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Adherence to COVID-19-Protective Behaviors in India Over Time: Evidence from a Nationally Representative Survey*

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ABSTRACT

Objectives: Since the onset of the COVID-19 pandemic, behavioral interventions to reduce disease transmission have been central to public health policy worldwide. Sustaining individual protective behavior is especially important in low- and middle-income settings, where health systems have fewer resources and access to vaccination is limited. This study seeks to assess time trends in COVID-19 protective behavior in India.

Design: Panel study.

Setting: We conducted a panel survey of Indian households to understand how the adoption of COVID-protective behaviors has changed over time. Our data spans peaks and valleys of disease transmission over May-December 2020.

Participants: Respondents included adults in Indian households enrolled in the Harmonized Diagnostic Assessment of Dementia for the Longitudinal Aging Study in India.

Analysis: We used ordinary least squares regression analysis to quantify time trends in protective behaviors.

Results: We find a 30.6 percentage point (95 percent confident interval [26.7, 34.5]; p<0.01) decline in protective behaviors related to social distancing over the observation period. Mask wearing and handwashing, in contrast, decreased only slightly from a high base. Our conclusions are unchanged after adjusting for recorded COVID-19 caseload and nationwide COVID containment policy; we also observe significant declines across socioeconomic strata spanning age, gender, education, and urbanicity.

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Conclusion: We argue these changes reflect, at least in part, "COVID fatigue," where adherence to social distancing becomes more difficult over time irrespective of the surrounding disease environment.

STRENGTHS AND LIMITATIONS OF THIS STUDY

- Our study leverages data from a nationally representative panel survey in India to study changes in COVID-19 protective behavior between May and December 2020.
- We link our survey data to contextual data measuring COVID-19 caseloads and national COVID-19 policy. This lets us assess robustness of our main results to the disease and policy environments.
- We study how time trends in protective behavior vary among key demographic groups.
- Our surveys were conducted over the phone, which runs the risk of under-representing India's most socio-economically disadvantaged households.
- Our measures of protective behavior do not capture frequency or intensity within the lookback period

Keywords: COVID-19, public health

1 INTRODUCTION

Throughout the COVID-19 pandemic, governments around the world have implemented nonpharmacological policies aimed at blunting disease spread. Although policies have shifted over time—changing in scope and stringency[1]—a common aim has been to drastically reduce the mobility of, and social contact among, people. Critical in assessing the efficacy of these policies, and thus how to improve them, is understanding how distancing behavior changes or persists in the face of easing restrictions and evolving disease environments.

Much of the existing research in this space leverages cellphone data (most notably, open-source mobility datasets like Google's COVID-19 Community Mobility Reports) to characterize movement patterns[2-5]. Cellphone-based mobility data, however, fail to fully capture important facets of behavior that matter for disease transmission. For example, such data cannot record maintaining physical distance, avoiding large crowds, or wearing masks, all of which are common components of containment policies.[2] In addition, macro-level mobility analyses that rely on data captured from mobile phones run the risk of concealing deep disparities in both adherence and impact.

These data limitations resonate particularly in low- and middle-income countries (LMICs), where smartphone usage remains far from universal and survey data remain scarce.[3] Understanding the ability of LMIC populations to maintain social-distancing practices over an extended period of time is especially pressing given (1) concerns that COVID-19 will disproportionately harm those living in LMICs[8-10], and (2) the fact that LMICs continue to lag in vaccine acquisition and administration[11] and, thus, may need to rely predominantly on nonpharmacological interventions for an extended period of time.

Understanding trends in distancing and other protective behaviors in India is significant, as it is the world's second largest LMIC and its population is uniquely vulnerable given the nation's high population density, large share of multigenerational households, and substantial population of individuals with COVID-19 risk factors like hypertension and diabetes[12]. This vulnerability was evident as the country experienced one of the world's deadliest waves of COVID-19, which began in April 2021. Various reasons have been cited for this resurgence, including the emergence of more contagious variants, a poorly coordinated,

[2] Evidence suggests that adherence to these types of behaviors may be more useful for forecasting disease trajectory than measurements of movement alone[6, 7].

[3] For example, Petherick et al. (2021) combine online survey data, mobility data, and policy data from multiple countries to track changes in protective behavior over time, but all survey data comes from high-income countries[4].

too-lax containment approach left in large part up to states[13], and a lagging vaccine campaign[14]. Critically, little rigorous data exist on the extent to which distancing behaviors were adopted and retained during the initial lockdown in 2020, or on how those behaviors changed during subsequent periods of reopening. Such insights could prove crucial to understanding the differing contexts of India's COVID waves and their severity.

To help fill this information gap, we designed and fielded a nationally-representative, high-frequency phone survey of Indian households to monitor knowledge, attitudes, and behaviors related to COVID-19. The survey, which also tracks the economic and health conditions of households, has been conducted bi-monthly since India's nationwide lockdown in March 2020. This initiative allows us to construct representative estimates of COVID-19 protective behaviors in India over time and to characterize how these behaviors differ across key socioeconomic groups. Unique in its scope, detail, and coverage, our study is a novel contribution to the existing literature, which has focused on adherence to COVID-19 protective behaviors in specific regions[15, 16] or on specific populations[17], or used cellphone data to understand broad trends in mobility patterns[18-20].

2 METHODS

2.1 Background: COVID-19 Containment in India

India's central government reacted to the hastening spread of COVID-19 with an initial lockdown on March 25, 2020, implemented with less than 24 hours' notice. Although initially meant to be in effect for one week, the directive was subsequently extended four times and ultimately lasted more than two months. The restrictions immediately halted public transportation, mandated mask wearing, closed all nonessential businesses, and banned many social gatherings.

After the national lockdown ended on May 31, 2020, the central government initiated reopening through various "unlock" phases while ceding future control over lockdowns and closures to individual states. Although decisions to reopen economically varied across geographies, protective behaviors—like maintaining social distance, avoiding unnecessary travel, and wearing masks—remained widely encouraged.[4] During the unlock phases, caseloads remained low; however, the country subsequently experienced a spike in cases late in the summer and early fall of 2020. Following a lull in cases during the winter, infections again began to grow at an alarming rate starting in March 2021; by April 15, 2021, India had clearly entered a second COVID-19 surge unparalleled in the rest of the world, with nearly every state reporting a rapid growth in infections[22]. Supplementary Figure S1 graphs the

[4] For a more in-depth look at India's initial lockdown timeline, refer to [21].

Indian COVID-19 caseload and an index capturing the stringency of India's national policy response against our survey waves, described in detail as follows.

2.2 The Data

We leveraged an existing study called the Harmonized Diagnostic Assessment of Dementia for the Longitudinal Aging Study in India (LASI-DAD), a nationally-representative study that aims to understand patterns in cognition and dementia among older Indians[23]. Out of the 3,316 LASI-DAD households, we contacted all 2,704 who had valid phone numbers in May 2020 to invite them to participate in a bi-monthly phone survey that covered various topics related to household wellbeing and COVID-19-related knowledge, attitudes, and behavior. All households contained at least one individual over the age of 60.

The analyses presented in this paper use four waves of survey data: Wave 1 took place from May 5 through June 25, 2020; Wave 2 took place from July 7 through August 26, 2020; Wave 3 took place from September 7 through October 23, 2020; and Wave 4 took place from November 9, 2020, through January 4, 2021. Most of the Wave 1 survey occurred while the nation was still under the initial mandatory lockdown. Additional waves of data collection are scheduled to continue through December 2021.

During Wave 1, two randomly selected household members over the age of 18 (one male and one female, if possible) were invited to participate.[5] In subsequent waves we aimed to maintain continuity in interviewed household members: if an enrolled individual could not be reached, the enumerator scheduled an appointment for a future time; if this follow-up was unsuccessful, another adult household member was selected to participate in that wave instead. In Wave 3, we attempted to enroll all primary LASI-DAD respondents (individuals over the age of 60 who had participated in prior in-person waves of data collection during 2017 through 2019). Each wave targeted all individuals who had ever participated in a past wave. As a result, some households have up to four individuals interviewed in some waves.

The final sample includes 3,719 individuals from 1,766 households; 1,019 of these individuals and 665 of the households participated in all four waves (refer to Figure S2 for a breakdown of our the final sample). We use sample weights to ensure estimates are nationally representative. Section 5 provides additional detail on weight construction. Table S1 provides summary statistics for our sample; column 5 includes weighted statistics for individuals who participated in all four waves, while column 6 contains the unweighted statistics. Our sample overrepresents older individuals (60+), as expected given our initial sample and the focus on interviewing LASI-DAD respondents. The sample also overrepresents those with higher levels of education, which may reflect the fact that our survey

[5] Names were drawn from a household roster collected as part of the earlier LASI-DAD survey.

is phone-based and phone ownership is correlated with higher education and socioeconomic status in India. The analyses herein employ weights, so they can be interpreted as nationally representative, and include all individuals from each wave. Figure S3 shows the geographic scope of our sample. Although our study sample is mostly rural, reflecting the population distribution of the country, we also cover some of India's megacities, including Mumbai and Delhi, which to date have experienced the country's worst COVID-19 outbreaks[24,25].

We use information on district of residence and survey date to attach contextual data on COVID-19 caseload in the preceding two weeks to each interview. Caseload, quantified as the daily number of new confirmed cases, was obtained from Covid19india.org, a crowd-sourced initiative that compiles daily statistics on COVID-19.[6] Due to delays in the processing and reporting of test results, we chose to smooth these estimates by taking a caseload average across the 14 days prior to the survey date. Finally, using total district-level population estimates from the 2011 Census of India, we calculated the number of cases per 10,000. District-level caseload statistics were not available in Assam, Telangana, and Delhi; thus, state-level statistics were used for these states.[7]

Finally, we account for national COVID-19 containment policy by using the "government response index" from the Oxford Covid-19 Government Response Tracker, which aggregates indicators of containment and health policy (such as school and workplace closings, restrictions on movement), economic policy (income support and debt relief), and health system policy (including facial covering policy and contract tracing). The index ranges from 0 to 100 with higher values indicating more aggressive policy action. Additional detail on index components and methodology is available in [26]. We use data on survey date to attach the average value of the index in the two weeks prior to interview onto each survey record.

2.3 Patient and Public Involvement

Survey respondents were not directly involved in the study design, including the development of research questions, survey design, or recruitment. There are no plans to directly disseminate the results to survey participants.

2.4 Measures of COVID-19-Protective Behavior

Nonpharmacological measures to curb the spread of COVID-19 have utilized a combination of mandates and public health messaging to minimize social contact across households and highlight the importance of personal hygiene. To understand the extent to which individual

[6] Covid19india.org collates state- and district-level data from official bulletins and Twitter handles. Data are validated by a group of volunteers before release. For a full list of their source sites, refer to Covid19india.org.
[7] Delhi is classified as a union territory rather than a state. However, we use the term "state" to refer to both states and union territories throughout the text to simplify exposition.

behaviors are aligned with these initiatives, we group behaviors tracked in our survey into three broad categories: market-based distancing behaviors, protective behaviors, and social-distancing behaviors. The recall period for each individual behavior is seven days. *Market-based behaviors* include activities that may not be fully discretionary—i.e., they may reflect maintaining a person's livelihood, either through work or buying food. These activities include attending a gathering with 10 or more people, having close contact (described to respondents as "two arms' lengths") with non-household members, traveling for work, and going shopping. We classify an individual as "market distancing" if s/he does not report any of the aforementioned behaviors. The second group is *protective behaviors*, which includes the two main hygiene behaviors consistently cited as key mechanisms for decreasing disease spread: handwashing and wearing a face mask[27]. We classify an individual as engaging in protective behavior if s/he reports having done both during the recall period. Finally, *social-distancing behaviors* include activities that reflect individuals' voluntary choices to gather for social reasons: visiting other households and having visitors over to one's own household. Respondents are classified as "social distancing" if they do not report either of these behaviors. If data for a given outcome is missing, e.g. because the respondent refused to answer the question, the observation is dropped from the relevant regression.

We acknowledge that the lines between these categories are not always clear; the purpose for each behavior was not explicitly stated, except for the question about work travel. Therefore, what we classify as market distancing may actually reflect social distancing and vice versa. To address this concern, we show that our main results are robust to re-categorizing some of the more ambiguous behaviors (attending 10+ person gatherings and having close contact with non-household members) either in the social- or market-distancing indicator (see Table S2).

Another potential concern is that fulfilling the criteria of social-distancing or protective behaviors may be more likely because they only encompass two behaviors each, while the market-distancing indicator encompasses four. Table S3 shows that our main results are robust to using fractional outcomes rather than binary outcomes. In addition, Tables S4, S5, and S6 provide estimates for each individual behavior within the protective, market-distancing, and social-distancing indicators, respectively.

2.5 Weight Construction

Weights were constructed in two steps. First, we created base weights to account for the probability of selection of a household, which is determined by the probability of selection of each LASI-DAD participant and the probability of selection of household members, calculated separately for men and women (as one over the number of adult men and women, respectively). Second, we implemented a raking algorithm to obtain post-stratification weights. For this purpose, we used the following raking factors: gender (male/female) × age (18–39/40–59/60–69/70+), gender × education (no school/primary or less/middle/secondary or higher/graduate), and a rural/urban indicator. Thus, the final weights allow us to match the sample distributions of these variables with their population counterparts while also reflecting differential probabilities of selection of survey participants. Population benchmark distributions were obtained from the 2011 Indian Census for individuals aged 18 and older.

2.6 Empirical Approach

To estimate time trends in COVID-19-protective behaviors, we use ordinary least squares regressions of the following form:

$$y_{it} = \beta_0 + \beta_1 wave2_t + \beta_2 wave3_t + \beta_3 wave4_t + \varepsilon_{it} \quad (1)$$

where y_{it} is the distancing outcome for individual i measured at time t and $wave2_t$–$wave4_t$ are survey wave dummies, which identify changes in distancing behavior relative to Wave 1.

In addition to this basic equation, we also assess whether our estimates are robust to the inclusion of individual fixed effects using the following specification:

$$y_{it} = \beta_0 + \beta_1 wave2_t + \beta_2 wave3_t + \beta_3 wave4_t + \delta_i + \varepsilon_{it} \quad (2)$$

Finally, we present results that additionally control for COVID-19 caseloads and the government response index:

$$y_{it} = \beta_0 + \beta_1 wave2_t + \beta_2 wave3_t + \beta_3 wave4_t + \beta_4 Caseload_{dt} + \beta_5 GovtResp_t + \delta_i + \varepsilon_{it} \quad (3)$$

where $Caseload_{dt}$ is the average number of positive COVID-19 cases reported in the district over the two weeks prior to survey date (per 10,000 people) and $GovtResp_t$ is the average value of the government response index in the two weeks prior to survey date.

All our equations use sampling weights to ensure our estimates are nationally representative. We cluster standard errors at the household level because multiple individuals per household are surveyed in any given wave.

We use the following equation to test for heterogeneity in behavior outcomes:

$$y_{it} = \beta_0 + \beta_1 Demo_i + \sum_{k=2}^{4} [\beta_k Wave_k + \beta_{k+3} Wave_k \times Demo_i] + \varepsilon_{it} \quad (4)$$

where y_{it} is one of three behavior outcomes (market-distancing, social-distancing, or protective behaviors), $Wave_k$ is a wave dummy, $Demo_i$ represents one of four dummy demographic cuts (gender, urbanicity, age older than vs. younger than 60, or highest level of education in the household is primary or less vs. middle school or higher). All estimates are weighted and standard errors are clustered at the household level.

3 RESULTS

3.1 Overall Time Trends

Figure 1 shows that initial adherence to protective and social-distancing behaviors was quite high (89.9% and 87.7%, respectively), which likely reflects that much of Wave 1 occurred either during or immediately after India's mandatory national lockdown. However, only 37.4% of individuals reported market distancing during this time, suggesting most Indians were still engaging in some economic activities during the strictest periods of the lockdown. Figure 1 also highlights declining vigilance over time. Patterns of decline differ in important ways by behavior type. Protective behaviors, the most stable of the four categories, saw a slight dip in Wave 2 and another in Wave 4 (declining by 3.2 and 4.3 percentage points, respectively). Social distancing, however, has seen significantly larger decreases, with a 30.6 percentage point decline by Wave 4. Finally, market-based distancing remained essentially steady between Waves 1 and 2, before dropping in Wave 3. By Wave 4, only 26.5% of individuals reported avoiding all the market-based behaviors we measure.

The first column for each behavior in Table 1 presents results in regression form; weighted differences in behavior for Waves 2–4 are presented relative to Wave 1. The second column assesses robustness to changes in sample composition by exploiting the panel nature of our data and using within-person variation to identify time trends. The final column adds controls for the COVID-19 caseload and the government response index in the previous two weeks as a simple way to test whether relaxing behavioral restrictions reflects a shifting disease or policy environment. We interpret this set of results with caution because the direction of causality is unclear (behavior could respond to these factors, but both caseloads and policy undoubtedly change in response to behavior). Moreover, we are not able to control for state and local policy, which may have varied more than the national response during this time. Section 5 provides additional detail on the estimating equation.

Estimated time trends are generally robust to adding these environmental controls. While time trends in protective behavior lose statistical significance, these coefficients were small in magnitude initially and do not change much. The time trends for social distancing are virtually unchanged and the decline in market-based distancing becomes even more pronounced. Higher caseloads are associated with more protective behavior (in line with a

Table 1: Behaviors Outcomes

	Protective Behaviors			Market-Based			Social Distancing		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	-0.032**	-0.041**	-0.029	-0.029	-0.017	-0.062	-0.113***	-0.105***	-0.101**
	(0.014)	(0.021)	(0.044)	(0.018)	(0.024)	(0.051)	(0.016)	(0.023)	(0.050)
Wave 3	-0.030**	-0.041**	-0.045	-0.077***	-0.079***	-0.119**	-0.177***	-0.175***	-0.171***
	(0.015)	(0.021)	(0.050)	(0.018)	(0.024)	(0.058)	(0.019)	(0.026)	(0.062)
Wave 4	-0.043**	-0.051**	-0.021	-0.109***	-0.112***	-0.209**	-0.306***	-0.305***	-0.296***
	(0.017)	(0.023)	(0.080)	(0.019)	(0.026)	(0.093)	(0.020)	(0.026)	(0.097)
COVID Caseload			0.049***			-0.040**			0.002
			(0.014)			(0.018)			(0.021)
Govt Response Index			0.003			-0.007			0.001
			(0.005)			(0.005)			(0.006)
Adj R-squared	0.002	0.156	0.160	0.008	0.315	0.316	0.065	0.209	0.209
Observations	9760	9760	9760	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.899			0.374			0.877		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. Individuals are considered to be following market-based distancing if they did report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. "Don't know" responses (n=15) and refusals (n=4) coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

behavioral response to underlying disease risk), but less market-based distancing. The latter relationship could reflect increased disease transmission following the reopening of the economy. There is no significant correlation between the government response index and our behavioral measures. We prefer not to over-interpret this result, as this coefficient is identified using *within-survey-wave* variation in the response index—if individuals take time to adjust to shifting government policy, our empirical strategy could understate the import of this variable.

3.2 Investigation of Disparities

Vulnerable groups in Indian society are susceptible to disproportionate effects from the pandemic for many reasons: less-educated individuals typically do not hold jobs that can be done remotely, older individuals living with children may not be able to avoid exposure to household visitors, and individuals living in densely populated cities may have a more difficult time avoiding contact with others. Behavior may also vary by gender, given the mobility restrictions and caregiving expectations faced by many Indian women. In this subsection, we quantify how behavioral changes vary based on age, gender, urbanicity, and household education.

Figure 2 shows trends in protective behavior by age (older than vs. younger than age 60), urbanicity, gender, and highest level of education in the household (primary or less vs. middle school or higher). At the beginning of the pandemic (survey Wave 1), we see minimal differences across groups, except that women—who are more likely to be homebound due to gender norms—are less likely to report engaging in both protective behaviors.[8] Adherence among men declines over time, diminishing the gender gap. In contrast, we see a divergence in protective behavior by age, urbanicity, and education. Older individuals (60+) are much more likely to report declining protective behavior over time, which is worrisome for a cohort that is more vulnerable to severe illness if infected. A decline is also more pronounced among rural dwellers (who have seen persistently lower caseloads) and less educated individuals, signaling higher vulnerability to future waves of infection.

Figure 3 reports trends in market-based distancing by group. During Wave 1, women and older individuals were significantly more likely to report this type of distancing, consistent with their lower levels of economic engagement. In contrast, there is virtually no difference in market-based distancing by urbanicity or education. Gender gaps remain large over time, while age gaps grow in subsequent waves, potentially driven by a return

[8] Consistent with the norms hypothesis, gender differences in handwashing are minimal, while differences in mask wearing are larger and significant.

to work among younger cohorts. Finally, Figure 4 reports differences in social distancing. We see high levels of social distancing in all groups during Wave 1, which decline significantly over time. Older individuals, women, and urban dwellers maintain slightly higher levels of distancing in subsequent survey waves.

4 CONCLUSION

We find evidence of significant behavioral "COVID fatigue" in a nationally representative sample of Indian adults. Declines in protective behavior do not simply reflect an increase in market-based behaviors accompanying India's economic reopening; individuals also increased social contact and (to a lesser extent) reduced mask wearing and handwashing. Our conclusions are unchanged after controlling for local caseload per capita and an index summarizing India's nationwide policy response; this suggests that individuals are not just responding to a less risky disease environment or changes in national directives. Rather, restrictive behavior appears difficult to sustain over time, even conditional on caseloads and policy.[9]

Another important finding is that declines, especially in social distancing, are found across demographic and socioeconomic groups. Particularly worrying is the significant decline in mask wearing and handwashing among older individuals. While older Indians are less likely to be exposed to others in work or market contexts, their rates of social distancing are like those of the young. Moreover, 69.4% of the sample live in multigenerational households, where isolating from family members is difficult. Intra-household spread is a major contributor to contagion[29]; thus, the steep declines we observe in protective behavior amount to a "double risk" for older Indians sharing living quarters and facilities with younger, economically active family members.

One limitation of our research is that it was conducted over the phone; thus, our study runs the risk of excluding poorer, more vulnerable households who lack reliable phone access. In addition, our binary measures of protective behavior cannot capture the intensity of adherence (e.g. respondents who socially distance half the time would still qualify as social distancers per our definition), which could have significant implications in terms of risk of disease exposure and spread.

Despite these limitations, the decline in protective behaviors we observe could have accelerated disease spread and contributed to COVID-19-related morbidity and mortality, as illustrated by the dramatic rise in caseloads in India starting in March 2021. Monitoring

[9] Here is it important to keep in mind that caseloads are an imperfect proxy of disease risk, especially in light of concerns about widespread underreporting, resulting in national statistics that fail to capture true infection and mortality rates[28].

adherence to distancing guidelines and assessing how public health messaging can be optimized to ensure continued adherence overtime will be essential components of India's ongoing battle against COVID-19.

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ETHICS STATEMENT

The study was approved by the following institutional review boards: USC IRB: UP-20-00277 AIIMS IRB: IEC-300/17.04.2020, RP-29/2020

CONTRIBUTORSHIP STATEMENT

DB, JL, and SS conceptualized, designed, and implemented the study and contributed to manuscript preparation. ABD contributed to conceptualization, design, and implementation of the study. NT contributed to data analysis and manuscript preparation. JB and PK contributed to the study design and managed data collection. SP contributed to project and data management. AA contributed to study design. MA constructed weights for the study and contributed to manuscript preparation. SC and BW contributed to data collection and management. AC, PC, and NM contributed to study implementation.

DATA AVAILABILITY

*NOTE TO REVEIWERS: Our data are not currently posted online website, but we will post them prior to manuscript publication. See below for the planned statement.

Data are available to download via the LASI-DAD website: https://lasi-dad.org/?section=access-data. Users must register and agree to a data use agreement before being granted access to the data.

FIGURE LEGENDS

Figure 1: Change in Individual Behavior Across Waves

Notes: Figure depicts regression coefficients of the wave terms from the Basic equations as shown in Table 1. Data are weighted, and standard errors are clustered at the household level. Whiskers denote 95 percent confidence intervals. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. Individuals are considered to be following market-based distancing if they did report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. "Don't know" responses and refusals coded to missing.

Figure 2: Heterogeneity in Protective Behaviors Across Key Demographics

Notes: Figures depict the regression coefficients of Wave x demographic interaction terms. Data are weighted, and standard errors are clustered at the household level. Whiskers denote 95 percent confidence intervals. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. "Don't know" responses and refusals coded to missing.

Figure 3: Heterogeneity in Market-Distancing Behaviors Across Key Demographics

Notes: Figures depict the regression coefficients of Wave x demographic interaction terms. Data are weighted, and standard errors are clustered at the household level. Whiskers denote 95 percent confidence intervals. Individuals are considered to be market distancing if they did not report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. "Don't know" responses and refusals coded to missing.

Figure 4: **Heterogeneity in Social-Distancing Behaviors Across Key Demographics**

Notes: Figures depict the regression coefficients of Wave x demographic interaction terms. Data are weighted, and standard errors are clustered at the household level. Whiskers denote 95 percent confidence intervals. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. "Don't know" responses and refusals coded to missing.

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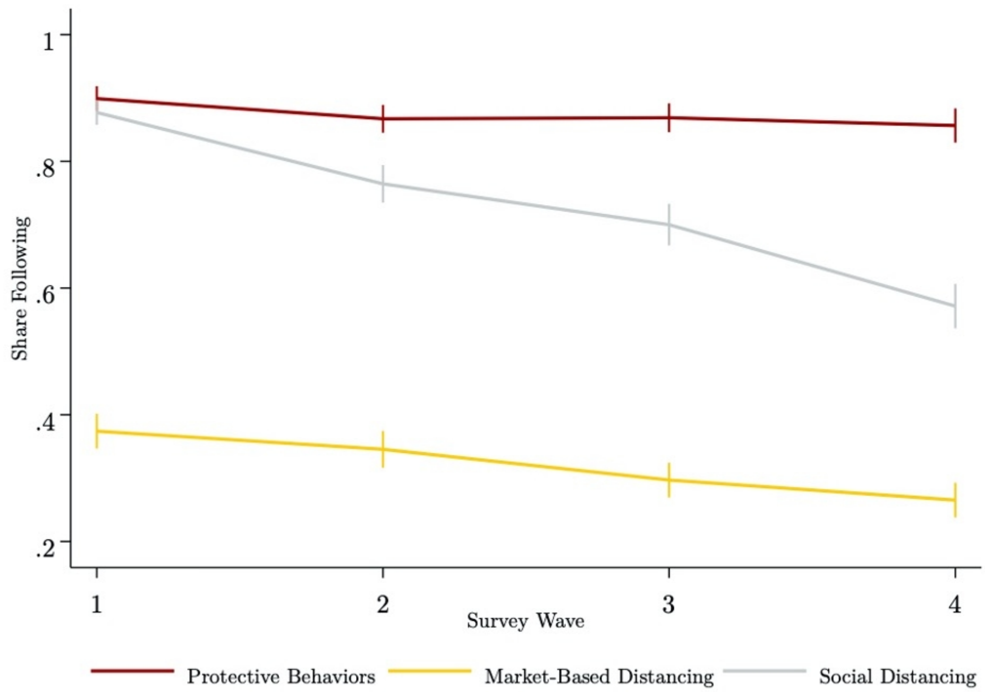

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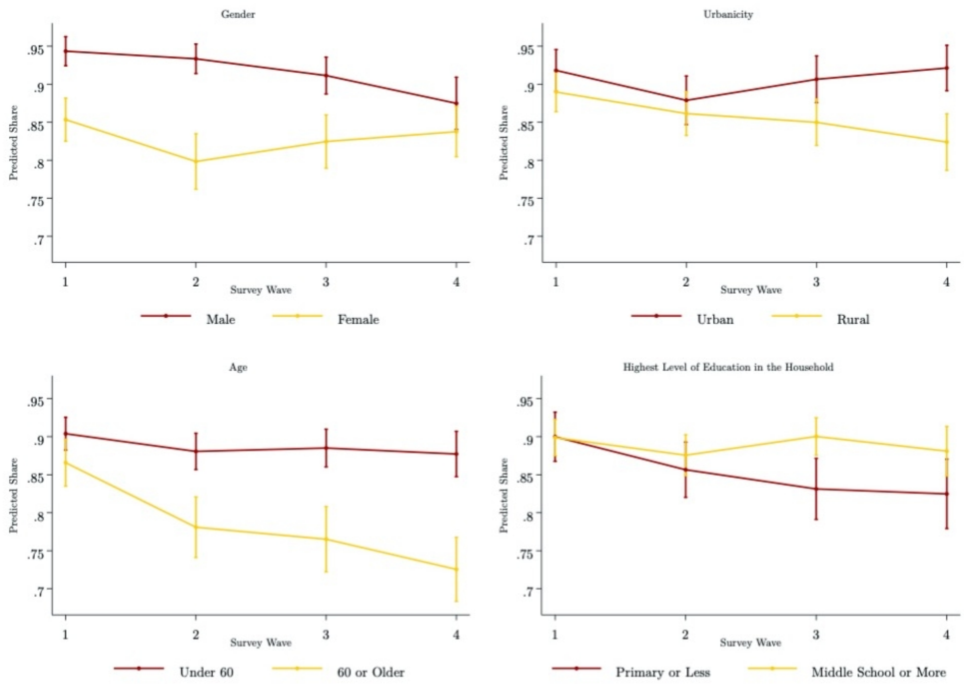

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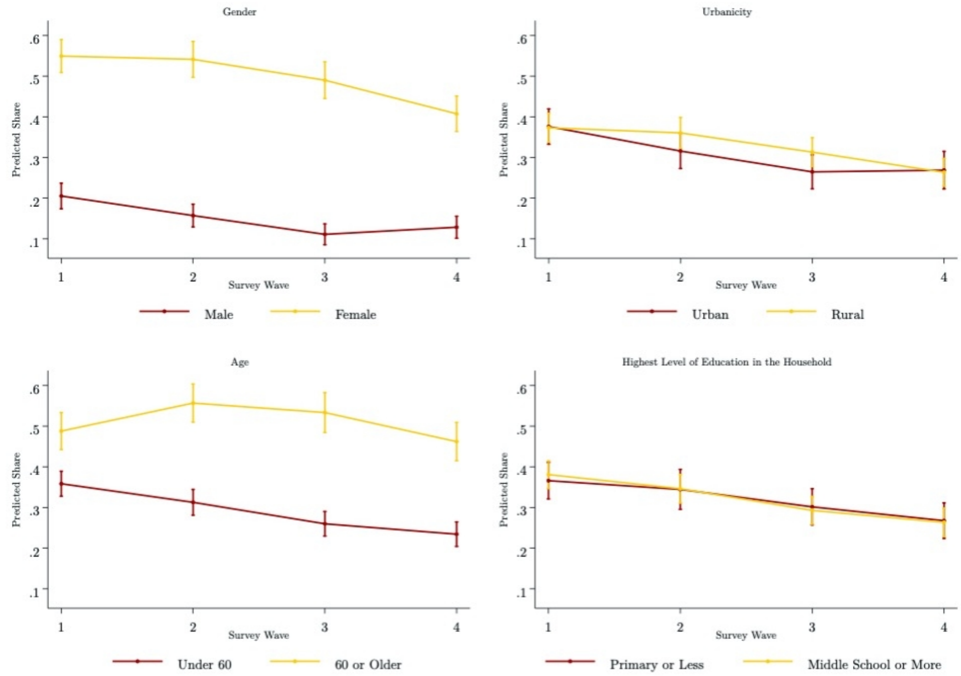

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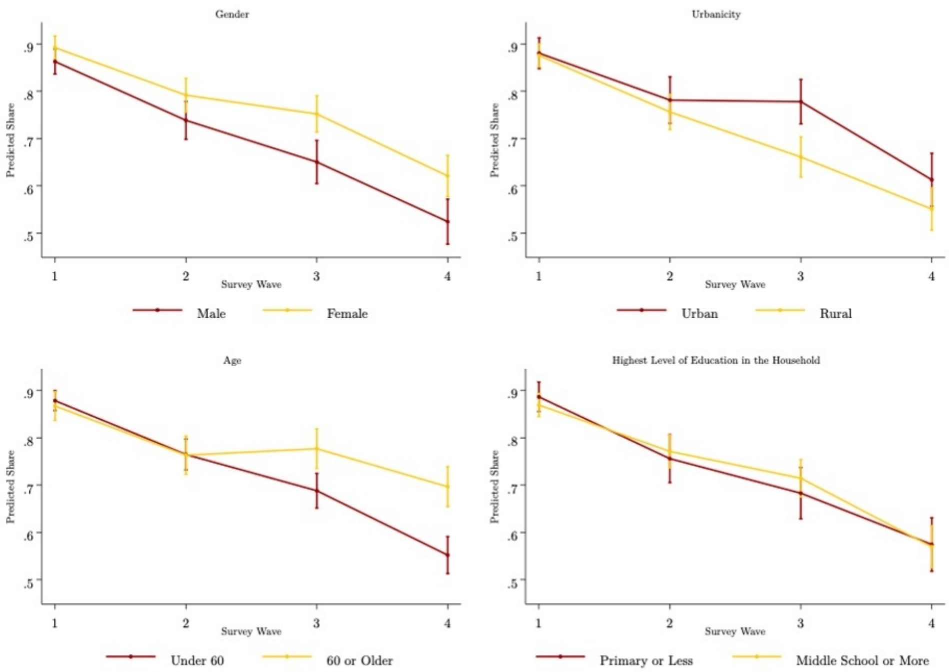

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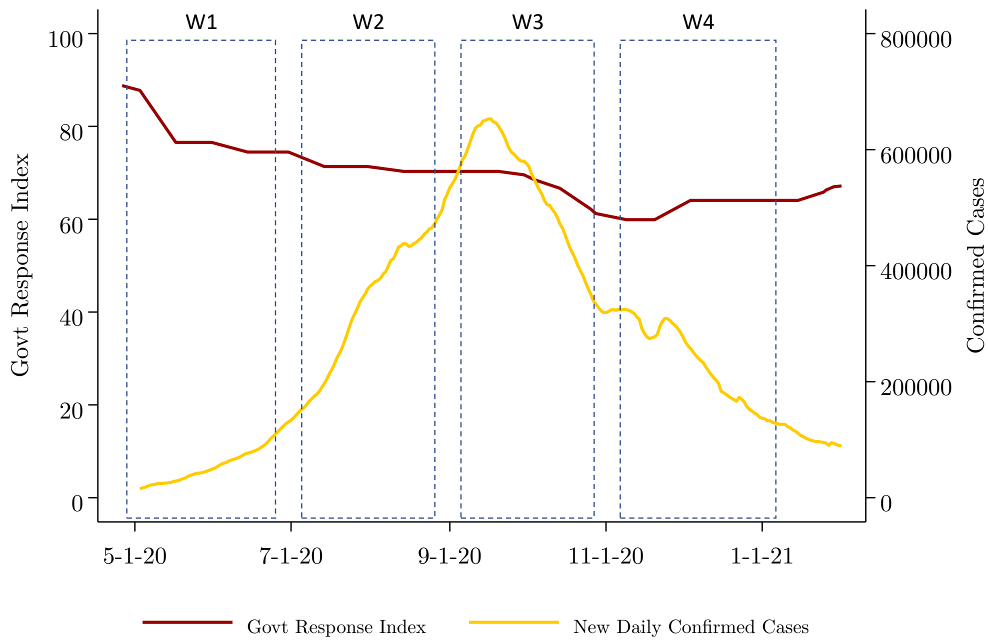
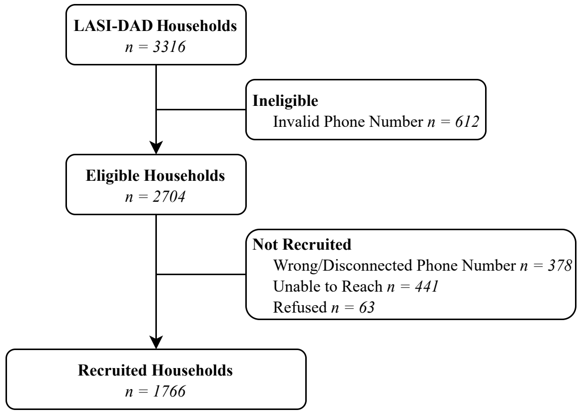
SUPPLEMENTARY MATERIALS

Figure S1: Waves of Data Collection and Caseload Trajectory in India



Notes: Visualization of daily new confirmed COVID-19 cases and overall government response index. COVID-19 caseload data are the 7-day average number of new confirmed cases in the entire country and are from Covid19india.org. Government response index is 7-day average of the overall government response index from the Oxford Covid-19 Government Response Tracker. Dates shown are the approximate date of the first survey in each wave, with width of the hollow bars representing how long a given survey wave was in the field.

Figure S2: Flow Chart of Household Participation



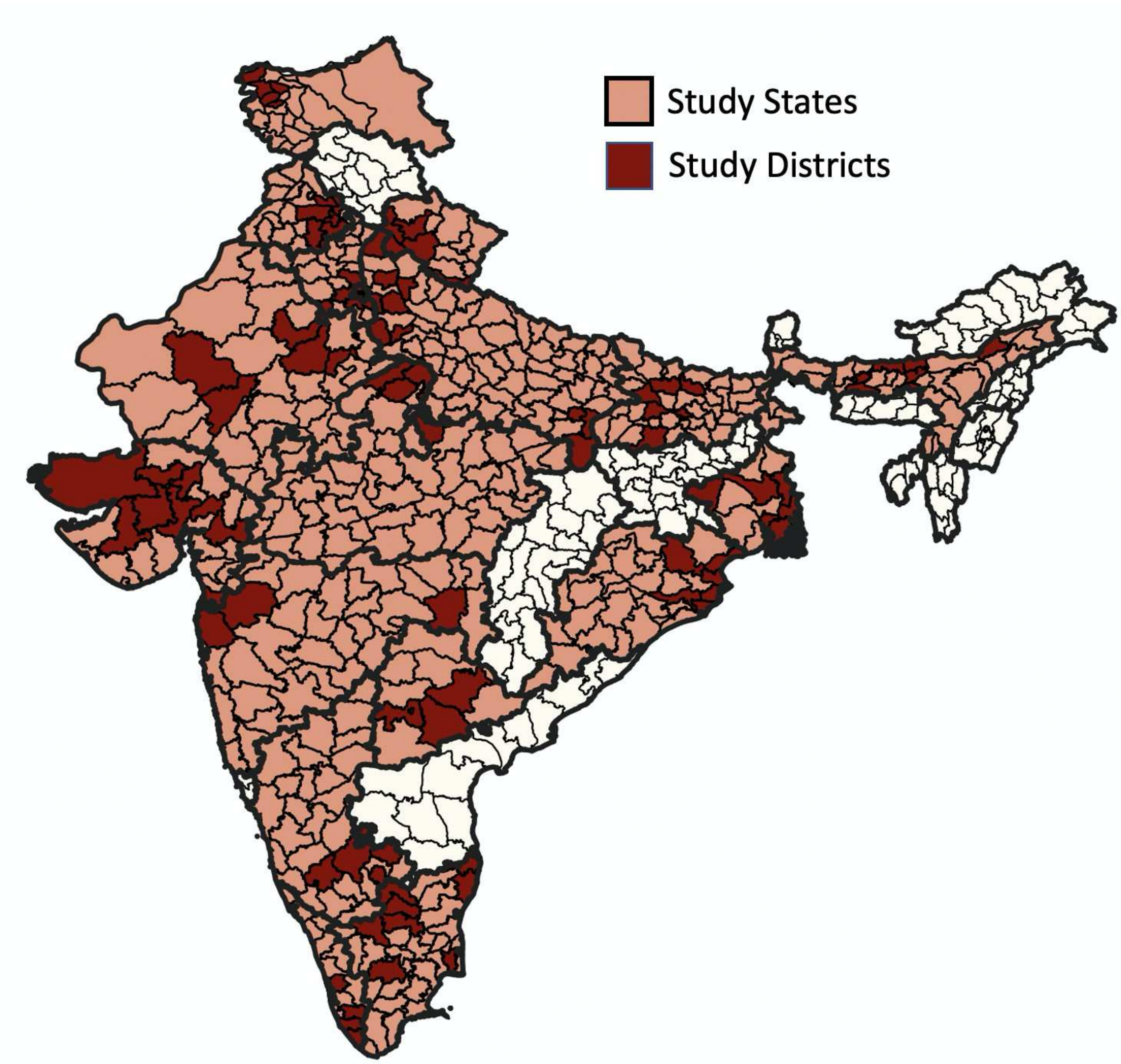
Notes: Numbers are aggregated across the four waves and indicate the number of households. Multiple individuals from a household often participated in a given wave.

Table S1: Demographic Characteristics of Sample, by Wave

	Weighted					Unweighted
	Wave 1	Wave 2	Wave 3	Wave 4	In All Waves	In All Waves
Female	0.49	0.49	0.49	0.49	0.51	0.48
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Rural	0.66	0.66	0.66	0.66	0.64	0.59
	(0.47)	(0.47)	(0.47)	(0.47)	(0.48)	(0.49)
Middle School Education or More	0.55	0.56	0.54	0.57	0.58	0.70
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.46)
16–44	0.69	0.68	0.66	0.67	0.67	0.35
	(0.46)	(0.47)	(0.47)	(0.47)	(0.47)	(0.48)
45–59	0.18	0.19	0.20	0.20	0.20	0.17
	(0.38)	(0.39)	(0.40)	(0.40)	(0.40)	(0.38)
60–70	0.08	0.09	0.09	0.09	0.10	0.36
	(0.28)	(0.29)	(0.29)	(0.29)	(0.29)	(0.48)
70+	0.05	0.04	0.04	0.04	0.04	0.11
	(0.21)	(0.21)	(0.20)	(0.20)	(0.20)	(0.32)
Observations	2,834	2,342	2,258	2,344	1,019	1,019

Notes: Standard deviations in parentheses. Columns 1–5 are weighted. Column 6 is unweighted. Columns 5 and 6 contain summary statistics for respondents who responded to all four waves.

Figure S3: Study Coverage



Notes: District boundaries from the 2011 census. Bold lines indicate state boundaries.

Table S2: Robustness Check for Categorization of Behaviors

	Contact and Gathering into Social Distancing						Gathering as Social Distancing					
	Market Distancing			Social Distancing			Market Distancing			Social Distancing		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	-0.002	0.009	-0.034	-0.190***	-0.174***	-0.211***	-0.024	-0.014	-0.059	-0.134***	-0.120***	-0.125**
	(0.019)	(0.025)	(0.050)	(0.019)	(0.026)	(0.057)	(0.018)	(0.024)	(0.050)	(0.018)	(0.024)	(0.053)
Wave 3	-0.079***	-0.089***	-0.129**	-0.230***	-0.219***	-0.255***	-0.076***	-0.080***	-0.120**	-0.195***	-0.192***	-0.199***
	(0.018)	(0.025)	(0.058)	(0.021)	(0.028)	(0.067)	(0.018)	(0.024)	(0.057)	(0.019)	(0.026)	(0.063)
Wave 4	-0.101***	-0.116***	-0.209**	-0.325***	-0.315***	-0.393***	-0.099***	-0.103***	-0.201**	-0.358***	-0.357***	-0.368***
	(0.019)	(0.027)	(0.091)	(0.022)	(0.029)	(0.109)	(0.019)	(0.026)	(0.091)	(0.020)	(0.026)	(0.102)
COVID Caseload			-0.036*			-0.024			-0.040**			0.000
			(0.020)			(0.021)			(0.019)			(0.021)
Govt Response Index			-0.006			-0.005			-0.007			-0.001
			(0.005)			(0.007)			(0.005)			(0.006)
Adj R-squared	0.008	0.321	0.322	0.062	0.244	0.245	0.007	0.322	0.324	0.081	0.231	0.231
Observations	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.412			0.768			0.381			0.861		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. Individuals are considered to be following market-based distancing if they did report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. "Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

Table S3: Robustness Check: Behavior Outcomes Using Fractions of Behaviors

	Protective Behaviors			Market Based			Social Distancing		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	-0.013	-0.018	-0.017	-0.071***	-0.071***	-0.122***	-0.073***	-0.071***	-0.105***
	(0.008)	(0.011)	(0.026)	(0.010)	(0.013)	(0.029)	(0.012)	(0.017)	(0.040)
Wave 3	-0.020**	-0.025**	-0.033	-0.107***	-0.118***	-0.176***	-0.134***	-0.139***	-0.182***
	(0.009)	(0.012)	(0.030)	(0.010)	(0.013)	(0.034)	(0.015)	(0.021)	(0.050)
Wave 4	-0.027***	-0.032**	-0.027	-0.157***	-0.163***	-0.268***	-0.243***	-0.249***	-0.319***
	(0.010)	(0.014)	(0.049)	(0.012)	(0.015)	(0.055)	(0.017)	(0.022)	(0.078)
COVID Caseload			0.025***			-0.007			0.004
			(0.008)			(0.010)			(0.016)
Govt Response Index			0.001			-0.006*			-0.004
			(0.003)			(0.003)			(0.004)
Adj R-squared	0.002	0.190	0.193	0.046	0.409	0.411	0.068	0.212	0.213
Observations	9760	9760	9760	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.942			0.780			0.915		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the “overall government response index” from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. Individuals are considered to be following market-based distancing if they did report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. “Don’t know” responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

S6

Table S4: Protective Behaviors Only

	Wear a Facemask			Wash Hands		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	-0.014	-0.019	-0.006	-0.012	-0.018*	-0.028
	(0.013)	(0.019)	(0.040)	(0.008)	(0.010)	(0.025)
Wave 3	-0.022	-0.032	-0.035	-0.017**	-0.018*	-0.031
	(0.014)	(0.020)	(0.046)	(0.008)	(0.011)	(0.030)
Wave 4	-0.023	-0.031	0.000	-0.031***	-0.033***	-0.054
	(0.016)	(0.020)	(0.074)	(0.009)	(0.012)	(0.045)
COVID Caseload			0.047***			0.002
			(0.013)			(0.006)
Govt Response Index			0.003			-0.001
			(0.005)			(0.003)
Adj R-squared	0.001	0.158	0.163	0.003	0.177	0.177
Observations	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.908			0.977		

Notes: Data are weighted, and errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. "Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

Table S5: Market Behaviors Only

	10+ Gathering			Close Contact			Shopping			Work Travel		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	0.039***	0.037**	0.114***	0.129***	0.119***	0.158***	-0.009	-0.018	0.002	0.125***	0.146***	0.213***
	(0.011)	(0.015)	(0.042)	(0.017)	(0.023)	(0.050)	(0.020)	(0.026)	(0.052)	(0.018)	(0.025)	(0.052)
Wave 3	0.061***	0.066***	0.163***	0.123***	0.111***	0.158***	0.057***	0.072***	0.084	0.187***	0.221***	0.300***
	(0.013)	(0.018)	(0.051)	(0.018)	(0.023)	(0.059)	(0.019)	(0.027)	(0.062)	(0.018)	(0.023)	(0.061)
Wave 4	0.200***	0.207***	0.364***	0.131***	0.110***	0.190**	0.079***	0.091***	0.136	0.217***	0.244***	0.382***
	(0.017)	(0.023)	(0.085)	(0.018)	(0.024)	(0.092)	(0.021)	(0.028)	(0.094)	(0.020)	(0.026)	(0.098)
COVID Caseload			-0.010			0.000			0.032			0.008
			(0.014)			(0.017)			(0.021)			(0.020)
Govt Response Index			0.009*			0.005			0.003			0.008
			(0.005)			(0.006)			(0.005)			(0.006)
Adj R-squared	0.057	0.161	0.164	0.019	0.219	0.220	0.005	0.295	0.296	0.035	0.323	0.324
Observations	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.040			0.128			0.543			0.171		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. " Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

Table S6: Social Behaviors Only

	Visit Other Households			Have Visitors		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	0.087***	0.086***	0.092**	0.058***	0.055***	0.118**
	(0.015)	(0.021)	(0.047)	(0.014)	(0.019)	(0.047)
Wave 3	0.138***	0.141***	0.152**	0.130***	0.137***	0.211***
	(0.017)	(0.023)	(0.059)	(0.017)	(0.024)	(0.059)
Wave 4	0.234***	0.241***	0.251***	0.251***	0.257***	0.387***
	(0.018)	(0.024)	(0.090)	(0.019)	(0.026)	(0.091)
COVID Caseload			-0.013			0.006
			(0.018)			(0.019)
Govt Response Index			0.000			0.008
			(0.005)			(0.005)
Adj R-squared	0.047	0.169	0.169	0.059	0.166	0.167
Observations	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.087			0.083		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. "Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01

Reporting checklist for cohort study.

Based on the STROBE cohort guidelines.

Instructions to authors

Complete this checklist by entering the page numbers from your manuscript where readers will find each of the items listed below.

Your article may not currently address all the items on the checklist. Please modify your text to include the missing information. If you are certain that an item does not apply, please write "n/a" and provide a short explanation.

Upload your completed checklist as an extra file when you submit to a journal.

In your methods section, say that you used the STROBE cohortreporting guidelines, and cite them as:

von Elm E, Altman DG, Egger M, Pocock SJ, Gotzsche PC, Vandenbroucke JP. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: guidelines for reporting observational studies.

		Reporting Item	Page Number
Title and abstract			
Title	#1a	Indicate the study's design with a commonly used term in the title or the abstract	1
Abstract	#1b	Provide in the abstract an informative and balanced summary of what was done and what was found	1
Introduction			
Background / rationale	#2	Explain the scientific background and rationale for the investigation being reported	3
Objectives	#3	State specific objectives, including any prespecified hypotheses	4
Methods			
Study design	#4	Present key elements of study design early in the paper	5
Setting	#5	Describe the setting, locations, and relevant dates, including periods of	5

		recruitment, exposure, follow-up, and data collection	
Eligibility criteria	#6a	Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up.	5
Eligibility criteria	#6b	For matched studies, give matching criteria and number of exposed and unexposed	NA
Variables	#7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	6-8
Data sources / measurement	#8	For each variable of interest give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group. Give information separately for for exposed and unexposed groups if applicable.	6-8
Bias	#9	Describe any efforts to address potential sources of bias	5,7
Study size	#10	Explain how the study size was arrived at	5
Quantitative variables	#11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen, and why	7-8
Statistical methods	#12a	Describe all statistical methods, including those used to control for confounding	
8			
Statistical methods	#12b	Describe any methods used to examine subgroups and interactions	9
Statistical methods	#12c	Explain how missing data were addressed	10
Statistical methods	#12d	If applicable, explain how loss to follow-up was addressed	5
Statistical methods	#12e	Describe any sensitivity analyses	
7			
Results			
Participants	#13a	Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible,	5

		included in the study, completing follow-up, and analysed. Give information separately for for exposed and unexposed groups if applicable.	
Participants	#13b	Give reasons for non-participation at each stage	5
Participants	#13c	Consider use of a flow diagram	
S2			
Descriptive data	#14a	Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders. Give information separately for exposed and unexposed groups if applicable.	5
Descriptive data	#14b	Indicate number of participants with missing data for each variable of interest	
10			
Descriptive data	#14c	Summarise follow-up time (eg, average and total amount)	
NA			
Outcome data	#15	Report numbers of outcome events or summary measures over time. Give information separately for exposed and unexposed groups if applicable.	
8			
Main results	#16a	Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	10
Main results	#16b	Report category boundaries when continuous variables were categorized	6-7
Main results	#16c	If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	
NA			
Other analyses	#17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	11
Discussion			
Key results	#18	Summarise key results with reference to study objectives	12

Limitations	#19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias.	12
Interpretation	#20	Give a cautious overall interpretation considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence.	12
Generalisability	#21	Discuss the generalisability (external validity) of the study results	12
Other Information			
Funding	#22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	13

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Adherence to COVID-19-Protective Behaviors in India from May-December 2020: Evidence from a Nationally Representative Longitudinal Survey

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Adherence to COVID-19-Protective Behaviors in India from May-December 2020: Evidence from a Nationally Representative Longitudinal Survey

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ABSTRACT

Objectives: Since the onset of the COVID-19 pandemic, behavioral interventions to reduce disease transmission have been central to public health policy worldwide. Sustaining individual protective behavior is especially important in low- and middle-income settings, where health systems have fewer resources and access to vaccination is limited. This study seeks to assess time trends in COVID-19 protective behavior in India.

Design: Nationally representative, panel-based, longitudinal study.

Setting: We conducted a panel survey of Indian households to understand how the adoption of COVID-protective behaviors has changed over time. Our data spans peaks and valleys of disease transmission over May-December 2020.

Participants: Respondents included 3,719 adults from 1,766 Indian households enrolled in the Harmonized Diagnostic Assessment of Dementia for the Longitudinal Aging Study in India.

Analysis: We used ordinary least squares regression analysis to quantify time trends in protective behaviors.

Results: We find a 30.6 percentage point (95 percent confident interval [26.7, 34.5]; $p<0.01$) decline in protective behaviors related to social distancing over the observation period. Mask wearing and handwashing, in contrast, decreased only 4.3 percentage points [95 percent confidence interval [0.97-7.6]; $p<0.05$) from a high base. Our conclusions are unchanged after adjusting for recorded COVID-19 caseload and nationwide COVID containment policy; we also observe significant declines across socioeconomic strata spanning age, gender, education, and urbanicity.

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Conclusion: We argue these changes reflect, at least in part, "COVID fatigue," where adherence to social distancing becomes more difficult over time irrespective of the surrounding disease environment.

STRENGTHS AND LIMITATIONS OF THIS STUDY

- Our study leverages data from a nationally representative panel survey in India to study changes in COVID-19 protective behavior between May and December 2020.
- We link our survey data to contextual data measuring COVID-19 caseloads and national COVID-19 policy, allowing us to assess robustness of our main results to the disease and policy environments.
- We study how time trends in protective behavior vary among key demographic groups.
- Our surveys were conducted over the phone, which runs the risk of under-representing India's most socio-economically disadvantaged households.
- Our measures of protective behavior do not capture frequency or intensity within the lookback period

Keywords: COVID-19, public health

1 INTRODUCTION

Throughout the COVID-19 pandemic, governments around the world have implemented nonpharmacological policies aimed at blunting disease spread. Although policies have shifted over time—changing in scope and stringency[1]—a common aim has been to drastically reduce the mobility of, and social contact among, people. Critical in assessing the efficacy of these policies, and thus how to improve them, is understanding how distancing behavior changes or persists in the face of easing restrictions and evolving disease environments.

Much of the existing research in this space leverages cellphone data (most notably, open-source mobility datasets like Google's COVID-19 Community Mobility Reports) to characterize movement patterns[2-5]. Cellphone-based mobility data, however, fail to fully capture important facets of behavior that matter for disease transmission. For example, such data cannot record maintaining physical distance, avoiding large crowds, or wearing masks, all of which are common components of containment policies, and evidence suggests that adherence to these types of behaviors may be more useful for forecasting disease trajectory than measurements of movement alone[6, 7]. In addition, macro-level mobility analyses that rely on data captured from mobile phones run the risk of concealing deep disparities in both adherence and impact.

These data limitations resonate particularly in low- and middle-income countries (LMICs), where smartphone usage remains far from universal and survey data remain scarce. Understanding the ability of LMIC populations to maintain social-distancing practices over an extended period of time is especially pressing given (1) concerns that COVID-19 will disproportionately harm those living in LMICs[8-10], and (2) the fact that LMICs continue to lag in vaccine acquisition and administration[11] and, thus, may need to rely predominantly on nonpharmacological interventions for an extended period of time.

Understanding trends in distancing and other protective behaviors in India is significant, as it is the world's second largest LMIC and its population is uniquely vulnerable given the nation's high population density, large share of multigenerational households, and substantial population of individuals with COVID-19 risk factors like hypertension and diabetes[12]. This vulnerability was evident as the country experienced one of the world's deadliest waves of COVID-19, which began in April 2021. Various reasons have been cited for this resurgence, including the emergence of more contagious variants, a poorly coordinated, too-lax containment approach left in large part up to states[13], and a lagging vaccine campaign[14]. Critically, little rigorous data exist on the extent to which distancing behaviors were adopted and retained during the initial lockdown in 2020, or on how those behaviors changed during subsequent periods of reopening. Such insights could prove crucial to understanding the differing contexts of India's COVID waves and their severity.

To help fill this information gap, we designed and fielded a nationally-representative, high-frequency phone survey of Indian households to monitor knowledge, attitudes, and behaviors related to COVID-19. The survey, which also tracks the economic and health conditions of households, has been conducted bi-monthly since India's nationwide lockdown in March 2020. This initiative allows us to construct representative estimates of COVID-19 protective behaviors in India over time and to characterize how these behaviors differ across key socioeconomic groups. Unique in its scope, detail, and coverage, our study is a novel contribution to the existing literature, which has focused on adherence to COVID-19 protective behaviors in specific regions[15, 16] or on specific populations[17], or used cellphone data to understand broad trends in mobility patterns[18-20].

2 METHODS

2.1 Background: COVID-19 Containment in India

India's central government reacted to the hastening spread of COVID-19 with an initial lockdown on March 25, 2020, implemented with less than 24 hours' notice. Although initially meant to be in effect for one week, the directive was subsequently extended four times and ultimately lasted more than two months. The restrictions immediately halted public transportation, mandated mask wearing, closed all nonessential businesses, and banned many social gatherings.

After the national lockdown ended on May 31, 2020, the central government initiated reopening through various "unlock" phases while ceding future control over lockdowns and closures to individual states. Although decisions to reopen economically varied across geographies, protective behaviors—like maintaining social distance, avoiding unnecessary travel, and wearing masks—remained widely encouraged; for a more in-depth look at India's initial lockdown timeline, refer to [21]. During the unlock phases, caseloads remained low; however, the country subsequently experienced a spike in cases late in the summer and early fall of 2020. Following a lull in cases during the winter, infections again began to grow at an alarming rate starting in March 2021; by April 15, 2021, India had clearly entered a second COVID-19 surge unparalleled in the rest of the world, with nearly every state reporting a rapid growth in infections[22]. Supplementary Figure S1 graphs the Indian COVID-19 caseload and an index capturing the stringency of India's national policy response against our survey waves, described in detail as follows.

2.2 The Data

We leveraged an existing study called the Harmonized Diagnostic Assessment of Dementia for the Longitudinal Aging Study in India (LASI-DAD), a nationally-representative study that aims to understand patterns in cognition and dementia among older Indians[23]. Out of the

3,316 LASI-DAD households, we contacted all 2,704 who had valid phone numbers in May 2020 to invite them to participate in a bi-monthly phone survey that covered various topics related to household wellbeing and COVID-19-related knowledge, attitudes, and behavior. All households contained at least one individual over the age of 60.

The analyses presented in this paper use four waves of survey data: Wave 1 took place from May 5 through June 25, 2020; Wave 2 took place from July 7 through August 26, 2020; Wave 3 took place from September 7 through October 23, 2020; and Wave 4 took place from November 9, 2020, through January 4, 2021. Most of the Wave 1 survey occurred while the nation was still under the initial mandatory lockdown. Additional waves of data collection are scheduled to continue through December 2021.

During Wave 1, two randomly selected household members over the age of 18 (one male and one female, if possible) were invited to participate.[2] In subsequent waves we aimed to maintain continuity in interviewed household members: if an enrolled individual could not be reached, the enumerator scheduled an appointment for a future time; if this follow-up was unsuccessful, another adult household member was selected to participate in that wave instead. In Wave 3, we attempted to enroll all primary LASI-DAD respondents (individuals over the age of 60 who had participated in prior in-person waves of data collection during 2017 through 2019). Each wave targeted all individuals who had ever participated in a past wave. As a result, some households have up to four individuals interviewed in some waves. By collecting these data at a relatively high frequency, we were able to capture behavior changes made in the face of fast changing and dynamic policy and disease environments. The panel nature of our data also allows us to estimate within-person changes in distancing behavior, a useful way of ensuring our results are not driven by changes in sample composition/selective survey response.

The final sample includes 3,719 individuals from 1,766 households; 1,019 of these individuals and 665 of the households participated in all four waves (refer to Figure S2 for a breakdown of the final sample). Prior to each wave of data collection, all participants were required to provide informed, verbal consent, following protocols as approved by the Institutional Review Board (IRB) at both the University of Southern California (USC; study number UP-20-00277) and the All India Institute of Medical Sciences (AIIMS; study number RP-29/2020). We use sample weights to ensure estimates are nationally representative. Section 2.5 provides additional detail on weight construction. Table S1 provides summary statistics for our sample; column 5 includes weighted statistics for individuals who participated in all four waves, while column 6 contains the unweighted statistics. Our sample overrepresents older individuals (60+), as expected given our initial sample and the focus on interviewing LASI-DAD respondents. The sample also overrepresents those with higher levels of education, which may

[2] Names were drawn from a household roster collected as part of the earlier LASI-DAD survey.

reflect the fact that our survey is phone-based and phone ownership is correlated with higher education and socioeconomic status in India. The analyses herein employ weights, so they can be interpreted as nationally representative, and include all individuals from each wave. Figure S3 shows the geographic scope of our sample. Although our study sample is mostly rural, reflecting the population distribution of the country, we also cover some of India's megacities, including Mumbai and Delhi, which to date have experienced the country's worst COVID-19 outbreaks[24,25].

We use information on district of residence and survey date to attach contextual data on COVID-19 caseload in the preceding two weeks to each interview. Caseload, quantified as the daily number of new confirmed cases, was obtained from Covid19india.org, a crowd-sourced initiative that compiles daily statistics on COVID-19.[3] Due to delays in the processing and reporting of test results, we chose to smooth these estimates by taking a caseload average across the 14 days prior to the survey date. Finally, using total district-level population estimates from the 2011 Census of India, we calculated the number of cases per 10,000. District-level caseload statistics were not available in Assam, Telangana, and Delhi; thus, state-level statistics were used for these states.[4]

Finally, we account for national COVID-19 containment policy by using the "government response index" from the Oxford Covid-19 Government Response Tracker, which aggregates indicators of containment and health policy (such as school and workplace closings, restrictions on movement), economic policy (income support and debt relief), and health system policy (including facial covering policy and contract tracing). The index ranges from 0 to 100 with higher values indicating more aggressive policy action. Additional detail on index components and methodology is available in [26]. We use data on survey date to attach the average value of the index in the two weeks prior to interview onto each survey record.

2.3 Patient and Public Involvement

Survey respondents were not directly involved in the study design, including the development of research questions, survey design, or recruitment. There are no plans to directly disseminate the results to survey participants.

2.4 Measures of COVID-19-Protective Behavior

Nonpharmacological measures to curb the spread of COVID-19 have utilized a combination of mandates and public health messaging to minimize social contact across households and

[3] Covid19india.org collates state- and district-level data from official bulletins and Twitter handles. Data are validated by a group of volunteers before release. For a full list of their source sites, refer to Covid19india.org.
[4] Delhi is classified as a union territory rather than a state. However, we use the term "state" to refer to both states and union territories throughout the text to simplify exposition.

highlight the importance of personal hygiene. To understand the extent to which individual behaviors are aligned with these initiatives, we group behaviors tracked in our survey into three broad categories: market-based distancing behaviors, protective behaviors, and social-distancing behaviors. The recall period for each individual behavior is seven days. *Market-based behaviors* include activities that may not be fully discretionary—i.e., they may reflect maintaining a person's livelihood, either through work or buying food. These activities include attending a gathering with 10 or more people, having close contact (described to respondents as "two arms' lengths") with non-household members, traveling for work, and going shopping. We classify an individual as "market distancing" if s/he does not report any of the aforementioned behaviors. The second group is *protective behaviors*, which includes the two main hygiene behaviors consistently cited as key mechanisms for decreasing disease spread: handwashing and wearing a face mask[27]. We classify an individual as engaging in protective behavior if s/he reports having done both during the recall period. Finally, *social-distancing behaviors* include activities that reflect individuals' voluntary choices to gather for social reasons: visiting other households and having visitors over to one's own household. Respondents are classified as "social distancing" if they do not report either of these behaviors. If data for a given outcome is missing, e.g. because the respondent refused to answer the question, the observation is dropped from the relevant regression.

We acknowledge that the lines between these categories are not always clear; the purpose for each behavior was not explicitly stated, except for the question about work travel. Therefore, what we classify as market distancing may actually reflect social distancing and vice versa. To address this concern, we show that our main results are robust to re-categorizing some of the more ambiguous behaviors (attending 10+ person gatherings and having close contact with non-household members) either in the social- or market-distancing indicator (see Table S2).

Another potential concern is that fulfilling the criteria of social-distancing or protective behaviors may be more likely because they only encompass two behaviors each, while the market-distancing indicator encompasses four. Table S3 shows that our main results are robust to using fractional outcomes rather than binary outcomes. In addition, Tables S4, S5, and S6 provide estimates for each individual behavior within the protective, market-distancing, and social-distancing indicators, respectively.

2.5 Weight Construction

Weights were constructed in two steps. First, we created base weights to account for the probability of selection of a household, which is determined by the probability of selection of each LASI-DAD participant and the probability of selection of household members, calculated separately for men and women (as one over the number of adult men and women, respectively). Second, we implemented a raking algorithm to obtain post-stratification weights. For this purpose, we used the following raking factors: gender (male/female) × age (18–39/40–59/60–69/70+), gender × education (no school/primary or less/middle/secondary or higher/graduate), and a rural/urban indicator. Thus, the final weights allow us to match the sample distributions of these variables with their population counterparts while also reflecting differential probabilities of selection of survey participants. Population benchmark distributions were obtained from the 2011 Indian Census for individuals aged 18 and older.

2.6 Empirical Approach

To estimate time trends in COVID-19-protective behaviors, we use ordinary least squares regressions of the following form:

$$y_{it} = \beta_0 + \beta_1 wave2_t + \beta_2 wave3_t + \beta_3 wave4_t + \varepsilon_{it} \quad (1)$$

where y_{it} is the distancing outcome for individual i measured at time t and $wave2_t$–$wave4_t$ are survey wave dummies, which identify changes in distancing behavior relative to Wave 1.

In addition to this basic equation, we also assess whether our estimates are robust to the inclusion of individual fixed effects using the following specification:

$$y_{it} = \beta_0 + \beta_1 wave2_t + \beta_2 wave3_t + \beta_3 wave4_t + \delta_i + \varepsilon_{it} \quad (2)$$

Finally, we present results that additionally control for COVID-19 caseloads and the government response index:

$$y_{it} = \beta_0 + \beta_1 wave2_t + \beta_2 wave3_t + \beta_3 wave4_t + \beta_4 Caseload_{dt} + \beta_5 GovtResp_t + \delta_i + \varepsilon_{it} \quad (3)$$

where $Caseload_{dt}$ is the average number of positive COVID-19 cases reported in the district over the two weeks prior to survey date (per 10,000 people) and $GovtResp_t$ is the average value of the government response index in the two weeks prior to survey date.

All our equations use sampling weights to ensure our estimates are nationally representative. We cluster standard errors at the household level because multiple individuals per household are surveyed in any given wave.

We use the following equation to test for heterogeneity in behavior outcomes:

$$y_{it} = \beta_0 + \beta_1 Demo_i + \sum_{k=2}^{4} [\beta_k Wave_k + \beta_{k+3} Wave_k \times Demo_i] + \varepsilon_{it} \quad (4)$$

where y_{it} is one of three behavior outcomes (market-distancing, social-distancing, or protective behaviors), $Wave_k$ is a wave dummy, $Demo_i$ represents one of four dummy demographic cuts (gender, urbanicity, age older than vs. younger than 60, or highest level of education in the household is primary or less vs. middle school or higher). All estimates are weighted and standard errors are clustered at the household level.

3 RESULTS

3.1 Overall Time Trends

Figure 1 shows that initial adherence to protective and social-distancing behaviors was quite high (89.9% and 87.7%, respectively), which likely reflects that much of Wave 1 occurred either during or immediately after India's mandatory national lockdown. However, only 37.4% of individuals reported market distancing during this time, suggesting most Indians were still engaging in some economic activities during the strictest periods of the lockdown. Figure 1 also highlights declining vigilance over time. Patterns of decline differ in important ways by behavior type. Protective behaviors, the most stable of the four categories, saw a slight dip in Wave 2 and another in Wave 4 (declining by 3.2 and 4.3 percentage points, respectively). Social distancing, however, has seen significantly larger decreases, with a 30.6 percentage point decline by Wave 4. Finally, market-based distancing remained essentially steady between Waves 1 and 2, before dropping in Wave 3. By Wave 4, only 26.5% of individuals reported avoiding all the market-based behaviors we measure.

The first column for each behavior in Table 1 presents results in regression form; weighted differences in behavior for Waves 2–4 are presented relative to Wave 1. The second column assesses robustness to changes in sample composition by exploiting the panel nature of our data and using within-person variation to identify time trends. If adding fixed effects substantively changes the estimates, this would indicate that individuals who regularly responded to the survey are different from those who sporadically responded, which would raise a concern about sample composition. The final column adds controls for the COVID-19 caseload and the government response index in the previous two weeks as a simple way to test whether relaxing behavioral restrictions reflects a shifting disease or policy environment: to the extent that behavior simply tracks these variables with a lag, controlling for them should attenuate our initial time trend estimates. It is not appropriate to interpret the coefficients on the caseload and policy indicators as causal, however, because the direction of causality is unclear (behavior could respond to these factors, but both caseloads and policy undoubtedly change in response to behavior). Moreover, we are not able to control for state and local policy, which may have varied more than the national response during this time. Estimated time trends are generally robust to adding these environmental controls. While time trends in protective behavior lose statistical significance, these coefficients were small in magnitude initially and do not change much. The time trends for social distancing are virtually unchanged and the decline in market-based distancing becomes even more pronounced. Higher caseloads are associated with more protective behavior (in line with a

Table 1: Behaviors Outcomes

	Protective Behaviors			Market-Based			Social Distancing		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	-0.032**	-0.041**	-0.029	-0.029	-0.017	-0.062	-0.113***	-0.105***	-0.101**
	(0.014)	(0.021)	(0.044)	(0.018)	(0.024)	(0.051)	(0.016)	(0.023)	(0.050)
Wave 3	-0.030**	-0.041**	-0.045	-0.077***	-0.079***	-0.119**	-0.177***	-0.175***	-0.171***
	(0.015)	(0.021)	(0.050)	(0.018)	(0.024)	(0.058)	(0.019)	(0.026)	(0.062)
Wave 4	-0.043**	-0.051**	-0.021	-0.109***	-0.112***	-0.209**	-0.306***	-0.305***	-0.296***
	(0.017)	(0.023)	(0.080)	(0.019)	(0.026)	(0.093)	(0.020)	(0.026)	(0.097)
COVID Caseload			0.049***			-0.040**			0.002
			(0.014)			(0.018)			(0.021)
Govt Response Index			0.003			-0.007			0.001
			(0.005)			(0.005)			(0.006)
Adj R-squared	0.002	0.156	0.160	0.008	0.315	0.316	0.065	0.209	0.209
Observations	9760	9760	9760	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.899			0.374			0.877		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. Individuals are considered to be following market-based distancing if they did report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. "Don't know" responses (n=15) and refusals (n=4) coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

behavioral response to underlying disease risk), but less market-based distancing. The latter relationship could reflect increased disease transmission following the reopening of the economy. There is no significant correlation between the government response index and our behavioral measures. We prefer not to over-interpret this result, as this coefficient is identified using *within-survey-wave* variation in the response index—if individuals take time to adjust to shifting government policy, our empirical strategy could understate the import of this variable.

3.2 Investigation of Disparities

Vulnerable groups in Indian society are susceptible to disproportionate effects from the pandemic for many reasons: less-educated individuals typically do not hold jobs that can be done remotely, older individuals living with children may not be able to avoid exposure to household visitors, and individuals living in densely populated cities may have a more difficult time avoiding contact with others. Behavior may also vary by gender, given the mobility restrictions and caregiving expectations faced by many Indian women. In this subsection, we quantify how behavioral changes vary based on age, gender, urbanicity, and household education.

Figure 2 shows trends in protective behavior by age (older than vs. younger than age 60), urbanicity, gender, and highest level of education in the household (primary or less vs. middle school or higher). At the beginning of the pandemic (survey Wave 1), we see minimal differences across groups, except that women—who are more likely to be homebound due to gender norms—are less likely to report engaging in both protective behaviors.[5] Adherence among men declines over time, diminishing the gender gap. In contrast, we see a divergence in protective behavior by age, urbanicity, and education. Older individuals (60+) are much more likely to report declining protective behavior over time, which is worrisome for a cohort that is more vulnerable to severe illness if infected. A decline is also more pronounced among rural dwellers (who have seen persistently lower caseloads) and less educated individuals, signaling higher vulnerability to future waves of infection.

Figure 3 reports trends in market-based distancing by group. During Wave 1, women and older individuals were significantly more likely to report this type of distancing, consistent with their lower levels of economic engagement. In contrast, there is virtually no difference in market-based distancing by urbanicity or education. Gender gaps remain large over time, while age gaps grow in subsequent waves, potentially driven by a return

[5] Consistent with the norms hypothesis, gender differences in handwashing are minimal, while differences in mask wearing are larger and significant.

to work among younger cohorts. Finally, Figure 4 reports differences in social distancing. We see high levels of social distancing in all groups during Wave 1, which decline significantly over time. Older individuals, women, and urban dwellers maintain slightly higher levels of distancing in subsequent survey waves.

4 CONCLUSION

We find evidence of significant behavioral "COVID fatigue" in a nationally representative sample of Indian adults. Declines in protective behavior do not simply reflect an increase in market-based behaviors accompanying India's economic reopening; individuals also increased social contact and (to a lesser extent) reduced mask wearing and handwashing. Our conclusions are unchanged after controlling for local caseload per capita and an index summarizing India's nationwide policy response; this suggests that individuals are not just responding to a less risky disease environment or changes in national directives. Rather, restrictive behavior appears difficult to sustain over time, even conditional on caseloads and policy – though here is it important to keep in mind that caseloads are an imperfect proxy of disease risk, especially in light of concerns about widespread underreporting, resulting in national statistics that fail to capture true infection and mortality rates[28].

Another important finding is that declines, especially in social distancing, are found across demographic and socioeconomic groups. Particularly worrying is the significant decline in mask wearing and handwashing among older individuals. While older Indians are less likely to be exposed to others in work or market contexts, their rates of social distancing are like those of the young. Moreover, 69.4% of the sample live in multigenerational households, where isolating from family members is difficult. Intra-household spread is a major contributor to contagion[29]; thus, the steep declines we observe in protective behavior amount to a "double risk" for older Indians sharing living quarters and facilities with younger, economically active family members.

One limitation of our research is that it was conducted over the phone. Although mobile phone ownership is high in India, with 93 percent of households owning a phone according to the nationally representative 2015-2016 National Family Health Survey, there are significant gaps by gender, wealth, and other indicators of socioeconomic status; thus, it is possible that vulnerable households without reliable access to phones may be underrepresented in our study [30,31]. Initial evidence also suggests that in India poorer households have suffered greater economic consequences from the lockdown [32], although it is less clear how this would translate into the behaviors measured in our paper; for example, market-distancing may be less common among phoneless households if they were financially unable to change work behavior, or market-distancing may be more common if this group faced higher rates of job loss. In addition, our binary measures of protective behavior cannot capture the intensity of adherence (e.g. respondents who socially distance half the time would still qualify as social distancers per our definition), which could have significant implications in terms of risk of disease exposure and spread. Finally, while we argue that our observed changes in behavior are suggestive of growing COVID fatigue, we cannot fully assess the extent to which changes in behavior reflect personal preferences versus changes in the economic and policy environment as we lack suitable data to completely control for the underlying economic, disease, and policy context. For example, reduced market-based distancing could reflect both the re-opening of the economy and businesses, as well as a reduced desire to adhere to protective behaviors.

Generalizability of our findings may be limited due to how varied government responses to the pandemic have been, and particularly how stringent and immediate India's early policy response to Covid was. However, this paper also provides important context in terms of how people were or were not following best practices to reduce disease spread very shortly before March 2021, one of the deadliest outbreaks to-date in India. For example, the decline in protective behaviors we observe could have accelerated disease spread and contributed to the high rates of COVID-19-related morbidity and mortality that started shortly after our last round of data collection. Additional research is needed to rigorously estimate the causal effect of observed behavior transmission on the trajectory of the pandemic. Additional descriptive research is also essential, as monitoring adherence to distancing guidelines and assessing how public health messaging can be optimized to ensure continued adherence over time will be essential components of India's ongoing battle against COVID-19.

FUNDING, ACKNOWLEDGEMENTS AND COMPETING INTERESTS

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Competing Interests: The authors have no competing interests to declare.
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ETHICS STATEMENT

The study was approved by the following institutional review boards: USC IRB: UP-20-00277 AIIMS IRB: IEC-300/17.04.2020, RP-29/2020

CONTRIBUTORSHIP STATEMENT

DB, JL, and SS conceptualized, designed, and implemented the study and contributed to manuscript preparation. ABD contributed to conceptualization, design, and implementation of the study. NT contributed to data analysis and manuscript preparation. JB and PK contributed to the study design and managed data collection. SP contributed to project and data management. AA contributed to study design. MA constructed weights for the study and contributed to manuscript preparation. SC and BW contributed to data collection and management. AC, PC, and NM contributed to study implementation.

DATA AVAILABILITY STATEMENT

Data are available to download via the LASI-DAD website: https://lasi-dad.org/?section=access-data. Users must register and agree to a data use agreement before being granted access to the data.

FIGURE LEGENDS

Figure 1: Change in Individual Behavior Across Waves

Notes: Figure depicts regression coefficients of the wave terms from the Basic equations as shown in Table 1. Data are weighted, and standard errors are clustered at the household level. Whiskers denote 95 percent confidence intervals. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. Individuals are considered to be following market-based distancing if they did report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. "Don't know" responses and refusals coded to missing.

Figure 2: Heterogeneity in Protective Behaviors Across Key Demographics

Notes: Figures depict the regression coefficients of Wave x demographic interaction terms. Data are weighted, and standard errors are clustered at the household level. Whiskers denote 95 percent confidence intervals. Individuals are considered to be engaging in protective behaviors if theyreport washing their hands and wearing a facemask. “Don’t know” responses and refusals coded tomissing.

Figure 3: Heterogeneity in Market-Distancing Behaviors Across Key Demographics

Notes: Figures depict the regression coefficients of Wave x demographic interaction terms. Data are weighted, and standard errors are clustered at the household level. Whiskers denote 95 percent confidence intervals. Individuals are considered to be market distancing if they did not report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. “Don’t know” responses and refusals coded to missing.

Figure 4: **Heterogeneity in Social-Distancing Behaviors Across Key Demographics**

Notes: Figures depict the regression coefficients of Wave x demographic interaction terms. Data are weighted, and standard errors are clustered at the household level. Whiskers denote 95 percent confidence intervals. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. “Don’t know” responses and refusals coded to missing.

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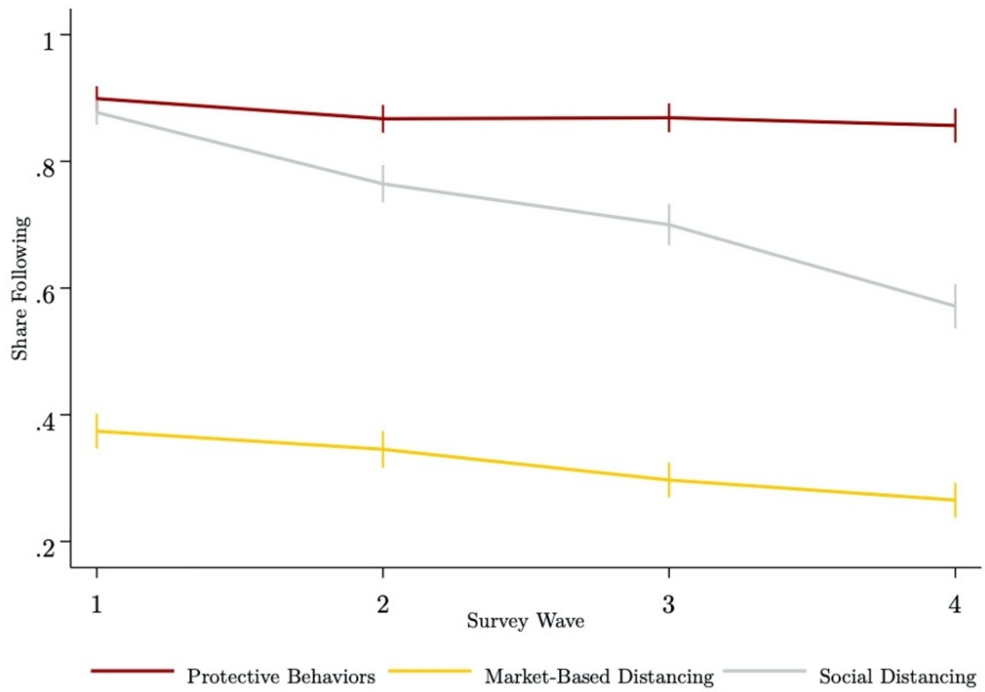

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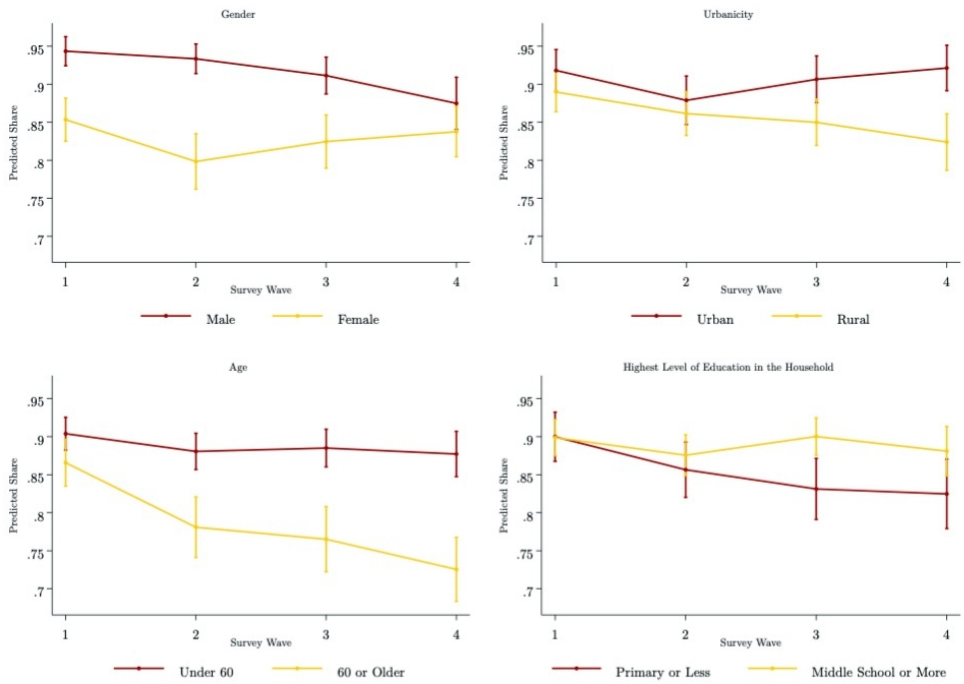

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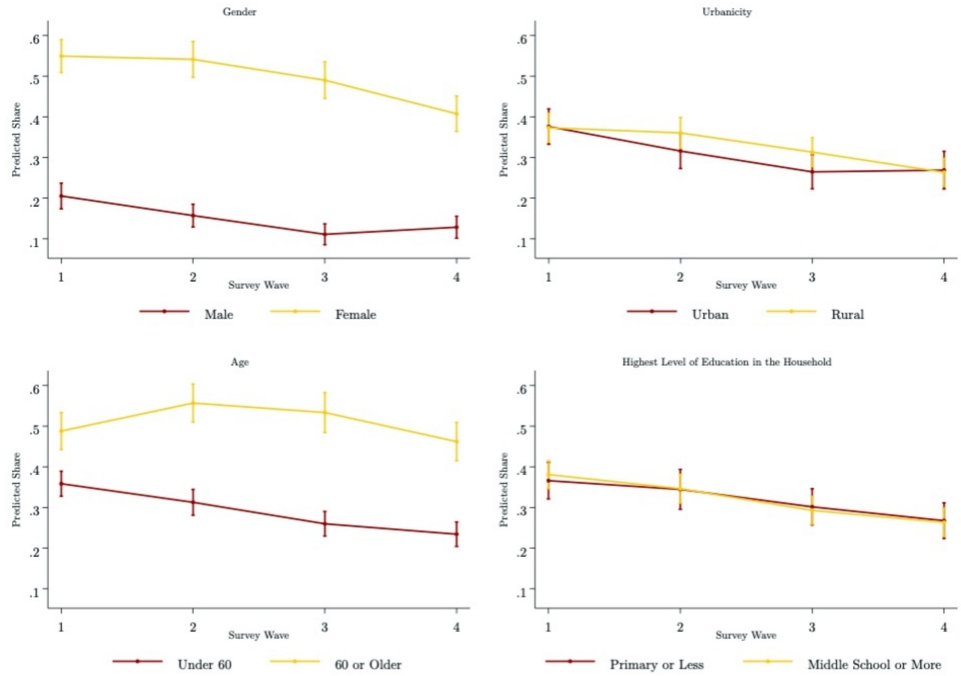

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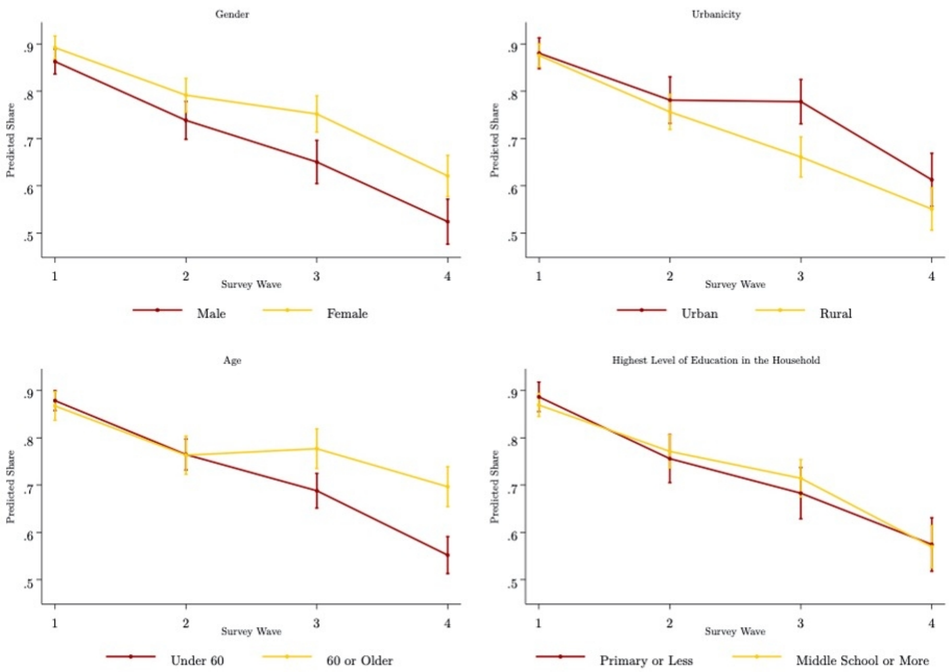

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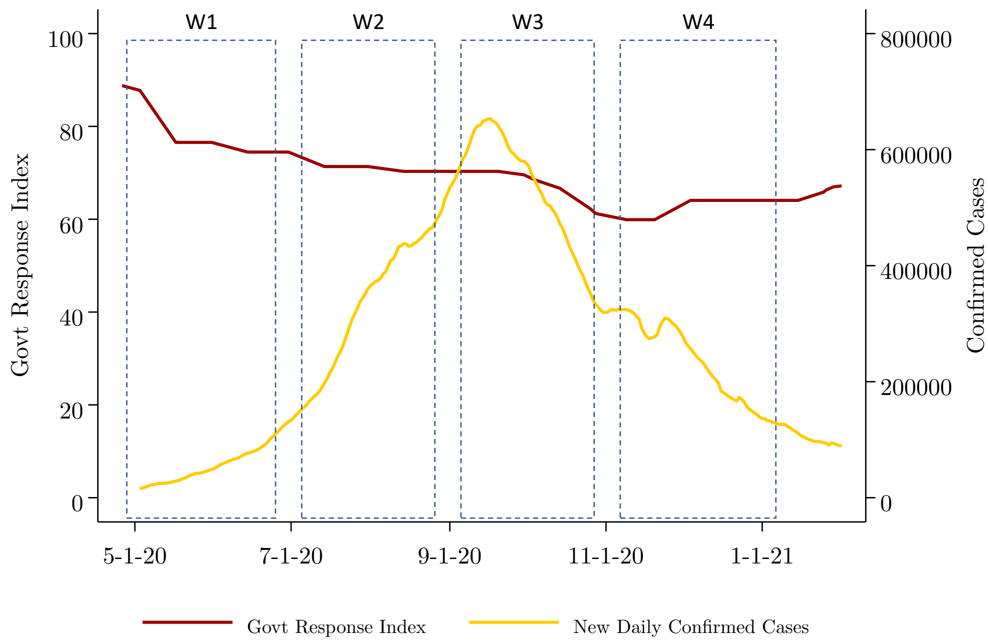
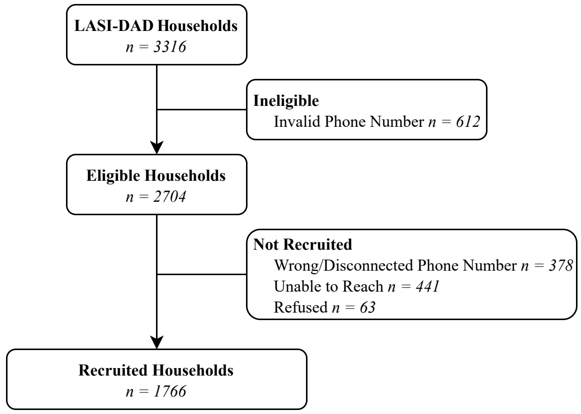
SUPPLEMENTARY MATERIALS

Figure S1: Waves of Data Collection and Caseload Trajectory in India



Notes: Visualization of daily new confirmed COVID-19 cases and overall government response index. COVID-19 caseload data are the 7-day average number of new confirmed cases in the entire country and are from Covid19india.org. Government response index is 7-day average of the overall government response index from the Oxford Covid-19 Government Response Tracker. Dates shown are the approximate date of the first survey in each wave, with width of the hollow bars representing how long a given survey wave was in the field.

Figure S2: Flow Chart of Household Participation



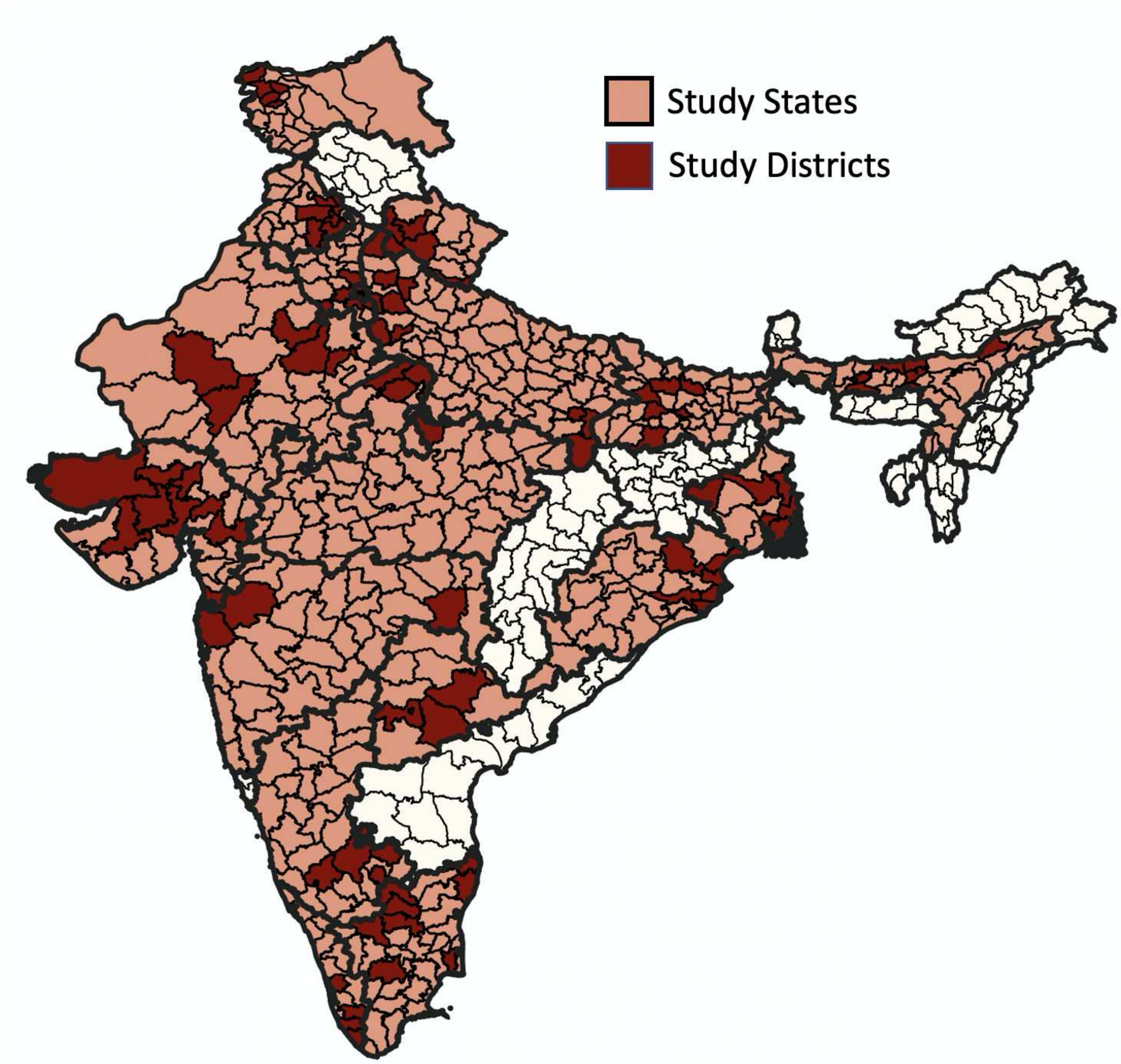
Notes: Numbers are aggregated across the four waves and indicate the number of households. Multiple individuals from a household often participated in a given wave.

Table S1: Demographic Characteristics of Sample, by Wave

	Weighted					Unweighted
	Wave 1	Wave 2	Wave 3	Wave 4	In All Waves	In All Waves
Female	0.49	0.49	0.49	0.49	0.51	0.48
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Rural	0.66	0.66	0.66	0.66	0.64	0.59
	(0.47)	(0.47)	(0.47)	(0.47)	(0.48)	(0.49)
Middle School Education or More	0.55	0.56	0.54	0.57	0.58	0.70
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.46)
16–44	0.69	0.68	0.66	0.67	0.67	0.35
	(0.46)	(0.47)	(0.47)	(0.47)	(0.47)	(0.48)
45–59	0.18	0.19	0.20	0.20	0.20	0.17
	(0.38)	(0.39)	(0.40)	(0.40)	(0.40)	(0.38)
60–70	0.08	0.09	0.09	0.09	0.10	0.36
	(0.28)	(0.29)	(0.29)	(0.29)	(0.29)	(0.48)
70+	0.05	0.04	0.04	0.04	0.04	0.11
	(0.21)	(0.21)	(0.20)	(0.20)	(0.20)	(0.32)
Observations	2,834	2,342	2,258	2,344	1,019	1,019

Notes: Standard deviations in parentheses. Columns 1–5 are weighted. Column 6 is unweighted. Columns 5 and 6 contain summary statistics for respondents who responded to all four waves.

Figure S3: Study Coverage



Notes: District boundaries from the 2011 census. Bold lines indicate state boundaries.

Table S2: Robustness Check for Categorization of Behaviors

	Contact and Gathering into Social Distancing						Gathering as Social Distancing					
	Market Distancing			Social Distancing			Market Distancing			Social Distancing		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	-0.002	0.009	-0.034	-0.190***	-0.174***	-0.211***	-0.024	-0.014	-0.059	-0.134***	-0.120***	-0.125**
	(0.019)	(0.025)	(0.050)	(0.019)	(0.026)	(0.057)	(0.018)	(0.024)	(0.050)	(0.018)	(0.024)	(0.053)
Wave 3	-0.079***	-0.089***	-0.129**	-0.230***	-0.219***	-0.255***	-0.076***	-0.080***	-0.120**	-0.195***	-0.192***	-0.199***
	(0.018)	(0.025)	(0.058)	(0.021)	(0.028)	(0.067)	(0.018)	(0.024)	(0.057)	(0.019)	(0.026)	(0.063)
Wave 4	-0.101***	-0.116***	-0.209**	-0.325***	-0.315***	-0.393***	-0.099***	-0.103***	-0.201**	-0.358***	-0.357***	-0.368***
	(0.019)	(0.027)	(0.091)	(0.022)	(0.029)	(0.109)	(0.019)	(0.026)	(0.091)	(0.020)	(0.026)	(0.102)
COVID Caseload			-0.036*			-0.024			-0.040**			0.000
			(0.020)			(0.021)			(0.019)			(0.021)
Govt Response Index			-0.006			-0.005			-0.007			-0.001
			(0.005)			(0.007)			(0.005)			(0.006)
Adj R-squared	0.008	0.321	0.322	0.062	0.244	0.245	0.007	0.322	0.324	0.081	0.231	0.231
Observations	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.412			0.768			0.381			0.861		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. Individuals are considered to be following market-based distancing if they did report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. "Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

Table S3: Robustness Check: Behavior Outcomes Using Fractions of Behaviors

	Protective Behaviors			Market Based			Social Distancing		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	-0.013	-0.018	-0.017	-0.071***	-0.071***	-0.122***	-0.073***	-0.071***	-0.105***
	(0.008)	(0.011)	(0.026)	(0.010)	(0.013)	(0.029)	(0.012)	(0.017)	(0.040)
Wave 3	-0.020**	-0.025**	-0.033	-0.107***	-0.118***	-0.176***	-0.134***	-0.139***	-0.182***
	(0.009)	(0.012)	(0.030)	(0.010)	(0.013)	(0.034)	(0.015)	(0.021)	(0.050)
Wave 4	-0.027***	-0.032**	-0.027	-0.157***	-0.163***	-0.268***	-0.243***	-0.249***	-0.319***
	(0.010)	(0.014)	(0.049)	(0.012)	(0.015)	(0.055)	(0.017)	(0.022)	(0.078)
COVID Caseload			0.025***			-0.007			0.004
			(0.008)			(0.010)			(0.016)
Govt Response Index			0.001			-0.006*			-0.004
			(0.003)			(0.003)			(0.004)
Adj R-squared	0.002	0.190	0.193	0.046	0.409	0.411	0.068	0.212	0.213
Observations	9760	9760	9760	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.942			0.780			0.915		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. Individuals are considered to be social distancing if they did not report visiting other households or having visitors to their own households. Individuals are considered to be following market-based distancing if they did report any of the following: attended a 10+ person gathering, had close contact with non-household members, traveled for work, or went shopping. Individuals are considered to be engaging in protective behaviors if they report washing their hands and wearing a facemask. "Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

S6

Table S4: Protective Behaviors Only

	Wear a Facemask			Wash Hands		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	-0.014	-0.019	-0.006	-0.012	-0.018*	-0.028
	(0.013)	(0.019)	(0.040)	(0.008)	(0.010)	(0.025)
Wave 3	-0.022	-0.032	-0.035	-0.017**	-0.018*	-0.031
	(0.014)	(0.020)	(0.046)	(0.008)	(0.011)	(0.030)
Wave 4	-0.023	-0.031	0.000	-0.031***	-0.033***	-0.054
	(0.016)	(0.020)	(0.074)	(0.009)	(0.012)	(0.045)
COVID Caseload			0.047***			0.002
			(0.013)			(0.006)
Govt Response Index			0.003			-0.001
			(0.005)			(0.003)
Adj R-squared	0.001	0.158	0.163	0.003	0.177	0.177
Observations	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.908			0.977		

Notes: Data are weighted, and errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. "Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

Table S5: Market Behaviors Only

	10+ Gathering			Close Contact			Shopping			Work Travel		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	0.039***	0.037**	0.114***	0.129***	0.119***	0.158***	-0.009	-0.018	0.002	0.125***	0.146***	0.213***
	(0.011)	(0.015)	(0.042)	(0.017)	(0.023)	(0.050)	(0.020)	(0.026)	(0.052)	(0.018)	(0.025)	(0.052)
Wave 3	0.061***	0.066***	0.163***	0.123***	0.111***	0.158***	0.057***	0.072***	0.084	0.187***	0.221***	0.300***
	(0.013)	(0.018)	(0.051)	(0.018)	(0.023)	(0.059)	(0.019)	(0.027)	(0.062)	(0.018)	(0.023)	(0.061)
Wave 4	0.200***	0.207***	0.364***	0.131***	0.110***	0.190**	0.079***	0.091***	0.136	0.217***	0.244***	0.382***
	(0.017)	(0.023)	(0.085)	(0.018)	(0.024)	(0.092)	(0.021)	(0.028)	(0.094)	(0.020)	(0.026)	(0.098)
COVID Caseload			-0.010			0.000			0.032			0.008
			(0.014)			(0.017)			(0.021)			(0.020)
Govt Response Index			0.009*			0.005			0.003			0.008
			(0.005)			(0.006)			(0.005)			(0.006)
Adj R-squared	0.057	0.161	0.164	0.019	0.219	0.220	0.005	0.295	0.296	0.035	0.323	0.324
Observations	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.040			0.128			0.543			0.171		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. " Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01.

Table S6: Social Behaviors Only

	Visit Other Households			Have Visitors		
	Basic	+Indiv FE	+Enviro	Basic	+Indiv FE	+Enviro
Wave 2	0.087***	0.086***	0.092**	0.058***	0.055***	0.118**
	(0.015)	(0.021)	(0.047)	(0.014)	(0.019)	(0.047)
Wave 3	0.138***	0.141***	0.152**	0.130***	0.137***	0.211***
	(0.017)	(0.023)	(0.059)	(0.017)	(0.024)	(0.059)
Wave 4	0.234***	0.241***	0.251***	0.251***	0.257***	0.387***
	(0.018)	(0.024)	(0.090)	(0.019)	(0.026)	(0.091)
COVID Caseload			-0.013			0.006
			(0.018)			(0.019)
Govt Response Index			0.000			0.008
			(0.005)			(0.005)
Adj R-squared	0.047	0.169	0.169	0.059	0.166	0.167
Observations	9760	9760	9760	9760	9760	9760
Wave 1 Mean	0.087			0.083		

Notes: Data are weighted, and standard errors are clustered at the household level. COVID caseload is the average number of cases per 10,000 in the past 14 days at the district level, except for Assam, Telangana, and Delhi, which use state-level caseload due to data constraints. Government response index is the 14-day average of the "overall government response index" from the Oxford Covid-19 Government Response Tracker, with higher values indicating heightened government restrictions. The second and third column for each outcome includes individual fixed effects. "Don't know" responses and refusals coded to missing. Significance is as follows: *=0.1, **=0.05, and ***=0.01

Reporting checklist for cohort study.

Based on the STROBE cohort guidelines.

Instructions to authors

Complete this checklist by entering the page numbers from your manuscript where readers will find each of the items listed below.

Your article may not currently address all the items on the checklist. Please modify your text to include the missing information. If you are certain that an item does not apply, please write "n/a" and provide a short explanation.

Upload your completed checklist as an extra file when you submit to a journal.

In your methods section, say that you used the STROBE cohortreporting guidelines, and cite them as:

von Elm E, Altman DG, Egger M, Pocock SJ, Gotzsche PC, Vandenbroucke JP. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: guidelines for reporting observational studies.

		Reporting Item	Page Number
Title and abstract			
Title	#1a	Indicate the study's design with a commonly used term in the title or the abstract	1
Abstract	#1b	Provide in the abstract an informative and balanced summary of what was done and what was found	1
Introduction			
Background / rationale	#2	Explain the scientific background and rationale for the investigation being reported	3
Objectives	#3	State specific objectives, including any prespecified hypotheses	4
Methods			
Study design	#4	Present key elements of study design early in the paper	5
Setting	#5	Describe the setting, locations, and relevant dates, including periods of	5

		recruitment, exposure, follow-up, and data collection	
Eligibility criteria	#6a	Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up.	5
Eligibility criteria	#6b	For matched studies, give matching criteria and number of exposed and unexposed	NA
Variables	#7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	6-8
Data sources / measurement	#8	For each variable of interest give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group. Give information separately for for exposed and unexposed groups if applicable.	6-8
Bias	#9	Describe any efforts to address potential sources of bias	5,7
Study size	#10	Explain how the study size was arrived at	5
Quantitative variables	#11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen, and why	7-8
Statistical methods	#12a	Describe all statistical methods, including those used to control for confounding	
8			
Statistical methods	#12b	Describe any methods used to examine subgroups and interactions	9
Statistical methods	#12c	Explain how missing data were addressed	10
Statistical methods	#12d	If applicable, explain how loss to follow-up was addressed	5
Statistical methods	#12e	Describe any sensitivity analyses	
7			
Results			
Participants	#13a	Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible,	5

		included in the study, completing follow-up, and analysed. Give information separately for for exposed and unexposed groups if applicable.	
Participants	#13b	Give reasons for non-participation at each stage	5
Participants	#13c	Consider use of a flow diagram	
S2			
Descriptive data	#14a	Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders. Give information separately for exposed and unexposed groups if applicable.	5
Descriptive data	#14b	Indicate number of participants with missing data for each variable of interest	
10			
Descriptive data	#14c	Summarise follow-up time (eg, average and total amount)	
NA			
Outcome data	#15	Report numbers of outcome events or summary measures over time. Give information separately for exposed and unexposed groups if applicable.	
8			
Main results	#16a	Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	10
Main results	#16b	Report category boundaries when continuous variables were categorized	6-7
Main results	#16c	If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	
NA			
Other analyses	#17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	11
Discussion			
Key results	#18	Summarise key results with reference to study objectives	12

Limitations	#19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias.	12
Interpretation	#20	Give a cautious overall interpretation considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence.	12
Generalisability	#21	Discuss the generalisability (external validity) of the study results	12
Other Information			
Funding	#22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	13