed effects. Additional controls include respondent's age, gender, and pre-pandemic depression level (CESD-10 score), whether the household belongs to an urban region, the household's pre-pandemic total assets (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 3,060 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Table A.8: Impacts on Mental Health - Dropping Households That Ever Reported Covid Infection

	PHQ-4 Score	Any Psychological Distress	Anxiety Score	Depression Score
	(1)	(2)	(3)	(4)
A. Overall Effect				
Treat × Post	0.79	0.17	0.44	0.35
	[0.050]	[0.062]	[0.025]	[0.15]
	{0.082}	{0.12}	{0.043}	{0.18}
Observations	12492	12492	12496	12494
B. Treatment Effects by Time Period				
Treat × Post × Short Run	0.66	0.15	0.38	0.27
	[0.097]	[0.087]	[0.049]	[0.28]
	{0.13}	{0.13}	{0.071}	{0.28}
Treat × Post × Long Run	1.33	0.24	0.66	0.66
	[0.032]	[0.097]	[0.028]	[0.042]
	{0.027}	{0.13}	{0.026}	{0.055}
Tests of Equality: Short vs. Long Run				
Randomization Inference P-value	0.10	0.32	0.23	0.056
Bootstrap P-value	0.10	0.30	0.21	0.063
Control Mean in Post Period	1.63	0.27	0.94	0.69
N	12492	12492	12496	12494

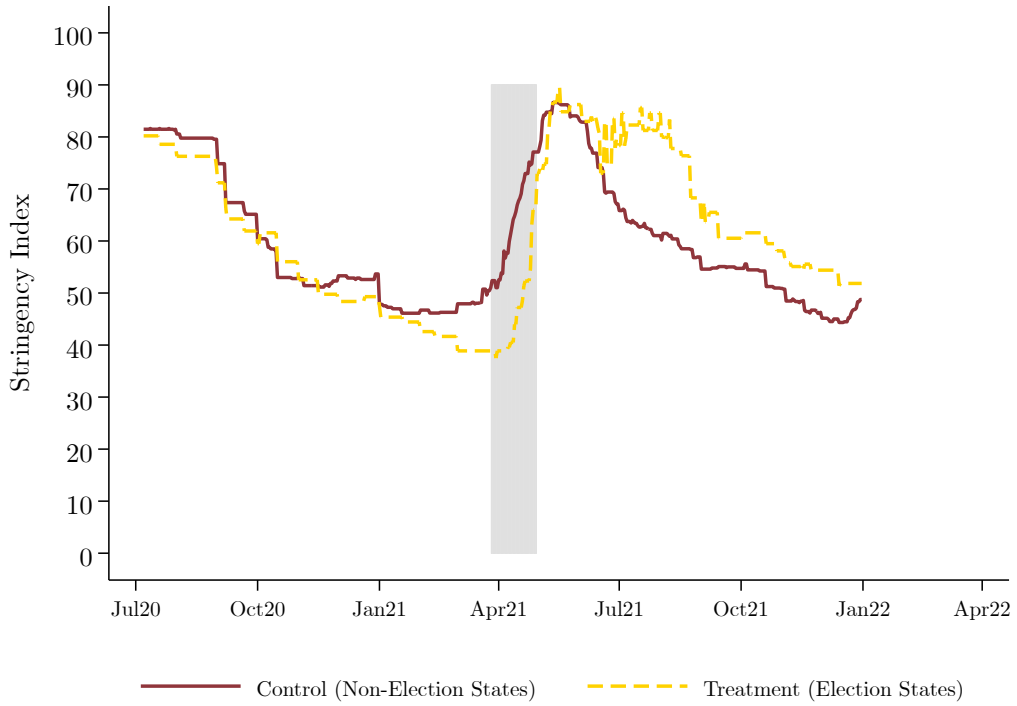
This table presents the difference-in-difference estimates of the effect of the 2021 state elections on the mental health outcomes reported in the RTI survey data. All regressions exclude households who reported a Covid case in any survey round. Panel A presents the overall treatment effect. Panel B presents the treatment effect split by short (up to 9 months post-election) and long run (12 to 14 months post-election) effects. Participants responded to the four-item Patient Health Questionnaire (PHQ-4) for anxiety and depression, reporting feelings of anxiety and depression on a 4 point scale, ranging from feeling the emotion 'not at all' (with a value of 0) to 'nearly every day' (value of 3). PHQ-4 Score (column 1) sums the scores of the four items; Any Psychological Distress (column 2) is an indicator variable equaling 1 if the respondent's total PHQ-4 score is 3 or above, signalling presence of at least mild psychological distress (Kroenke et al., 2009); Anxiety Score (column 3) is the sum of the two anxiety-related questions; Depression Score (column 4) is the sum of the two depression-related questions. All regressions are specified at the level of the individual and control for state and wave fixed effects as well as the respondent's age, gender, pre-pandemic depression level (CESD-10 score), whether the household is in an urban region, the household's pre-pandemic total asset value (net of debt), the highest level of education in the household, and whether at least one member of the household belongs to a lower caste (SC/ST). All missing values for controls are recoded as zero and regressions include a dummy variable for variable-specific missing values. Randomization inference p-values in square brackets are based on all the possible unique combinations of the state-level treatment assignment, resulting in 2,380 replications. Sub-cluster wild bootstrap p-values in curly brackets are based on 9,999 replications and are clustered at the household level.

Figure A.1: Key Events during the LASI RTI Survey Period



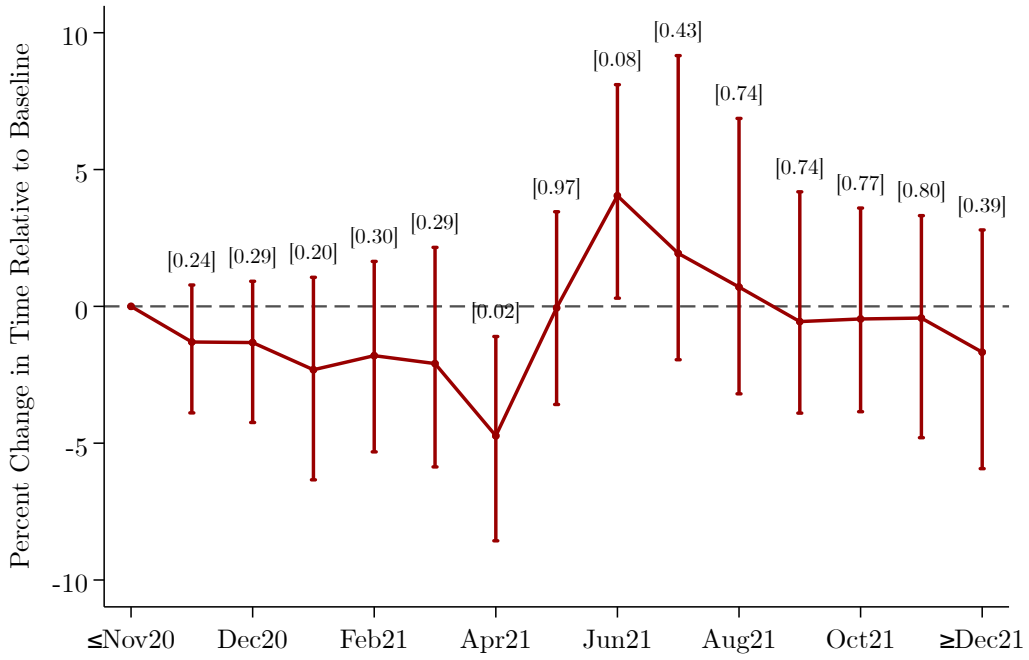
This figure plots key events during the analysis period. Yellow bars correspond to the RTI survey waves 1-9. The gray bar corresponds to the election period, inclusive of campaigning and voting in the four treatment states. The solid red line plots the 14-day rolling average of the Covid caseloads from administrative data in all sample states on the left axis. The dotted black line plots the average Oxford University's Covid-19 Government Response Tracker stringency index averaged across all sample states on the right axis. The index ranges from 0 to 100, with higher values indicating more stringent policy action.

Figure A.2: Stringency Index in Election and Non-Election States



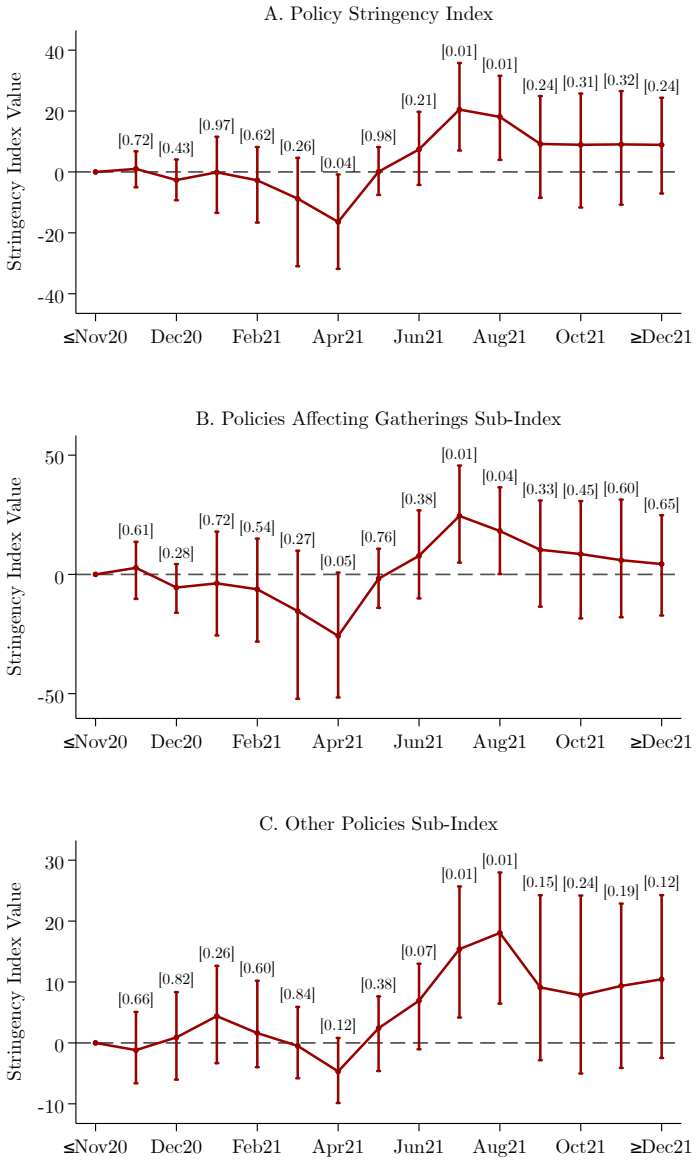
This figure plots the day-level average value of Oxford University's Covid-19 Government Response Tracker stringency index in Treated (election) and Control (non-election) states over time. The index is computed as the average of indices capturing policies for vaccinated and non-vaccinated individuals. The red line represents Control (non-election) states and the yellow line represents Treated (election) states.

Figure A.3: Treatment Effects on Time Spent at Residence



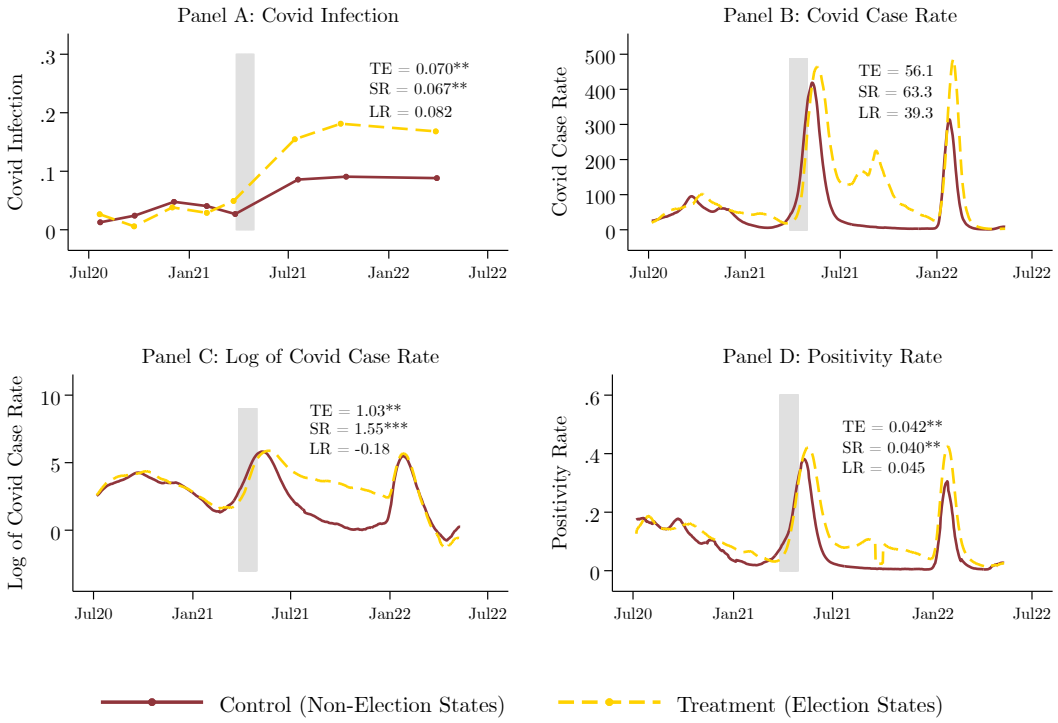
This figure plots the difference-in-difference treatment effects of the 2021 state elections on mobility. Time spent at residence is the 7-day rolling average of time spent at one's place of residence, aggregated from the Google mobility data. The variable, produced by Google, is calculated by comparing time spent in places of residence relative to a pre-pandemic period (Jan 3 to Feb 6, 2020). In this data, a value of X would be interpreted as spending $X\%$ more time at home in that period relative to the pre-pandemic period. Whiskers give wild bootstrapped 95 percent confidence intervals, clustered at the state level, based on 9,999 replications. Randomization inference p-values using all 2,380 possible combinations of state-specific treatment status are displayed in brackets above each point estimate. The regression is specified at the level of state and month, relative to the timing of the election. The omitted reference period is July 2020 through November 2020.

Figure A.4: Treatment Effects on Policy Stringency Over Time



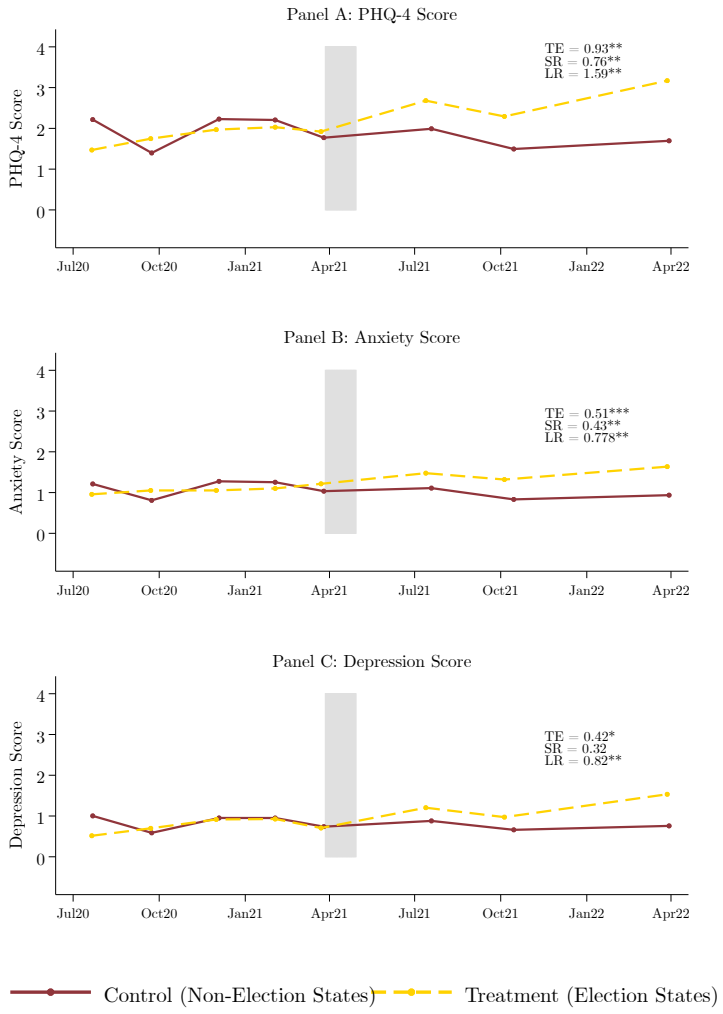
This figure plots the treatment effects of the 2021 state elections on policy stringency, using the same regression specification as Figure A.3. The overall policy stringency index (panel A) is Oxford University's Covid-19 Government Response Tracker (OxCGRT) state-level stringency index. Panel B and C split the components of overall stringency index into policies likely to affect individuals' ability to attend political rallies and other public gatherings and other policies, respectively. Gathering-related policies (panel B) include cancellation of public events, restrictions on gatherings, closure of public transport, stay at home requirements, and restrictions on internal movement. Other policies (panel C) include school closures, work place closures, international travel controls, and public information campaigns. The regressions are specified at the level of state and month. The omitted reference period is time prior to six months before the elections.

Figure A.5: Time Trends in Covid Infection Measures



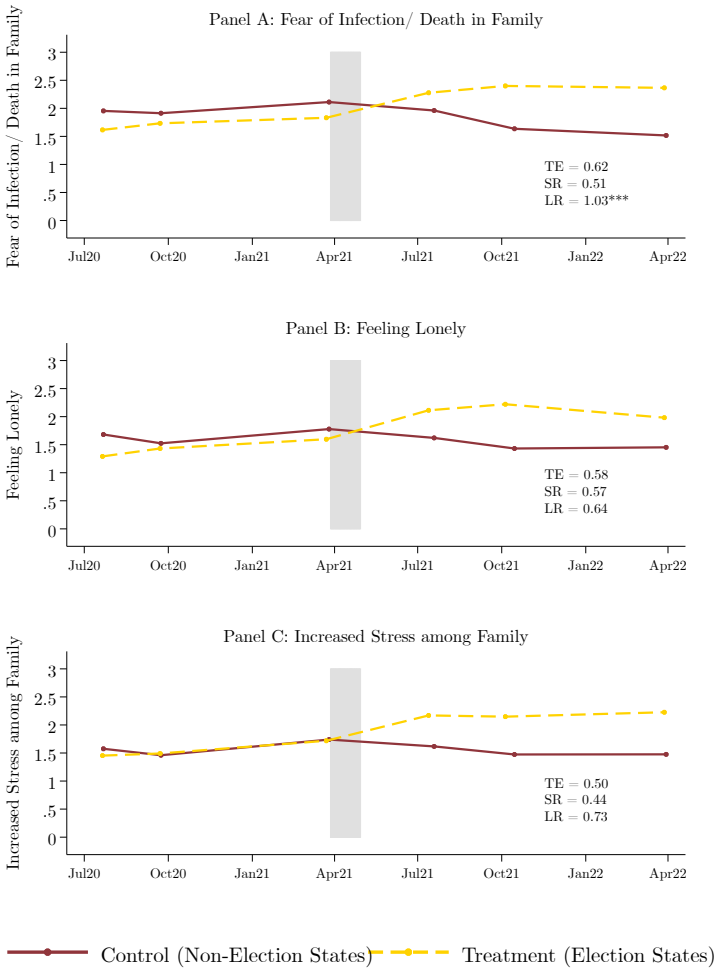
This figure plots the survey round-level average values of Covid infection in Treated (election) and Control (non-election) states. The vertical gray bar denotes the election period. Covid Infection in the Household (panel A) is self-reported in the RTI survey. For rounds 2-8, respondents were asked if anyone in their household has been diagnosed with a Covid-19 infection by a healthcare professional. In round 9, one respondent from each household (female in case there was a female respondent in the household) was asked to list all the episodes of suspected or confirmed Covid sickness in the household. Outcomes in panels B-D are from the administrative data corresponding to the RTI survey period. Covid Case Rate (panel B) is the 14-day rolling average of state-level daily Covid cases per one million population. Log Covid Case Rate (panel C) is the logarithmic transformation of the variable in panel B. Positivity rate (panel D) is the 14-day rolling average of the state-level daily Covid test positivity rate. The coefficients noted on the figures correspond to the difference-in-difference estimates of the effect of the 2021 state election on the outcome variables as reported in Table 1. TE refers to the overall treatment effect, SR refers to the short run treatment effect, and LR refers to the long run treatment effect. The stars denote the p-values based on randomization inference ($\star < 0.10$, $\star\star < 0.05$, $\star\star\star < 0.001$).

Figure A.6: Mental Health Outcomes in Election and Non-Election States



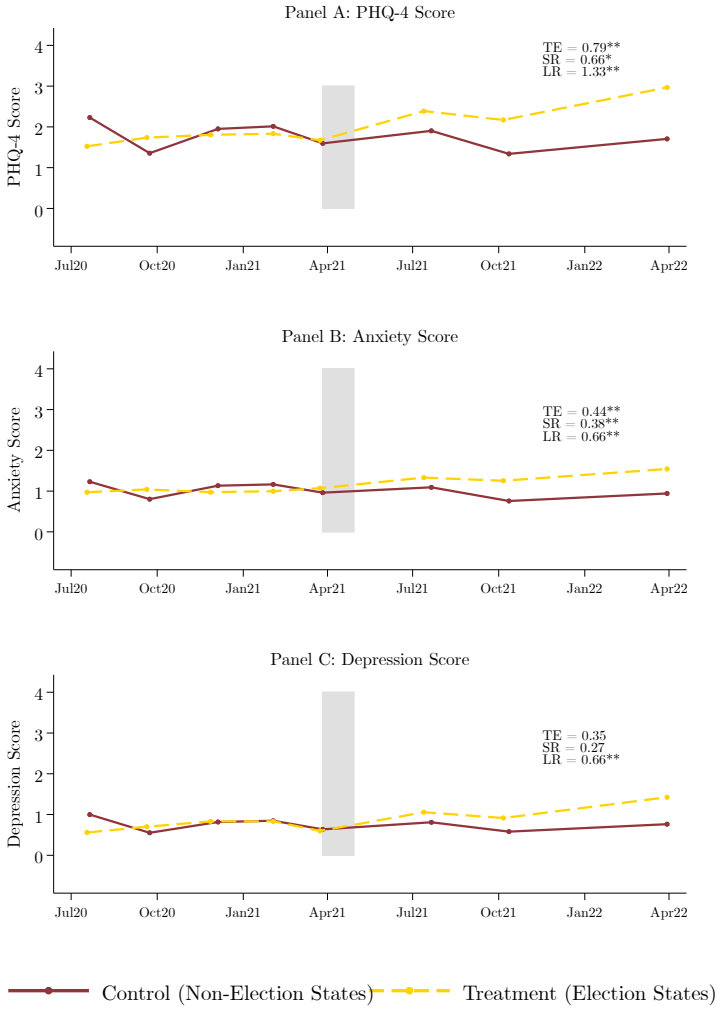
This figure plots the survey round-level average values of mental health outcomes from the RTI survey in Treated (election) and Control (non-election) states. The gray bar denotes the election period. Respondents are administered the four-item Patient Health Questionnaire (PHQ-4) where they self report feelings of anxiety and depression on a 4 point scale, ranging from feeling the emotion 'not at all' (with a value of 0) to 'nearly every day' (value of 3). The PHQ-4 score (panel A) aggregates the scores of the four items; Anxiety Score (panel B) is the sum of the two anxiety-related questions; Depression Score (panel C) is the sum of the two depression-related questions. The coefficients noted on the figures correspond to the difference-in-difference estimates in the Table 2; the effect of the 2021 state election on the outcome variable. TE refers to the overall treatment effect, SR refers to the short run treatment effect, and LR refers to the long run treatment effect. The stars denote the p-values based on randomization inference ($\star < 0.10$, $\star\star < 0.05$, $\star\star\star < 0.001$).

Figure A.7: Self Reported Concerns



This figure plots the survey round-level average values of respondents' pandemic-related concerns from the RTI survey in Treated (election) and Control (non-election) states. The gray bar denotes the election period. Respondents are asked to report how concerned they are about the impacts of coronavirus on three dimensions. Reporting is on a scale of 1 to 4, where 1 denotes 'not at all concerned' and 4 denotes 'extremely concerned.' Infection/Death in family (panel A) captures concern about fear of infection or death in the family; Feeling Lonely (panel B) captures concern about feeling lonely or unable to meet relatives or friends; Increased Stress (panel C) captures concern about increased stress among household members. The coefficients noted on the figures correspond to the difference-in-difference estimates reported in Table A.7. TE refers to the overall treatment effect, SR refers to the short run treatment effect, and LR refers to the long run treatment effect. The stars denote the p-values based on randomization inference ($\star < 0.10$, $\star\star < 0.05$, $\star\star\star < 0.001$).

Figure A.8: Mental Health Outcomes in Election and Non-Election States – Dropping Households That Ever Reported Covid Infection



This figure plots the survey round-level average values of mental health outcomes from the RTI survey in Treated (election) and Control (non-election) states. The gray bar denotes the election period. Respondents are administered the four-item Patient Health Questionnaire (PHQ-4) where they self report feelings of anxiety and depression on a 4 point scale, ranging from feeling the emotion 'not at all' (with a value of 0) to 'nearly every day' (value of 3). The PHQ-4 score (panel A) aggregates the scores of the four items; Anxiety Score (panel B) is the sum of the two anxiety-related questions; Depression Score (panel C) is the sum of the two depression-related questions. The coefficients noted on the figures correspond to the difference-in-difference estimates in the Table 2; the effect of the 2021 state election on the outcome variable. TE refers to the overall treatment effect, SR refers to the short run treatment effect, and LR refers to the long run treatment effect. The stars denote the p-values based on randomization inference ($\star < 0.10$, $\star\star < 0.05$, $\star\star\star < 0.001$).

B Online Appendix: Data

In this section, we provide and overview of the datasets and main variables used in our analysis.

B.1 Datasets

- **RTI Covid** Our primary data source is a unique panel survey spanning the first two years of the pandemic (May 2020 to May 2022), the Real Time Insights: COVID-19-India (RTI) survey. This survey is an extension of the Harmonised Diagnostic Assessment of Dementia for the Longitudinal Aging Study in India (LASI-DAD), a nationally representative panel survey of households with at least one individual over the age of 60. The LASI-DAD is itself an outgrowth of the larger Longitudinal Aging Study in India (LASI), a nationally representative survey of households with at least one individual over the age of 45. The first wave of LASI took place between 2017 and 2019, with more than 72,000 individuals from 35 of India's 36 states and union territories (Bloom et al., 2021).

  The LASI-DAD enrolled a sub-sample of 4,096 LASI respondents aged 60 and older for the purposes of studying cognition and dementia at older ages. LASI-DAD interviews took place between 2017 and 2019 in 18 Indian states and union territories and over-sampled individuals at high risk of cognitive impairment. When weighted, the survey is representative of the 60+ population in India (Lee et al., 2023).

  The RTI survey initially targeted two individuals per LASI-DAD household (one male and one female whenever possible), over the age of 18. The target respondents were randomly selected from the LASI household rooster. These original respondents were prioritized in future waves, but replacement respondents were enrolled if a household was contacted and the original respondents were not available for interview. Sampling was expanded again in wave three to include all LASI-DAD participants who had not yet been selected to participate. Each wave targeted all respondents who had participated in the survey before (Schaner et al., 2022).

- **Administrative Data on Covid-19.** Indian state governments reported data on Covid-19 tests, cases, test-positivity, and Covid-related deaths throughout the pandemic. These data were published in a variety of forms (e.g. state bulletins), but reports were not centralized by the national government. However, several open source initiatives aimed to collate these data and make them available for analysis. We use data from two initiatives: first, `covid19india.org`, which published state-specific

counts for caseloads, deaths, tests, and the test positivity rate from January 2020 to October 2021. This work was taken up by DataKind Bengaluru with support from the Development Data Lab. At the time of writing the data, including data prior to November 2021 collected by covid19india.org, was accessible at `https://covid19bharat.org`. Our analysis uses administrative data from July 2020 to May 2022, corresponding to Waves 2-9 of the RTI Covid Survey.

The state administrative data were nominally tallied daily, however reporting was often batched. Given this, we calculate two-week rolling averages to reduce noise and measurement error. In addition, we adjust all statistics (except test-positivity) to per capita rates using data from the 2011 Census of India.

Although data exist for all 18 states that were surveyed in the RTI, it is likely that all states under-counted cases and deaths to some degree and the quality of the data varies (Vasudevan et al., 2021; Jha et al., 2022). Because it is not possible to assess whether the quality of the reporting is differential across time and location, we consider these data a secondary source.

- **Google Mobility Data.** Google mobility data is not representative as individuals must (a) own a smartphone and (b) opt-in to location tracking.

  Google's data processing allocates a person's time to categories of locations including home/residential, grocery and pharmacy, parks, transit stations, retail and recreation, and workplaces. In addition, the data is presented as a relative allocation compared to a 5-week baseline period just prior to the beginning of the pandemic. So, for example, a value of 5 would mean that there are 5% more visitors in that location category than during the baseline period.

  In Jammu and Kashmir, 4G mobile internet services were banned in August 2021 and restored in early February 2022. Due to this restriction as well as long standing curfews, we do not include this state in our mobility data analysis.

- **Centre for Monitoring Indian Economy Consumer Pyramids Household Survey (CMIE CPHS).** The CMIE CPHS is a nationally-representative, longitudinal survey of over 170,000 Indian households, first fielded in 2014. Prior to the pandemic, CMIE interviewed roughly 45,000 households in person each month. CMIE continued to field the CPHS throughout the pandemic, though mode of administration varied. Notably, CMIE pivoted to phone surveys during the initial national lockdown in March 2020, returning to nearly all in person surveys in February 2021. Use of phone surveys increased again between April-July 2021, during the Delta wave. We

draw on the data captured in the "People of India," "Aspirational India," and "Income Pyramids" datasets from January 2020 onward to mirror the period of data collection in the RTI survey.

- **Oxford Covid-19 Government Response Tracker.** The Government Response Tracker is the result of an Oxford-led initiative to collect data on Covid-19 related policies across the world between 2020 and 2022. The data were collected by a team of in-country volunteers, who reported on government policies and regulation; these reports were reviewed, coded, and standardized by the Oxford research team. Additional detail on the project is available in Wade et al. (2023); data are available at `https://github.com/OxCGRT/covid-policy-dataset`.

B.2 Variable Details and Construction

B.2.1 RTI Covid

- *Covid infection in the household:* For rounds 2-8, respondents were asked if anyone in their household was ever diagnosed with or suspected to have contracted Covid-19. In round 9, one respondent from each household (female when available for interview) was asked to list all the episodes of suspected or confirmed Covid-19 in the household. Covid Infection in the Household is an indicator variable for whether the respondent reported a Covid infection in the household in rounds 2-8, and whether the household reported any Covid infection in the household in the round 9.

- *PHQ-4 score:* This is the respondent's PHQ-4 score computed by summing the respondent's score on the four items of the PHQ-4 questionnaire. Respondents were asked "Over the last two weeks, how often have you been bothered by the following problems? (0. Not at all concerned; 1. Somewhat concerned; 2. Very concerned; 3. Extremely concerned). a) Feeling nervous, anxious or on edge, b) Unable to stop worrying, c) Feeling down, depressed or hopeless, d) Little interest or pleasure in doing things".

- *Any psychological distress:* This is a dummy variable that takes value 1 if the respondent's PHQ-4 score takes on a value of 3 or higher.

- *Anxiety score:* This is the total score achieved on the two anxiety related questions of the PHQ-4: a) Feeling nervous, anxious or on edge, b) Unable to stop worrying.

- *Depression score:* This is the total score achieved on the two depression related questions of the PHQ-4: c) Feeling down, depressed or hopeless, d) Little interest or pleasure in doing things.

- *Income:* This variable captures reported household income over the past month. The respondents were first asked the "What is your family's main sources of income right now?", followed by "In the past month, how much income did your household have?". The second question was skipped if the respondents reported "We have no source of income". All the male members of the household were asked this question. If more than one male member in the household per round responded to this question, we use the value from the respondent who reported in the previous round to maintain consistency. The RTI survey included a series of unfolding bracket questions to capture income intervals for those who were not able to report specific income values. The RTI data team uses these responses to create imputed values of income. We use imputed values of income which include closed bracket imputations, meaning there is a lower and upper bound on income available for a given respondent. Income is zero when the household reports that they do not have any source of income. We topcode this variable at the 99th percentile.

- *Any income:* This is a dummy variable indicating positive household income in the past month.

- *Financial health:* This variable captures individuals' self-reports of the impact the coronavirus pandemic had on the household's ability to meet financial obligations on a likert scale. The male respondents of the household were asked the following question and the response from the member classified as the financial respondent was recorded for the whole household. Respondents were asked "Which of the following best describes the impact of the coronavirus pandemic on your ability to meet financial obligations or essential needs such as rent or mortgage payments, utilities, and groceries? "1. Major Impact" "2. Moderate Impact" "3. Minor Impact" "4. No Impact" "5. Too Soon to Tell". We code all "too soon to tell" responses to missing, which affects less than one percent of observations.

- *Food security:* This variable captures household food security. It counts the number of the following items the respondent answered *no* to, when reflecting on the past week: worried would run out of food, ate less than wanted, ate differently due to cost, did not eat for a whole day, and could not eat usual food due to unavailability.

- *Infection/death in family:* This variable captures respondents' self reported concern regarding infection or death in the family on a 4 point scale. Respondents were asked "How concerned are you about each of the following impacts of coronavirus? : Fear

of infection/death in your family [1. Not at all concerned; 2. Somewhat concerned; 3. Very concerned; 4. Extremely concerned]".

- *Feeling lonely:* This variable captures respondents' self reported concern regarding loneliness on a 4 point scale. Respondents were asked "How concerned are you about each of the following impacts of coronavirus? : Feeling lonely/cannot meet relatives or friends [1. Not at all concerned; 2. Somewhat concerned; 3. Very concerned; 4. Extremely concerned]".

- *Increased stress:* This variable captures respondents' self reported concern regarding increased stress in the household on a 4 point scale. Respondents were asked "How concerned are you about each of the following impacts of coronavirus? : Increased stress among household members [1. Not at all concerned; 2. Somewhat concerned; 3. Very concerned; 4. Extremely concerned]".

- *Pandemic attitudes - summary index:* This variable is a summary index built from the likert variables capturing concern related to infection/death, feeling lonely, and increased stress. We standardize each component relative to the mean and standard deviation in non-election states during the post-election period, and then take the average of these components.

- *Short run:* Short Run is an indicator variable equaling 1 if the interview occurred in the period corresponding to the LASI RTI survey waves 2-8, and 0 otherwise.

- *Long run:* Long Run is an indicator variable equaling 1 if the interview occurred in the period corresponding to the LASI RTI survey wave 9, and 0 otherwise.

- *Any post-secondary education:* This variable takes the value 1 if the highest educational attainment of any member in the household is post-secondary or higher and 0 otherwise. It is derived from the LASI data "Highest education in the household" variable described below.

- *Top asset tercile:* The variable takes the value one if the household is in the top tercile of assets pre-covid and 0 otherwise. It is derived from the LASI data "Pre-pandemic household assets" variable described below.

B.2.2 Administrative Data on Covid-19

- *Covid cases per capita:* This is the 14-day rolling average of state-level daily Covid cases per one million population.

- *Log Covid cases per capita:* This is the logarithmic transformation of the 14-day rolling average of state-level daily Covid cases per one million population. There were no zeros in the Covid cases per capita variable, so the log transformation is fully defined.

- *Positivity rate:* This is the 14-day rolling average of the state-level daily test positivity rate.

B.2.3 Google Mobility Data

- *Time spent at residence:* This is the seven-day rolling average of time spent at place of residence per Google Mobility data. The variable tracks the change in time spent at places of residence compared to a "baseline day". A baseline day endeavors to capture a normal value for a given day of the week, and is the median value from the five week period Jan. 3 to Feb. 6, 2020.

B.2.4 CMIE CPHS

- *Income:* This variable captures household's total income in the past month, topcoded at the 99th percentile.

- *Any income:* This variable equals one if the household reported non-zero income in the past month and zero if the household reported zero income in the past month. This variable excludes transfers from government or private sources focus on economic activity (which is not possible to decompose in RTI). However, results are very similar with or without transfers as transfers are a very small component of overall income.

- *Urban*: This is a dummy indicator for the household's location in CMIE's People of India dataset. A code of 0 indicates that the household is located in a rural area, and a code of 1 indicates that the household is located in an urban area.

- *Scheduled caste/tribe:* This variable identifies households where at least one respondent from the household reported belonging to a scheduled caste or scheduled tribe group.

- *Any post-secondary education:* This variable takes the value 1 if the highest educational attainment of any member in the household is post-secondary or higher and 0 otherwise.

- *Top asset tercile:* The variable takes the value 1 if the household is in the top tercile of assets pre-pandemic and 0 otherwise. To do this, we first calculate the number of washing machines, tractors, televisions, refrigerators, houses, generators, coolers, computers, cars, air conditioners, and two wheelers owned by a household, using CMIE

wave 18 (September to December 2019) as the baseline. If a household was not interviewed in wave 18, we use values in wave 17 (May to August 2019), or if not in wave 17, wave 16 (January to April 2019). Households not interviewed in all three of these waves have missing values for the wealth index. We extract the first principal component of these variables and use this as our index which is then divided into terciles.

B.2.5 Oxford Covid-19 Government Response Tracker

- *Policy stringency index:* To capture overall policy stringency, we use the Oxford Government Response Tracker's average stringency index. This captures policy related to nine containment policies: cancellation of public events, restrictions on gatherings, closure of public transport, stay at home requirements, restrictions on internal movement, school closures, work place closures, international travel controls, and public information campaigns. The Oxford team began capturing policy stringency separately for vaccinated and unvaccinated individuals once vaccines became available. The average index that we use takes the simple average of the vaccinated and unvaccinated stringency values when both are available.

- *Election-related policy stringency index:* We generate this sub-index using the following Oxford-coded policy variables which could influence election gatherings: c3 (cancel public events), c4 (restrictions on gatherings), c5 (close public transport), c6 (stay at home requirements), and c7 (restrictions on internal movements). These variables code the stringency of the policy using an ordinal scale. We follow the same formula the Oxford team uses to aggregate variables in the overall policy stringency index, renormalizing so the sub-index ranges from 0 to 100.

- *Non-election related policy stringency index:* We generate this sub-index using all Oxford-coded policy variables not included in the Election-related sub-index: c1 (school closing), c2(workplace closing), c8 (international travel controls), h1 (public information campaigns). Individual policy variables are used from the OxCGRT India subnational data. These variables code the stringency of the policy using an ordinal scale. We follow the same formula the Oxford team uses to aggregate variables in the overall policy stringency index, renormalizing so the sub-index ranges from 0 to 100.

B.2.6 LASI and LASI-DAD

- *CESD-10 score*: This variable captures respondent scores on the CESD-10, and is available in the main LASI and LASI-DAD data. Respondents are asked 10 questions

related to how often they had certain feelings in the past week on a likert scale ranging from "rarely/none of the time" to "all of the time". Question scoring is assigned so responses with the least amount of negative affect receive 0 while the highest receive 3. Thus the overall scale ranges from 0 to 30, with higher scores indicating more negative feelings during the past week. More details on the scale's construction can be found in the LASI codebook.

- *At risk for depression:* This variable is an indicator equal to 1 if a respondent's CESD-10 score is greater than 10 (a commonly used cut point to indicate risk for depression), and zero otherwise (Andresen et al., 1994).

- *Pre-pandemic household assets:* This variable is used as a control in our differences-in-differences analyses of RTI data. It is the total value of household wealth recorded during the LASI study (HHwATOTB), calculated as the sum of all wealth components less all debt components. Specifically, it is the sum of the value of a household's rental security deposits paid, primary residence, other real estate, land, agricultural equipment, livestock, businesses, personal loans, household durables and valuables, and financial assets, subtracted by the values of a household's other security deposits received, debt, and rental security deposits received. The values include imputations when the values for the components are missing and an associated flag variable (HHwAFTOTB) indicates the highest level of imputation of the components of the variable. We only include the imputed values based on a closed bracket, in addition to values for which continuous values are available for all the components. Missing values are assigned a value of 0 and a separate dummy variable that identifies missing values are included in all regressions.

- *Respondent age:* In the RTI survey, respondents' ages were recorded at the time of their first interview.

- *Scheduled caste/tribe:* This variable identifies households where at least one respondent from the household reported belonging to a scheduled caste or scheduled tribe group during the LASI Wave 1 survey.

- *Urban:* This is a dummy indicator for the household's location obtained from the LASI study. A code of 0 indicates that the household is located in a rural area, and a code of 1 indicates that the household is located in an urban area.

- *Female:* This dummy variable identifies female respondents.

- *Highest education in the household:* This variable captures the highest educational attainment among household members listed during the main LASI survey. For the LASI respondents, their self reported education measure is used. For the other household members, education levels as reported in the household roster are used. In our regression analyses, we include dummy variables indicating less than primary education (no education or standards 1-4), primary education (standard 5-7), middle school education (standard 8-9), lower secondary (standard 10-11), and upper secondary (standard 12). Postsecondary is the omitted category.