We examine the effect of testing and social distancing measures on the severity of COVID-19 across Indian states during the 68th day nationwide lockdown period. We also explore whether pre-existing socio-economic factors such as quality of health care and the ability to practice social distancing influences the effect of these policy measures across states. Using daily level data between April 1 and May 31 for 18 of the major states, we find that both testing and social distancing have a negative effect on COVID-19 fatalities in India. Further, testing is more helpful in reducing CFR for states with lower per capita health expenditure and weaker medical infrastructure. This highlights how ramping up testing can aid states that have a weak health care system through the detection of infection, contact tracing and isolation. In contrast, social distancing measures are more effective in states that are less populous and have lesser people dwelling in single-room houses. Our results confirm the role of pre-existing institutional factors in shaping the effect of policy actions on health outcomes.

KEYWORDS
COVID-19, fatality, India, social distancing, testing

1 | INTRODUCTION

The outbreak of COVID-19 in 2020 was one of the most severe health crises that policymakers and governments continue grappling with even now (Wang & Tang, 2020). With no vaccine or established cure in place in 2020, most governments had resorted to nonpharmaceutical intervention measures ranging from stay-at-home orders to stringent lockdowns (Demirgüç-Kunt et al., 2020; Tian et al., 2021). These measures ensured social interaction and mobility restrictions in common and public spaces. Given the highly infectious nature of COVID-19, social distancing and lockdowns acted as a cushion in mitigating unusual spikes in cases and hence avoided overstraining health care systems (Arshed et al., 2020; Chetterje, 2020; Yang et al., 2021).

Since the outbreak of the pandemic, there has been a plethora of research documenting different aspects and impacts of COVID-19. Several papers have examined various factors, including seasonality (Liu et al., 2021), lockdown stringency (Hartl et al., 2020), and social network that determine the spread of COVID-19. However, fewer studies have focused on exploring deaths due to it (Briggs et al., 2021; Pormohammad et al., 2020; Wang et al., 2021). An essential aspect of COVID-19 infection is that all deaths occur only in critical cases. Thus, people with mild to moderate levels of illness do not die unless their illness severity worsens to the critical level (Pormohammad et al., 2020; Wang et al., 2021). This implies that timely testing can be crucial in identifying infections at early stages, and with sufficient care postdetection, it can avert deaths. Additionally, testing also aids in constraining future infections and deaths by isolating the infected and hence advert-
organizations will be necessary for advertising COVID-19-related health adversities (Abdullah & Kim, 2020).

Against this background, we examine the effect of testing efforts and social distancing patterns on COVID-19-related fatalities in India. After 600 odd cases of COVID-19 infections on March 24, the Government of India announced a strict three-week nationwide lockdown beginning on March 25, 2020, with two subsequent extensions. The Central government of India imposed the Disaster Management Act of 2005 that inhibited state governments from diluting the lockdown restrictions. It was only after May 31 that gradual unlocking of the nation was initiated.

During the nationwide lockdown period of April 1 to May 31, all states were under a similar lockdown regime. This enables us to examine variation in COVID-19 deaths across states under a uniform regulatory environment. The primary objective of our study is to examine if pre-existing socio-economic and institutional factors play a role in spatial variation in fatalities from COVID-19. We aim to identify which strategy works better in which states and if pre-existing conditions play a role in their success/failure. Specifically, we investigate if the presence of a strong medical infrastructure base in a state is critical for testing to reduce COVID-19 deaths (Koshta et al., 2021; Shen et al., 2019). Further, in a populous country like India, practicing social distancing is impractical for a large share of the population. Given that the imposition of lockdown involves choosing between lives and livelihoods, prudent decision-making requires identifying regions where returns from lockdowns in reducing fatality are highest. We integrate the ability to practice social distancing into our analysis to explore how social distancing measures affect COVID-19-related deaths (Chiu & Tucker, 2020).

We use data from multiple sources and examine how case fatality rate (CFR), a measure of fatality, varies across the 18 major states of India during the nationwide lockdown between April 1 and May 31. We find that both testing and social distancing aid in reducing CFR in India. Our findings also validate the relevance of institutional factors in shaping these effects. Specifically, we find that testing efforts are higher in states with weaker medical infrastructure and states with lower per capita health spending. This suggests that testing can effectively aid states that are at a disadvantage due to a weaker health system. In contrast, we find that the effect of social distancing is conditioned by the ability to practice it: social distancing is more effective in states that are less populous and that have a lower proportion of households staying in a single-room homes. These results validate the more significant role that institutions play in influencing the effect of policies on outcomes.

Our findings are robust across a series of alternate measures of COVID-19 deaths and social distancing. The results emphasize that aggressive testing in states with a weaker medical infrastructure base may help advert COVID-19 severities through timely detection followed by contact tracing and isolation. On the other hand, lockdowns aiming at reducing mobility is strongly conditioned by the pre-existing socio-economic characteristics of households. Thus, the decision to impose lockdown requires careful scrutiny.

The rest of the article is organized as follows. We present India’s COVID-19 experience in Section 2. We explain our data and methods in Sections 3 and 4. Results are presented in Section 5. We conclude in Section 6.

## 2 | INDIA’S COVID-19 EXPERIENCE – THE ROLE OF INSTITUTIONS

India recorded its first COVID-19 case on January 30, 2020. With 600 (approximately) confirmed cases as of March 24, 2020, the country was led into a 68-day lockdown that spanned the entire country. Meanwhile, the Indian Council of Medical Research (ICMR), the apex body for formulating and coordinating testing guidelines related to COVID-19 in India, had issued strict guidelines for testing. Thus, with a nationwide lockdown and ICMR testing guidelines, the regulatory environment for states in managing the COVID-19 health crisis was uniform. However, infection and death numbers varied substantially across states in India. This opens the possibility of investigating factors that explain this variation.

Coming to our outcome variable, the moot question is how to capture COVID-19 severity? The choice of health outcomes is crucial amid concerns of underreporting of COVID-19 cases and deaths in India. In this article, we rely on COVID-19-related fatality to capture the severity of the pandemic (similar to Balakrishnan & Namboodhiry, 2021; Upadhyay & Shukla, 2021). We believe that the possibility of under-reporting is potentially higher for cases compared to deaths due to the following reasons. First, as per ICMR guidelines of testing only symptomatic individuals, the number of cases reported will be lower than the actual cases. In contrast, the death of an asymptomatic COVID-19 patient is improbable (Pormohammad et al., 2020). Thus, death numbers will have a lower degree of underreporting due to testing strategies (that did not test the asymptomatic cases) than cases in India (Jain and Chatterjee, 2020).

Second, with earlier reports of some states’ under-reporting deaths, ICMR had set up inter-ministerial committees to investigate the matter. Consequently, state governments have been found to revise their statistics on deaths and cases after a certain period. These points make the underreporting of death during the nationwide lockdown less problematic. However, this in no way implies that

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1. Government Response Stringency Index is developed by Blavatnik School of Governance, University of Oxford. It is based on publicly available information on 17 indicators of government responses. These indicators range from information on containment and closure policies to income support for citizens and health system policies. Source: https://www.bsg.ox.ac.uk/research/research-projects/oxford-Covid-19-government-response-tracker
2. https://www.thehindu.com/opinion/op-ed/riding-roughshod-over-state-governments/article3156809.ece
3. This policy response has also revealed mismanagement of the central and state governments - unplanned exodus of millions of migrant workers from cities, swift communal turn due to a huge spike in the number of cases post a religious gathering in Mid-March in Delhi, soaring joblessness and unemployment, limited support in kind and cash, and chaos in acquiring rapid testing kits.
4. Source: https://www.icmr.gov.in/pdf/covid/strategy/Strategy_COVID19_testing_India.pdf
5. Source: https://theprint.in/health/icmr-issues-new-guidelines-to-record-covid-deaths-says-this-will-help-build-robust-data/419004/
death-related measures of COVID-19 are entirely free of underreporting. Even after hospitalization, misreporting of the cause of death in COVID-19 patients might lead to underreporting of deaths. However, it is relatively easier to hide mass cases but not mass deaths. These issues make death-related measures more reliable than case-related measures.

We next focus on the two effective tools in controlling the COVID-19 health crisis—testing and social distancing (Kuniya & Inaba, 2020). With a nationwide lockdown and uniform testing guidelines issued by the ICMR, the important point is that all states had a similar regulatory environment for testing policies and social distancing practices. However, in its enormity, India exhibited huge spatial variation in mobility and testing rates across the states (Kumar & Nataraj, 2020). For instance, Maharashtra, Delhi and Gujarat had lower mobility, whereas states such as Bihar, Orissa and Himachal Pradesh had higher community mobility.8 Similarly, Andhra Pradesh and Delhi conducted a higher number of tests per thousand population, whereas Kerala and Uttar Pradesh had lower rates.7

Further, the effect of policy actions and interventions is conditioned by institutional factors and the pre-existing socio-economic characteristics across states in India (Mukherjee & Zhang, 2007; Rolfstam, 2009). For instance, the effect of testing in states with a weaker health infrastructure could be systematically different from states with a relatively stronger public healthcare system and medical infrastructure (Koshta et al., 2021; Shen et al., 2019). One may argue that a strong health care system is critical for the effective management of a health crisis. Alternatively, testing can act as a tool for compensating for weaker health capacity by effective contact tracing and isolating detected cases. This ambiguity in how medical infrastructure shapes the effect of testing on COVID-19 health adversities calls for an empirical investigation.

In contrast, the effect of social distancing patterns will depend on the feasibility of practicing it (Chio & Tucker, 2020). With a population of 1.3 billion, an average household size of five members and 40% of households dwelling in a single room home, social distancing is a privilege that few population groups can afford to enjoy.9 Similarly, most states in India have several slum clusters that are populous and have common drinking and toilet facilities outside their house premises. Social distancing is a distant dream for these groups of Indian populations (Nupur, 2021; Rahman, 2020). One needs to account for the ability to practice social distancing when examining its effect on COVID-19 health adversities. We expect that densely populated states and states with a higher proportion of families dwelling in one-room homes will exhibit lower effects of social distancing on health outcomes (Cable & Sacker, 2019; Lopoo & London, 2016; Nkosi et al., 2019).

To summarize, while examining the effect of testing and social distancing on COVID-19 fatalities in India, we take a detailed account of these pre-existing socio-economic factors that may explain the fatalities across states.

3 DATA AND METHODOLOGY

Data related to COVID-19 (cases, deceased, recoveries) and testing have been compiled from http://www.covid19india.org, a crowdsourced initiative that had curated data related to COVID-19 cases in India from state bulletins and official handles. The period of analysis spans from April 1, 2020, to May 31, 2020, and across major 18 states in the country.9 While COVID-19-related information was available for all 61 days, testing data availability is less uniform across the states.

The data for social distancing is extracted from the Google Community Mobility dataset that provides information on the percentage change in mobility for various locations (residential, workplace, parks and so on) across states at the daily level. Based on GPS location data, the mobility change is measured against a reference period for the 6 weeks between January and February 2020. To avoid weekly variation, each day is compared to the same day of the median day in the 6-week reference period.

We also use data on existing socio-economic conditions across the states. The impact of such measures on health outcomes have been documented in several studies (Chen et al., 2020; Fang et al., 2020; Lasry et al., 2020). Health and medical infrastructure variables are collected from the National Health Profile (2019). Data related to population density is from the Handbook of Urban Statistics (2019), published by the Ministry of Housing and Urban Affairs. We collect data on housing from the latest national sample survey report on drinking water, sanitation, hygiene and housing condition in India (76th round, 2017–2018). State-wise, population data has been collected from the Census of India, 2011. We also control for growth in state-level per capita state domestic product and percentage of rural consumption as of 2018–2019 from the Economic Survey (2019–2020).

Our final dataset is panel data across 18 states and 61 days (April 1–May 31). The dataset has daily information related to COVID-19, testing and social distancing. We also have time-invariant data on all other socio-economic factors.

3.1 Variable construction

Our outcome variable focuses on COVID-19 deaths in Indian states. Death-related measures are categorized into two groups—mortality rates and fatality rates. Mortality rate is defined as the proportion of the total population that succumbs to a disease during a specific period. A limitation of the mortality rate is that it does not take into account the number of infected cases.

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8This is based on the workplace mobility observed by people using GPS location on their mobile phones. We will discuss this measure in detail in the future sections. The data source is Google Community Mobility Reports. 
9This is based on the average testing rate observed during the data period. Source: Authors’ calculations
6Source: https://www.bbc.com/news/world-asia-india-52393382
To account for the number of cases, infection fatality rate (IFR) is defined as the number of deaths divided by the total number of cases. However, deaths are a consequence of past infection, and IFR does not account for it. On the other hand, the CFR is defined as the ratio of cumulative deaths to the sum of cumulative deaths and recoveries (Ghani et al., 2005). Notationally, for state $i$ and day $t$, CFR is defined as

$$\text{CFR}_{it} = \frac{\text{Cumulative deaths}_{it}}{\text{Cumulative deaths}_{it} + \text{Cumulative recoveries}_{it}}.$$ 

By using cases with outcomes as the denominator, that is, recovered or dead, it considers only those cases closed on a particular day. Therefore, for an ongoing pandemic like COVID-19, a better measure would be CFR. We calculate the CFR for each state at a daily level between April 1 and May 31.

The most important explanatory variables in our analysis are testing and social distancing. We define testing as the logarithm transformation of cumulative tests per thousand population for a state on a given date. We focus on residential mobility to measure the extent of social distancing. It is the percentage change in mobility compared to the same day of the week during the reference period. A rise in residential mobility implies better social distancing patterns in the state.

We use four broad pre-existing factors that may explain fatalities across states (Blundell et al., 2020). For the ability to socially distance, we use the population density and the proportion of households dwelling in a single-room home. We use two measures to capture the quality of health services in India—per capita health expenditure by states to measure health spending by various states in India and doctors per million population to capture the availability of medical infrastructure across states.

Internationally, the experience of COVID-19 suggests that incidences of death are higher in certain sections of the population (Liu et al., 2020; Yang et al., 2020). To capture population vulnerability at the state level, we use the proportion of people aged 60 and above to capture the elderly at the state level. We also use the proportion of people screened at noncommunicable disease clinics diagnosed with hypertension and diabetes. Finally, we use growth in state domestic product per capita and rural consumption share to capture income and the rural–urban divide across states. Summary statistics for each of the variables are presented in Table 1.

Table 1 shows considerable variation in CFR, testing rate and residential mobility in our sample. While overall CFR in India sharply reduced from 27% on April 1 to 4.75% on May 31, there was considerable variation across states.

Next, we explore if pre-existing socio-economic factors explain state-level CFR patterns. We group states in two subsamples—one with a higher than median value and the second with a lower than the median value. The state-wise composition of these categories is presented in Table A1. Next, we examine CFR differences between these groups Table 2.

Table 2 shows that all pre-existing factors (except income growth) play a significant role in explaining CFR differences across states. This
Empirically, the following model is estimated.

\[ y_{it} = \alpha + \gamma y_{jt} + R_i + \delta_1 x_{1t} + \beta_1 x_{1t-1} + \beta_2 x_{2t-2} + \beta_3 x_{3t} + \epsilon_{it}. \]  

(1)

where \( y_{it} \), \( x_{1t} \), and \( x_{2t} \) are the CFR, testing rate and mobility in state \( i \) on date \( t \). \( x_{it} \) is a vector of state-specific time-invariant socio-economic variables. \( \epsilon_{it} \) is the error term. Since the fatality of a case is conditioned on testing conducted in the past, we measure testing using different lag intervals (denoted by \( n \) in the model). Using a similar logic, we use mobility as the average mobility observed for \( n \) days before \( t \). \( y_{jt} \) and \( \delta_1 \) are the unobserved state and time fixed effects. \( R_i \) is the unobserved heterogeneity at the region \( j \) level. The use of lagged testing rates and past averages of mobility controls for the issue of any potential reverse causality. Similarly, the possibility of omitted variables affecting testing and CFR is also eliminated by controlling for both state and region* date unobserved heterogeneity. We use robust standard errors to control for heteroscedasticity.

Further, to explore if institutional factors drive the impact of testing and lockdowns on Covid related fatality, we estimate Equation (2) where in addition to variables used in Equation (1), we interact mobility with socio-economic time-invariant variables.

\[ y_{it} = \alpha + \gamma y_{jt} + R_i + \delta_1 + \beta_1 x_{1t-1} + \beta_2 x_{2t-2} + \beta_3 x_{3t} + \beta_4 x_{4t-2} + \beta_5 x_{5t} + \beta_6 x_{6t-1} + D_{ij} + \epsilon_{it}. \]  

(2)

\( D_{ij} \) and \( D_{ij} \) are vectors of dummy variables constructed from health care capacity and ability to practice social distancing measures using median deviation, respectively. All other controls and outcome variables remain the same as used in Equation (1).

4 | ECONOMETRIC METHODOLOGY

We estimate a fixed-effects regression model to compute the impact of testing on CFR. Empirically, the following model is estimated.

\[ y_{it} = \alpha + \gamma y_{jt} + R_i + \delta_1 + \beta_1 x_{1t-1} + \beta_2 x_{2t-2} + \beta_3 x_{3t} + \beta_4 x_{4t-2} + \beta_5 x_{5t} + \beta_6 x_{6t-1} + \epsilon_{it}. \]  

(1)

Note: *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

requires integrating these variables into our existing analysis to examine the effect of testing and social distancing on CFR.

5 | RESULTS

5.1 | Main results

We start with our baseline model of estimating equation (Abdullah & Kim, 2020). Models I, II, III, and IV use seven, nine, 11, and 13-day lagged values for testing. For residential mobility, the four models use averages over the same lags. The results are reported in Table 3.

Table 3 indicates that testing has a negative and significant effect on CFR, similar to Liang et al. (2020) and Vincent and Taccone (2020). Residential mobility that captures social distancing also has a negative and significant effect. This is in line with Flaxman et al. (2020), that found that nonpharmaceutical interventions like lockdown are highly effective in adverting COVID-19 related adversities. Table 3 emphasizes the joint role of testing and social distancing in mitigating deaths due to COVID-19.

We also find that certain pre-existing socio-economic factors such as the ability to socially distance and public health spending directly affect CFR. Specifically, states with a higher proportion of households staying in a one-room house and with lower per capita health expenditure have higher fatality rates, similar to Balakrishnan and Namboodhiry (2021). All models include unobserved effects at the state level. We also include region and daily date interactions to account for unobserved effects. To explore whether certain pre-existing conditions affect our main variables’ influence on COVID-19.
fatality, we estimate Equation (2) for the same models. We present the results in Table 4.

Testing rate and social distancing continue to have a strong negative effect on COVID-19 fatality rates in Table 4. Moreover, these effects are conditioned by the pre-existing factors prevailing in the states. We find that testing is more effective in states with fewer doctors per million population and states that spend lower per capita public health expenditure. Thus, testing aids in reducing CFR through screening and timely detection of infection more effectively in states that are at a disadvantage due to low quality and availability of medical infrastructure.

Higher residential mobility indicates better social distancing implementation, and we find that it continues to have a negative effect on CFR. Social distancing reduces fatalities in states that have a lower proportion of single-room households and in states that lower a higher population density. This suggests that the effect of social distancing is dependent on the ability of states to practice social distancing more strictly (by staying at home). Table 4 affirms that the relevant pre-existing socio-economic conditions influence both testing and social distancing. While testing aids in reducing deaths more effectively in states with a weak health infrastructure, social distancing is effective only in states with lower intra-household congestion and population density.

5.2 Robustness tests

We employ some robustness tests for validating our main findings based on alternate ways to define some of our variables of interest.

5.2.1 An alternative way to measure social distancing

We redefine our social distancing measure as the percentage change in workplace mobility. In contrast to the previous measure, a rise in workplace mobility indicates a drop in community mobility and hence a lower degree of social distancing. We present the results in Table 5.

Table 5 indicates a similar pattern as observed in Table 4. Testing continues to have a negative effect on CFR across Indian states. Additionally, a decline in workplace mobility, indicating stricter social distancing practices, is also associated with a drop in COVID-19-related fatalities. Further, the effect of testing accentuates if states have lower public health capacity and weaker medical infrastructure. Similarly, social distancing is higher in less populous states and have a lower population proportion dwelling in single-room households.
### TABLE 4  Effect of testing and social distancing with interactions on CFR

| Variables lags (n) | Model I 7 days | Model II 9 days | Model III 11 days | Model IV 13 days |
|-------------------|----------------|----------------|--------------------|------------------|
| Testing rate      | –0.090*** (0.014) | –0.091*** (0.012) | –0.080*** (0.012) | –0.065*** (0.012) |
| Doctors * testing rate | 0.088*** (0.010) | 0.101*** (0.007) | 0.098*** (0.007) | 0.084*** (0.007) |
| PCHE * testing rate | 0.038*** (0.006) | 0.048*** (0.006) | 0.053*** (0.006) | 0.054*** (0.004) |
| Residential mobility | –0.009** (0.004) | –0.013*** (0.004) | –0.012*** (0.003) | –0.007** (0.003) |
| One room households * residential mobility | 0.006*** (0.003) | 0.011*** (0.002) | 0.012*** (0.002) | 0.010*** (0.002) |
| Population density * residential mobility | 0.011*** (0.002) | 0.008*** (0.002) | 0.006*** (0.002) | 0.004** (0.002) |
| Controls          |                |                |                    |                  |
| State level income and inequality |                |                |                    |                  |
| Per capita GDP    | 0.030*** (0.011) | 0.041*** (0.008) | 0.041*** (0.009) | 0.042*** (0.009) |
| Rural share of consumption | –0.005 (0.003) | –0.001 (0.003) | –0.001 (0.003) | –0.004 (0.003) |
| Vulnerability in population |                |                |                    |                  |
| Prop of population with comorbidities | 0.611 (1.357) | 0.484 (1.404) | 0.400 (1.385) | 1.260 (1.257) |
| Prop of population above 60 years | 0.107 (0.072) | 0.105 (0.589) | 0.277 (0.485) | 0.791 (0.465) |
| Social distancing ability |                |                |                    |                  |
| Prop of households with 1 room houses | 0.359** (0.145) | 0.448*** (0.142) | 0.495*** (0.143) | 0.591** (0.124) |
| Population density | 0.001 (0.001) | 0.002 (0.001) | 0.003** (0.001) | 0.004*** (0.001) |
| Medical infrastructure and capacity |                |                |                    |                  |
| Doctors per million population | –0.001 (0.001) | –0.001 (0.001) | –0.001 (0.001) | –0.003** (0.001) |
| Per capita health expenditure | –0.006* (0.003) | –0.005* (0.002) | –0.002*** (0.000) | –0.003*** (0.000) |
| Other controls     |                |                |                    |                  |
| State fixed effects | Yes            | Yes            | Yes                | Yes              |
| Date*region fixed effects | Yes           | Yes            | Yes                | Yes              |
| No. of observations | 1026           | 988            | 950                | 912              |
| R- squared         | 84.95          | 86.90          | 87.77              | 88.51            |

Note: The table compiles results from the effect of testing rate and social distancing on CFR. All models include pre-existing economic, demographic and social factors as explanatory variables. All models have state level fixed effects and a date-region-level fixed effects. Model I uses seven day lagged testing rate. Models II, III, and IV use nine, eleven, and thirteen day lagged testing rates, respectively. The low number of observations is because testing is not reported regularly and lagged variables are used. Values indicate coefficients and robust standard errors are reported in parentheses. *, **, and *** indicate significance at 1%, 5%, and 10%.

### TABLE 5  Effect of testing and workplace mobility on CFR

| Variables lags (n) | Model I 7 days | Model II 9 days | Model III 11 days | Model IV 13 days |
|-------------------|----------------|----------------|--------------------|------------------|
| Testing rate      | –0.085*** (0.013) | –0.086*** (0.013) | –0.079*** (0.011) | –0.072*** (0.010) |
| Doctors * testing rate | 0.076*** (0.008) | 0.089*** (0.006) | 0.090*** (0.006) | 0.085*** (0.006) |
| PCHE * testing rate | 0.038*** (0.007) | 0.054*** (0.007) | 0.058*** (0.006) | 0.059*** (0.005) |
| Workplace mobility | 0.001* (0.0006) | 0.002*** (0.0008) | 0.003*** (0.0007) | 0.003*** (0.0006) |
| One room households * workplace mobility | –0.001 (0.007) | –0.001 (0.008) | –0.001* (0.006) | –0.002*** (0.0008) |
| Population density * workplace mobility | –0.005*** (0.001) | –0.004*** (0.0009) | –0.003*** (0.0008) | –0.003*** (0.0007) |
| Other controls     | Yes            | Yes            | Yes                | Yes              |
| State fixed effects | Yes            | Yes            | Yes                | Yes              |
| Date*region fixed effects | Yes           | Yes            | Yes                | Yes              |
| No. of observations | 1026           | 988            | 950                | 912              |
| R- squared         | 84.46          | 86.90          | 87.77              | 88.51            |

Note: The table compiles results from the effect of testing rate and social distancing on CFR. All models include pre-existing economic, demographic and social factors as explanatory variables. All models have state level fixed effects and a date-region-level fixed effects. Model I uses seven day lagged testing rate. Models II, III, and IV use nine, eleven, and thirteen day lagged testing rates, respectively. The low number of observations is because testing is not reported regularly and lagged variables are used. Values indicate coefficients and robust standard errors are reported in parentheses. *, **, and *** indicate significance at 1%, 5%, and 10%.
5.2.2 | Two alternate measures related to COVID-19 deaths

As an additional robustness test for our main findings, we use two alternative ways to measure COVID-19 deaths. We start with an alternate variable for case fatality ratio, defined as the proportion of COVID-19 daily deaths to cases. We present the results in Table 6.

Table 6 indicates that the effect of testing and social distancing measures continue to exhibit a similar pattern, as observed in our main findings. While our primary outcome variable, CFR, is
6 | CONCLUSION

With no vaccine or treatment in 2020, countries across the globe had opted for lockdowns, social distancing and testing. India followed suit and announced a nationwide lockdown around the last week of March. This article looks at the severity of the pandemic in India mainly through the lens of CFR. We validate our main findings with other death-related measures.

During the nationwide lockdown, although nationally, CFR plummeted, we found state-level variation in levels of CFR. We examine the effect of the twin actions of testing and social distancing on CFR. Our analysis confirms that both are important in reducing CFR. We further found that pre-existing socio-economic factors such as health care capacity and social distancing ability drive the impact of the two strategies of lockdowns and testing. Our regression results validate that these factors shape the extent of the effect of both testing and social distancing on fatality rate. Our results are robust to alternative measures of social distancing and fatality rates.

This article provides empirical support for the effective role of both testing and social distancing. However, the effect of policy measures and interventions requires a closer examination of the existing institutional and socio-economic factors that shape the main effects. While testing acts as a “catch up” tool in states with a weaker health system, social distancing measures remain a distant dream for states characterized by a vast presence of slums and one-room houses. Imposing stringent lockdowns will not render desired results in such situations. Thus, the article pushes for a coordinated effort between the government and citizens to manage COVID-19-related adversities.

7 | LIMITATIONS AND FUTURE DIRECTION

There are a few caveats to the analysis. Due to a lack of data on testing at the district level, the article limits the analysis to a state-level investigation. This does not allow us to capture inter-district variation within each state. Further, we cannot ignore the possibility of under-reporting of COVID-19-related deaths in India. However, since this is a problem plaguing all states of India, our broad finding of the vital role of pre-existing socio-economic factors influencing the impact of policies will probably still be valid. Additionally, we acknowledge that the current article focuses on the early days of the pandemic, and the situation has altered since then. India experienced the brutal second wave of the pandemic from April to June 2021, when deaths were at a record high level. The current study chalks out a basic pattern of the relevance of pre-existing factors. It opens the possibility of integrating these factors when focusing on the more detailed and recent COVID-19 deaths. An additional important area to explore is the role of some important factors such as attitude toward social distancing and medical awareness in determining severity of the illness. These aspects underscore the need for primary surveys for better health management in the future.

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DATA AVAILABILITY STATEMENT

Data available on request from the authors.

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APPENDIX A: I

TABLE A1 Category wise composition of states for the time-invariant factors of CFR

| PCHE | Doctors | Pop density | One rooms |
|------|---------|-------------|-----------|
| AP   | CT      | HP          | AP        |
| BR   | DL      | HR          | BR        |
| HR   | GJ      | KA          | CT        |
| KA   | HP      | KL          | DL        |
| MH   | JK      | OR          | GJ        |
| MP   | KL      | PB          | JK        |
| OR   | RJ      | RJ          | MH        |
| PB   | TG      | UP          | MP        |
| UP   | TN      | UT          | TG        |
| WB   | UT      | WB          | TN        |

Note: Above and below group median categories are denoted by “1” and “0,” respectively. The state codes are as follows: AP (Andhra Pradesh), BR (Bihar), CT (Chhattisgarh), GJ (Gujarat), HR (Haryana), HP (Himachal Pradesh), JK (Jammu and Kashmir), KA (Karnataka), KL (Kerala), MH (Maharashtra), MP (Madhya Pradesh), OR (Odisha), PB (Punjab), TG (Telangana), TN (Tamil Nadu), UT (Uttarakhand), UP (Uttar Pradesh), WB (West Bengal).

APPENDIX B: II

TABLE B1 The Hausman test results of the four main models have been presented below. The null hypothesis of random effects specification is rejected across all models suggesting that the fixed effects estimation is more suitable

| Independent variables | Hausman test statistic (chi-squared) | p-value |
|-----------------------|-------------------------------------|---------|
| 7 days lagged testing rate | 33.72 | 0.000 |
| 9 days lagged testing rate | 29.30 | 0.000 |
| 11 days lagged testing rate | 27.71 | 0.000 |
| 13 days lagged testing rate | 25.21 | 0.000 |

APPENDIX C: III

TABLE C1 Results of the panel data unit root tests have been compiled below. The null hypothesis assumes that Panels contain unit root. Since the p-value is <0.01, all variables are stationary

| Variable | Levin-Lin-Chu unit root test statistic | p-value |
|----------|---------------------------------------|---------|
| CFR      | −9.138                                | 0.000   |
| 7 days lagged testing rate | −16.358 | 0.000 |
| 9 days lagged testing rate | −15.614 | 0.000 |
| 11 days lagged testing rate | −15.322 | 0.000 |
| 13 days lagged testing rate | −14.841 | 0.000 |