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ORIGINAL ARTICLE

COVID-19 and Federalism in India: Capturing the Effects of State and Central Responses on Mobility

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Abstract

In response to the rapidly spreading COVID-19 pandemic, governments resorted to containment and closure measures to reduce population mobility and ensure social distancing. Initially, India's state governments enacted varying social-distancing policies until the Central government overrode states to impose a nationwide lockdown on 24th March. This paper examines the relative impact of state- and central-level social-distancing policies on changes in mobility, comparing the periods before and after the national lockdown. A district-level panel dataset is formed, compiling data on social-distancing policies and changes in population mobility patterns. Panel regressions reveal that the incremental effect of each social-distancing policy varied across states in the pre-24th March period. The national lockdown led to much larger, though varying, reductions in mobility across all states. Overall, states which were able to achieve higher compliance in terms of reducing mobility in the pre-lockdown phase performed better in the national lockdown.

Keywords COVID-19 · Mobility · Social distancing · Federalism · Lockdown

JEL Classifications I18 · H11 · H77 · C23

Résumé

Pour faire face à la propagation rapide de la pandémie COVID-19, les gouvernements on fait recours à des mesures de contention et de clôture, afin de réduire la mobilité des populations et d'assurer la distanciation sociale. Initialement, les gouvernements des états de l'Inde ont promulgué différentes mesures de distanciation sociale jusqu'à que le gouvernement centrale les a contournés, imposant un confinement nationale

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le 24 mars 2020. Cet étude examine l'impact relative des mesures de distanciation sociale au niveau nationale et régionale sur les changements en mobilité, comparant les périodes avant et après le confinement nationale. Compilant des données sur les politiques de distanciation sociale et les changements dans les tendances de mobilité de la population, nous avons construit un fichier de données de panel au niveau des districts. Utilisant des modèles de régression sur ces donnes, nous trouvons que l'effet incrémental de chaque politique de distanciation variait parmi les états avant le confinement du 24 mars. Le confinement national a fortement réduit la mobilité dans tous les régions de l'Inde, même si variablement. Globalement, les états qui ont réussi des niveaux de conformité plus élevés dans la réduction de la mobilité avant le confinement ont été plus performants pendant le confinement nationale.

Introduction

With the emergence of COVID-19 in early 2020, governments resorted to an array of non-pharmaceutical measures to arrest the spread of infections and prevent health infrastructure from being overwhelmed. Social-distancing (SD) or containment policies were the primary form of non-pharmaceutical interventions (NPIs) implemented by nations, aimed at reducing mobility and contact between individuals. As non-essential activities were restricted and people were ordered to stay home, this triggered a crash in consumption, production, and employment, leading to the largest global recession since 1929 (IMF 2020). Huge drops in population mobility were the immediate manifestation of these policies. The unprecedented nature of the pandemic meant that the optimal combination of policies was not known, and government responses varied substantially even at the subnational level. This article aims to analyse the effects of social-distancing policies on changes in mobility in India, focusing on the variations in the impact of state- and national-level policies.

In almost all countries, containment policies consist of the following measures: closures of educational institutions, recreational establishments, bars and restaurants, and non-essential businesses; restrictions on public gatherings; travel restrictions; and emergency declarations. These measures translated into large reductions in population mobility as people spent more time in their residences. Mobility changes, thus, reflect the immediate impact of social-distancing policies and indicate how effective governments are at enforcing policies and ensuring compliance. International evidence shows that such restrictions significantly reduced mobility, and consequently, the rate of spread of infections. For example, mobility restrictions such as travel regulations delayed the overall spread of the epidemic by 3 to 5 days and reduced movements by 54–76% in Wuhan in China (Chinazzi et al. 2020; Fang et al. 2020). However, all SD policies did not have similar impacts on mobility. In the United States, contesting results are found regarding the efficacy of closure orders over 'stay-at-home' orders (Gupta et al. 2020; Wellenius et al. 2020).

This article also engages with a broader policy debate that has emerged during the pandemic: the role of federalism in public health crises. Indian state governments were empowered to enact any necessary SD policies under the Epidemic Diseases Act

(EDA), 1897, which was invoked on 11 March 2020 after an advisory from the national government. Till 21 March, the set of SD policies adopted by states varied substantially, until the Prime Minister called for a nationwide voluntary curfew (a 'Janta' Curfew) on 22nd March. This was followed by the sudden declaration of a nationwide lockdown on 24th March. This lockdown brought the country to an almost complete halt and was ranked among the most stringent government responses to COVID at the time (Hale et al. 2020). The order overrode states' autonomy to formulate SD policies and laid out regulations relating to all aspects of administration. Starting in May, the central government gradually relaxed restrictions and handed back decision-making authority to the states. The extent of the Indian central government's intervention stood out among other major federal nations, where subnational governments had more autonomy in determining their policy response to the pandemic.

Several studies have focused on the effects of the national lockdown on mobility. Denis et al (2020) found that for most states, mobility declined by around 40%. Among the Delhi's poor, the national lockdown reduced intra-city mobility by 80%, working days by 73%, and income by 53% (Lee et al. 2020). However, evidence for the efficacy of state-level restrictions is relatively scarce, likely due to the lack of comprehensive data on SD policies at the subnational level.

Compiling information on state and national government executive orders, an additive index of SD policies was constructed for 609 districts across 28 states, for the time period from 10th March to 26th April 2020. This is merged with data on aggregate mobility levels provided by Google, to form a district-level panel dataset. Using a fixed effects (FE) panel regression, we analyze how states' own actions fared in terms of reducing mobility till 23 March. Second, we estimate the mean change in mobility levels for each state in the period after the national lockdown, compared to pre-24 March levels. The findings indicate that there was substantial heterogeneity in the efficacy of state-level response before 22 March, with multiple states not achieving any significant reductions in mobility through their own actions. The national lockdown led to a huge rise in time spent in residences across all states, though they subsequently tapered off to different levels. More importantly, states which were better in enforcing initial SD policies experienced better compliance with the national lockdown as well.

The remainder of the paper is organized as follows. The "Analytical Framework" section describes the analytical framework used in this paper. The "Data and Variables" section introduces the data and construction of variables. Models and methodology used in the paper are described in the "Empirical strategy" section. Empirical results are discussed in "Results" section. The "Discussion" section engages in a discussion of the insights related to the findings. The paper ends with concluding remarks in the "Concluding Remarks" section.

Analytical Framework

The spread of COVID-19 provoked two types of responses to reduce mobility: voluntary actions and explicit social-distancing policies enacted by governments. The risk of illness and death associated with the virus acts as an incentive for people to

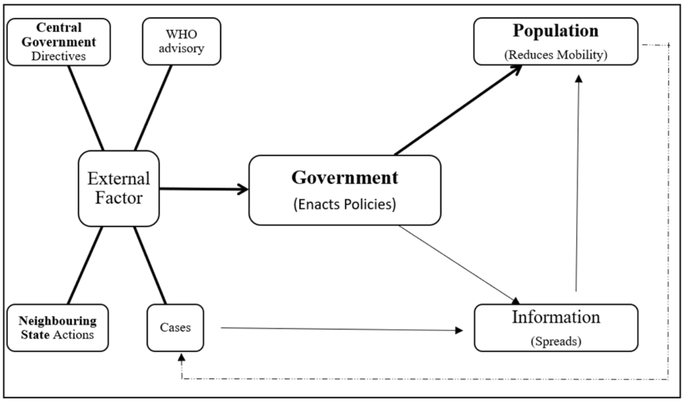


Fig. 1 Schematic diagram of channels leading to reduction in mobility

voluntarily reduce mobility. Information of positive cases and policy actions taken in response to COVID-19 spreads awareness across society, further accelerated by media coverage (Choudhury et al 2020; Suwanprasert 2020).

Apart from the above voluntary channel, governments across the world enacted restrictions on commercial and recreational activity. People's compliance with such measures largely depends on the government's ability to enforce them, which is related to the quality of institutions and level of trust in authority (van Rooij et al. 2020; Painter and Qiu 2020).

The sequence of actions that reduce mobility—the policy channel and the information/voluntary channel—are traced in Fig. 1. From the perspective of a subnational government, the policy channel (thicker arrow) is invoked with an external event—the trigger event can be an international or national advisory, reports of cases, and adoption of policies in other regions. Social-distancing policies are imposed to reduce mobility and consequently the transmission of infections, as shown by the dotted arrow. Information about the rising risks spreads rapidly among the population, propelled by external events and government actions, and induces people to voluntarily reduce mobility as well (thin arrows). The current study focuses specifically on the policy channel.

Data and Variables

Social-Distancing Policies

Under the powers of the EDA (1897), state governments enacted multiple policies to implement social distancing and reduce mobility. Orders enacted under the EDA are enforceable under law, with penalties prescribed for violators. The existing legal framework enabled district authorities to declare curfews and restrict public gatherings through section 144 of the Criminal Procedure Code (CrPC) 1973. Consistent with this, states and the Central government initially imposed stringent containment policies—including lockdowns in a targeted manner in some districts. This makes it necessary to record SD policies at the district level for a comprehensive accounting of subnational responses.

An additive index is constructed, comprising the number of SD policies implemented by each state government. The policies considered in this index are organized under the following categories:

a. *Declaration of an Epidemic/Emergency:*
   By acknowledging and publicly declaring the situation as an emergency, the government sends a signal to its citizens to prepare for precautionary steps.
b. *Closures:*
   Closure of several services and prohibiting the functioning of many institutions have been a crucial policy to ensure social distancing. This category comprises four measures:

   (i)Closures of educational institutions
   (ii)Closures of bars and restaurants
   (iii)Closures of recreational centres (theatre, gymnasiums, museums).
   (iv)Closures of non-essential services (private business enterprises, shops, and public sector institutions)

c. *Internal Travel Restrictions:* Another category of SD policy is restrictions imposed on traveling and public transportation. It comprises two measures:

   (i)Restrictions on public transport (buses, cabs, trains and flights)
   (ii)Border closures (all inter-state movements are banned, including private transport)

d. *Restrictions on Public Gatherings:* To ensure social distancing, many governments have enacted a restriction on public gathering. This effectively puts an upper limit on the number of people who can gather at a particular place like parks or events like weddings.

Using state government executive orders and national and regional news reports, we compile data on these eight indicators. They conform to the 'containment and closure' category of the OxCGRT (Hale et al 2020), a widely used framework to categorize government responses to COVID-19.[1] Further details of each policy are provided in Appendix A1. Each policy is indicated through a binary variable, assigned a value of 1 for all the days, the policy was in effect in a state, and 0 otherwise.

[1] The indicators differ from OxCGRT, while the OxCGRT uses an ordinal measure.

However, binary coding may not capture the subtle differences between state policies (Curley and Federman 2020).

The index is a simple sum of all the eight binary indicators (S^j) where $j = 1,\ldots,8$. S^j takes the value of 1 for all those days the jth policy was in effect in a district and is 0 otherwise.

$$I_{it} = \sum_{j=1}^{8} S_{it}^{j}.$$

This index I_{it} represents the additive index of the ith district at the tth time period. It yields a minimum score of 0 and rises to a maximum of 8. A 'lockdown' is a separate order, but in effect, it is a situation where all eight variables are simultaneously equal to one.

Bans on public gatherings varied widely among states, based on the permitted threshold, i.e. the maximum number of people allowed in each gathering. We take the inverse of the threshold of public gatherings, which rises from 0 to 1 as the threshold decreases. A state which bans all gatherings—threshold of 1—is assigned the maximum score of 1, while a state which bans gatherings of 20 people or more is assigned a value of 0.05. States which have not passed any ban on public gatherings are assigned a value of 0.

An implicit assumption in the construction of the index is that social-distancing policies carry equal weightage. However, the policies might differ in terms of scope. School closures might be more far reaching than public gathering bans, affecting daily movement patterns of a larger section of the population. It also assumes that similar policies are identically designed and enforced across different states. Other measures were more ambiguous and conceal minor variations among states. While some states closed all recreational establishments in a single order, others gradually closed services through successive orders. The quality of enforcement is also not captured in the index.

Disentangling the effect of any specific policy is difficult, as several states imposed multiple policies concurrently (Wellenius et al. 2020). This analysis, therefore, evaluates the effect of an *additional* social-distancing policy for states, irrespective of the exact policy. Under the EDA, states were free to enact any policy they deemed necessary. In this respect, the additive index is helpful in providing a broad picture of the efficacy of state-wise policies.

Search Trends

Recent statistics indicate that a majority of Indian smartphone users access news primarily online (Aneez et al. 2019). The relative volume of searches on issues related to COVID-19 indicates the awareness levels of the population. We include Google Trends data on the state-wise relative frequency of online searches related to COVID-19. The data are based on a sample of the total searches for the topic

COVID-19 in a state within the time range of our study, expressed as an index of relative volumes of searches. A higher value of the index means that searches related to the topic increased as a proportion of all searches (Rogers 2016). This is obtained by dividing the daily number of searches for the topic COVID-19—which includes different words like ‘coronavirus’, ‘covid’, and ‘SARS-ncov 2’—by the maximum number of daily searches. The index ranges from 0 to 100, with 100 representing the day with the highest search volumes, and 0 indicating the day with the minimum searches (Brodeur et al 2020).

Mobility

Google Community Mobility Reports at the district level are used to measure changes in mobility. The data record changes in mobility trends for six categories of locations: grocery and pharmacy stores, parks, transit stations, retail and recreational establishments, workplaces, and residences. The metrics are based on the aggregated and anonymized data of Google users who have enabled ‘Location History’ on their devices (the default setting is off).

Our primary variable of interest is percentage change in time spent in residences relative to the baseline level, which is inversely related to the change in out-of-residence mobility. The value of each category shows the change in mobility for each day of the week, relative to that day’s baseline level (the median for all Tuesdays during Jan 3–Feb 6, 2020). For example, the value on 24 March (Tuesday) was the percentage change in time spent in residences, relative to the median value for all Tuesdays in the period from January 3 to February 6. In other words, a higher value of residential mobility on Tuesday may not mean a relative increase in the number of people staying at home compared to Monday. To make this mobility comparable over each day, the time series is smoothed using an exponential filter with an optimal smoothing parameter (Appendix A2). Summary statistics of all the variables are given in Appendix A3.

There may be concerns regarding the representativeness of the data for low income and less digitally literate persons. The accuracy of mobility data is also sensitive to internet connectivity.[2] Further, Google’s official documentation of the data states that they “use signals like relative frequency, time and duration of visits to calculate metrics related to places of residence”. (Aktay et al. 2020). The definition of ‘residence’ is kept vague because of privacy issues; users’ residences are likely identified from location history data from the period from January to February 2020. An implication of this is that the data may not accurately reflect migration between districts or states (see “Discussion” section for details).

[2] Meghalaya and Manipur witnessed large spikes in mobility measurements on 1st and 17th March, respectively. The state governments had shut down mobile internet services in response to civil unrest due to ethnic clashes. (https://www.newindianexpress.com/nation/2020/mar/17/naga-kuki-clash-puts--manipur-on-edge-2117563.html) (https://indianexpress.com/article/north-east-india/meghalaya/meghalaya-tense-another-death-amid-sporadic-violence/).

Despite its limitations, with growing internet penetration in India, such device-based mobility data should capture movement patterns of a substantial part of the population. In 2019, rural internet users outnumbered urban users (Iamai and Nielsen 2020). Most of these users accessed the internet through mobile phones. In 2018, there were an estimated 390 million mobile internet users in India. Around 77% of smartphones have Google search engines pre-installed (Agnihotri and Chetan 2019).

Empirical Strategy

The analysis is conducted on a panel dataset of social-distancing policies, mobility, and search trends of 609 districts in 28 states, over a period of 72 days from 15th February to 26th April. State policies varied widely till 23 March, after which the national lockdown imposed a uniform set of policies from 24th March. Two fixed effect (FE) panel OLS models are estimated. The first model is estimated over the period from 15 February to 23 March, allowing us to evaluate the 'pure' effect of state-level social-distancing policies. The second regression is estimated separately for each state over the entire time range, to calculate the state-wise average impact of the national lockdown.

Impact of State-Level SD Policies

The main explanatory variable is the social-distancing index I_{it}. The possibility of differential policy impacts across states is accommodated by specifying separate slope coefficients for each state. The panel regression is estimated using Eq. (1)

$$M_{it}^{k} = \alpha_0 + \alpha_1^k I_{it}^k + \beta_{1j} X_{it}^k + \theta_i^k + \varepsilon_{it}^k, \tag{1}$$

where M_{it}^{k} is the time spent in residence of the ith district of the kth state at the tth time period. I_{it}^k is the value of the SD index for district i of the kth state at time t. α_1^k is the slope coefficient of I_{it}^k for the k^{th} state. X_{it}^k is the vector of control variables (search index and the inverse of public gathering threshold) of the ith district of the kth state at the tth time period. β_{1j} is the vector of slope coefficients of the control variables. θ_i^k is the unobserved district specific fixed effect.[3] ε_{it}^k is the random component.

Due to differences in state-specific characteristics the errors may not have constant variance *across* states. Additionally, the error terms are also likely to be dependent on their own past values, i.e. they are autocorrelated *within* states. We specify cluster robust standard errors to correct for heteroskedasticity and autocorrelation in the residuals within clusters.

The Prime Minister called for a voluntary '*Janta* curfew' (citizens' curfew) across the nation on 22 March, Sunday, where every citizen was requested to stay at home.

[3] We estimated a random effects model with no significant differences. Results are available on request.

The high compliance achieved on that day cannot be ascribed solely to state-specific policies. Hence, the above model is estimated for two time periods: from 15 Feb to 23 March, and 15 Feb to 21 March. The second model is a better way to estimate the pure effect of state-level policies, uncontaminated by Central government directives.

Impact of National Lockdown

For each state, Eq. 2 separately estimates the effect of the national lockdown on mobility.

$$\mathrm{M}_{it}^{k} = \alpha_0^k + \alpha_1^k \mathrm{Lockdown}_t^k + \alpha_2^k \mathrm{search}_{it}^k + \theta_i^k + \varepsilon_{it}^k. \tag{2}$$

M_{it}^{k} is the time spent in residence for the ith district of the kth state at time period t, as earlier mentioned. Since, the state-level SD policy index shifts to 8 when the lockdown dummy is equal to 1, a time dummy variable $\mathrm{Lockdown}_t^k$ is considered in the model which takes the value 1 corresponding to the national lockdown period (from 24th March onwards) and 0 otherwise for each state k. α_1^k is the average mobility change associated with the national lockdown for the kth state. search_{it}^k is the search volume related to COVID-19 for the ith district of the kth state at time period t. θ_i^k is the district-level fixed effect for each state k.

Results

Descriptive Statistics

The figure in Appendix A4 plots the values of SD policy index for each state within a time span of two weeks, from 10th March to 23rd March. All the values of the index reach the maximum with the imposition of the national lockdown on 24 March and subsequently do not change till 26th April.[4] Each jump in the line indicates that additional policies were enacted. The patterns in which the SD policies were implemented can broadly be identified as ‘gradual’ or ‘abrupt’. The example of a completely gradual response would be the enactment of 8 policies in a calibrated, sequential manner over 12 days. The most abrupt response would consist of a state which implements all the SD policies in a single day, raising the index directly from 0 to 8. The states’ policy responses lie between one of these approaches. Figure 2 plots the movement patterns of the SD Policy Index for three states. Himachal Pradesh enacted policies in a relatively gradual approach, in a staircase-like pattern. In contrast, an abrupt policy response can be identified where the line remains flat for most of the time range, with steep ‘cliffs’ at the beginning or at the end of the time range. Kerala was an example of an early and abrupt responder, enacting 4 policies by 11th March—declaration of an emergency, closing schools, movie theatres,

[4] Although in the time period of our analysis, the values of SD index do not fall, it would theoretically decline when the restrictions would begin to be lifted, as witnessed after 4th May in India.

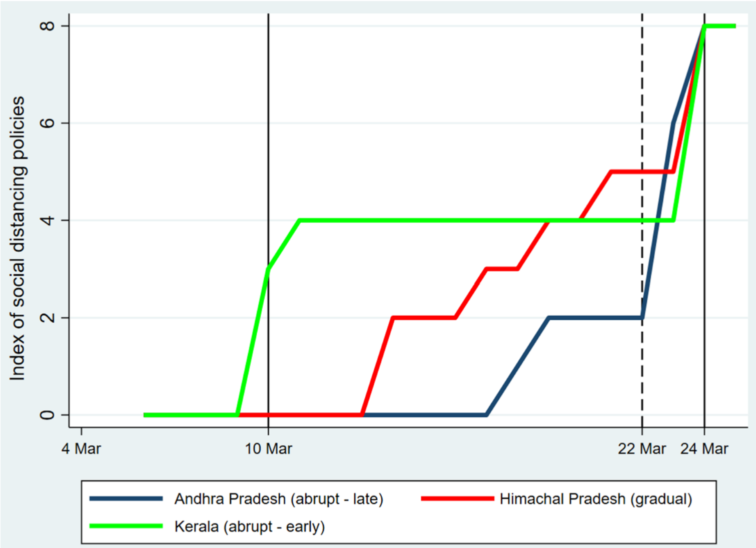


Fig. 2 Values of SD Policy Index for three states (March 4 to March 25). *Note*: Black vertical line on 10th March denotes declaration of pandemic by WHO. The one on 24th March denotes national lockdown. Dashed line on 22nd March represents *Janta* Curfew

and banning public gatherings. Andhra Pradesh acted relatively late, closing schools only on 18th March, and imposing a flurry of measures between 22nd and 24th March (see Appendix A4). These variations indicate considerable heterogeneity between states in the policy responses to the pandemic. These serve as motivation to check for state-specific effects of social-distancing policies on mobility.

School closures were the most common first measures—23 states had closed educational institutions as their first action. 13 of those states had closed malls, and two states had also imposed restrictions on public gatherings on the same day as well. Maharashtra was the only state to impose bans on public gatherings as the first restriction. Three states in the Northeastern region imposed travel restrictions on domestic and foreign tourists by pausing the issue of new Inner Line Permits.[5]

Time spent in residences started rising from 10th march onwards with the imposition of SD policies. As depicted in Appendix A5, two sharp, distinct jumps in stay-at-home rates are visible. The first one was immediately after the declaration of COVID-19 as a pandemic by the WHO on 11th March. The second spike was on Sunday, 22nd March, the day the *Janta* Curfew was declared. The patterns till March 21 capture the effects of state-level actions more accurately. Compliance with mobility restrictions was not proportional to SD policies across states even in the period before the national lockdown. With two policies implemented, Maharashtra saw the highest fall in mobility, with a 17% rise in time spent in residences. In

[5] Indian citizens require travel permits called Inner Line Permits from the state governments of Arunachal Pradesh, Mizoram, Nagaland, and Manipur to enter these states.

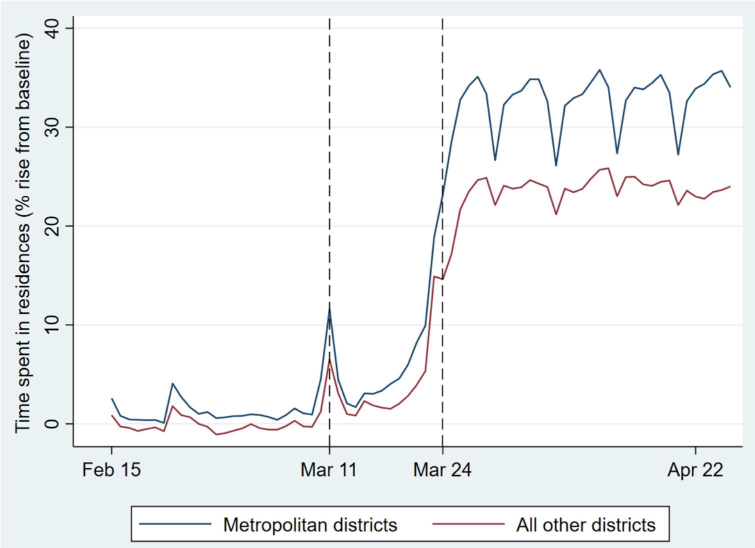


Fig. 3 Avg. values of time spent in residences, metropolitan vs all other districts

contrast, Bihar had enacted 4 policies with a corresponding rise in time spent in residences by 1%.

With the imposition of the national lockdown, time spent in residences reached its highest levels in the duration of the data. However, levels of time spent in residences varied considerably across states during the lockdown phase. Rajasthan and UP were among the states that kept mobility close to levels prevailing at the beginning of the national lockdown; while states like Delhi and Punjab were characterized by larger fluctuations. The states with the highest levels of time spent in residences post-24th March were Goa, Delhi, Puducherry, and Kerala. The states which were the least effective in keeping people at home after 24th March included the Northeastern states and Bihar. This result corresponds to the observed inverse relation between individual compliance and the duration of social-distancing policies (Moraes 2020; Briscese et al. 2020).

The behaviour of district mobility differs markedly for metropolitan and non-metropolitan districts. This might be caused by measurements being more sensitive in cities because of higher internet connectivity or possession of smartphones than rural areas. Voluntary compliance could also be higher due to higher awareness and risk perception. However, these patterns may also arise from stricter enforcement of social-distancing policies in metropolises due to greater rule of law, police presence, and coverage of violations through news and social media. Figure 3 reveals that after the declaration of national lockdown, metropolitan regions reported much higher levels of reduction in mobility than non-metropolitan districts. After the imposition of national lockdown, there is a periodic

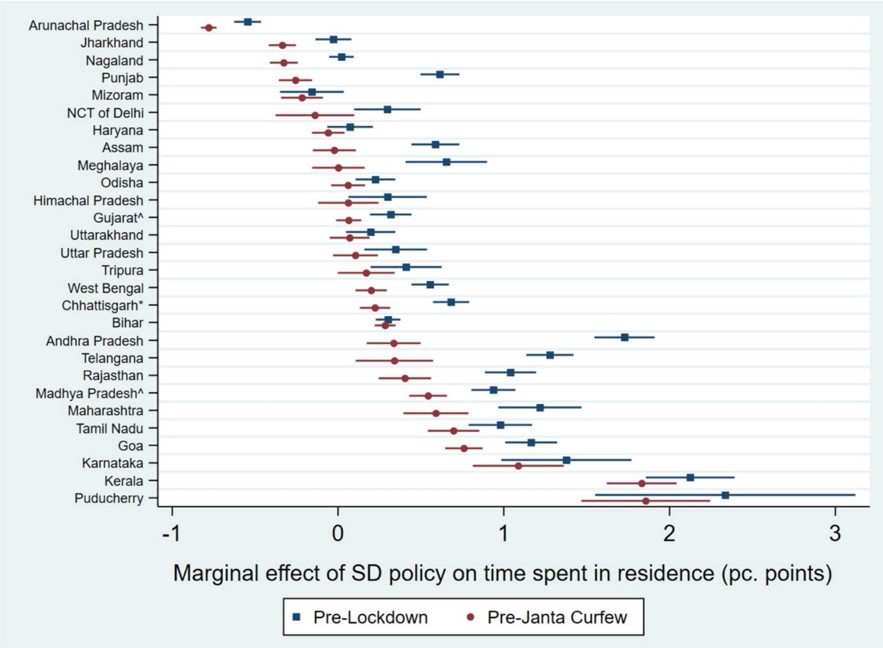


Fig. 4 Coefficient plot: effect of social-distancing policy on Mobility (before national lockdown). *Note*: * represents states which declared state-level lockdown and ^ represents states which locked down particular districts before 24th March

increase in relative mobility during the weekends for both type of regions. This is a consequence of the way mobility data are measured, with each day's value of time spent in residences being calculated in terms of percentage change from the baseline value for that day. As many people spent more time in residences on the weekends during the baseline period, the relative increase is lower.

Panel Regressions

Figure 4 plots the coefficients of state-level SD indices from Eq. (2), for two periods: before the national lockdown (11 Mar–24 Mar) and before the *Janta* Curfew on 22nd March (regression results in Appendix A6). The pre-national lockdown estimates in blue show the incremental effect of an additional social-distancing policy on time spent in residence. States successful in reducing mobility were Puducherry (2.34%), Kerala (2.13%), and Andhra Pradesh (1.73%). Lowering the permitted threshold of public gatherings and rising search volumes for COVID-19 had a positive effect on the time spent in residences. The *Janta* Curfew on 22nd March acted as a catalyst for several lagging states to ramp up the stringency of their restrictions, as multiple states shut down non-essential services and enacted travel restrictions. The maroon markers in Fig. 4 plot the coefficients from Eq. 1. When the effects of the *Janta* Curfew are excluded, the pure effect

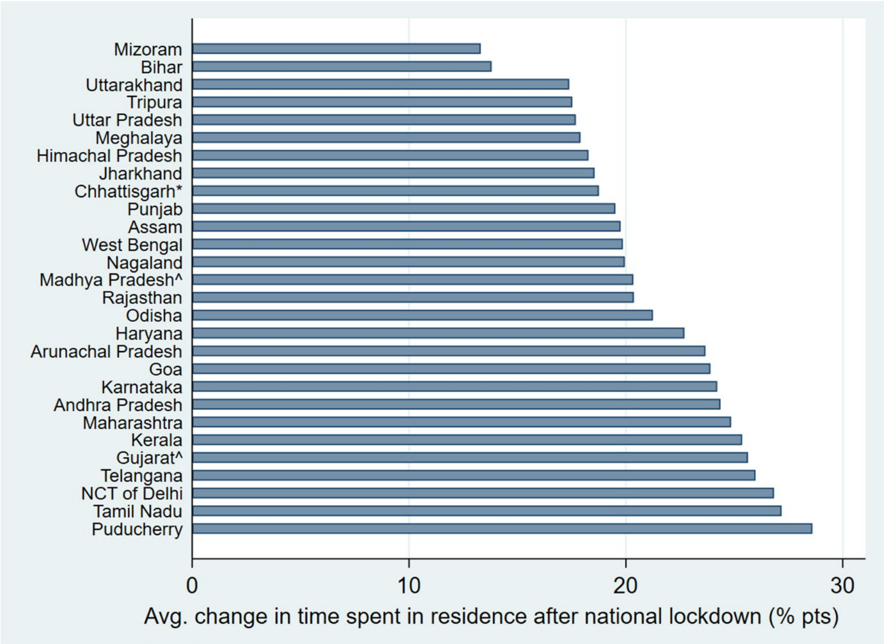


Fig. 5 Coefficient of effect of national lockdown for each state

of the state-level policies turns out to be insignificant for nine states, including several major states like Delhi, Uttar Pradesh, Gujarat, and Odisha. Kerala and Puducherry remain unchanged as the most successful states. These two states experienced the largest mobility reductions after the *Janta* Curfew, as their marginal effects of SD policies increase substantially. Their marginal effects on time spent in residences were actually higher than the corresponding effects for all states even after including 22nd and 23rd March. The ordering of the other states remains roughly similar, though the magnitude of the coefficients is lower. Telangana and Andhra Pradesh registered the highest additional drops in mobility with the *Janta* Curfew. In general, southern states achieved better results through their own policies in both phases of the pre-national lockdown period (Fig. 5).

Negative and significant coefficients of social-distancing policy for a state would mean, counter-intuitively that an additional SD policy enacted by the state led to declines in time spent in residence. It is possible that these negative coefficients indicate that state governments failed to reduce mobility with their own policies. However, such coefficients are seen for six states—Arunachal Pradesh, Mizoram, Nagaland, Manipur, Punjab, and Jharkhand. Four of these states are in India's remote Northeastern region, and all of them except Punjab have relatively high forest cover and low internet penetration (see " Mobility" section and endnote ii). However, the negative coefficient for Punjab disappears in further robustness checks ("Adjusting for Endogeneity in the Model section).

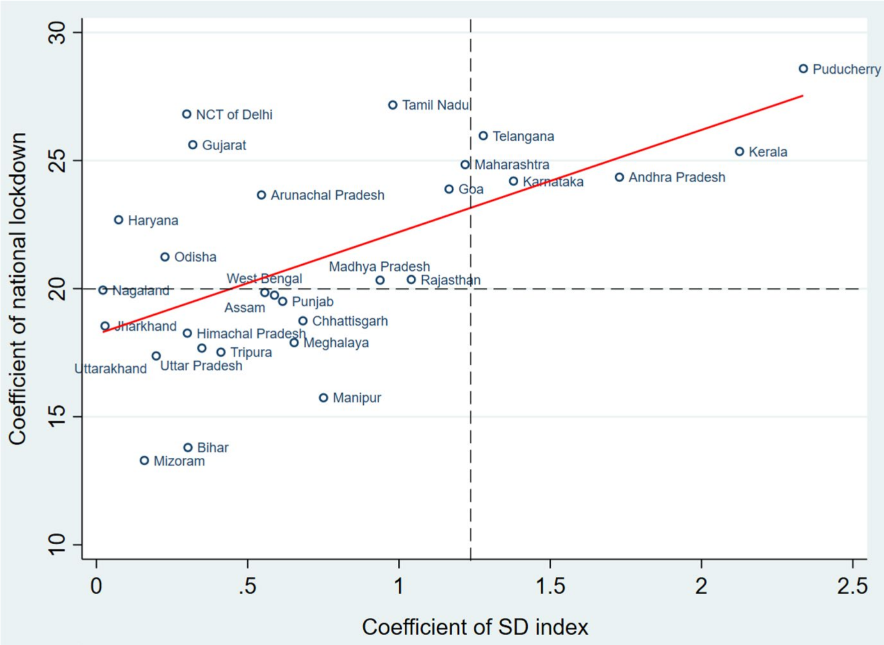


Fig. 6 Scatter Plot of state-wise marginal effect of SD policy and mean effect of national lockdown. *Note*: State-wise coefficients of SD policy index are drawn from column 1 of table A9. Coefficients of national lockdown are drawn from column 2 of table A10

The huge effect of the national lockdown is seen in Fig. 6. The effect is calculated with respect to the mean mobility levels prevailing in the period from 15th February to 23rd March. The declaration of the national lockdown was associated with an average increase in time spent in residence ranging from 13.8% in Bihar to a maximum of 28.6% for Puducherry (although it was significant at the 10% level).

To compare the effectiveness of SD policies and national lockdown across states, Fig. 6 plots a scatter diagram of the state-wise impact of SD policies (horizontal axis) and the average impact of the national lockdown (vertical axis).

States towards the right of the plot were characterized by larger coefficients of state-level policies. Analogously, states towards the upper region had larger effects of the national lockdown. The positive slope of the fitted line indicates that states which were able to elicit higher responses in the initial phase also saw a higher effect of the national lockdown. The graph can be divided into four quadrants, as indicated by the dashed lines drawn through the midpoints of the axes. The lower left and upper right quadrants contain states which performed similarly, with both the phases characterized by low or high changes in mobility (compared to the median), respectively. The upper left quadrant depicts states which performed below median in the pre-lockdown phase but achieved much larger mobility reductions after the national lockdown. Interestingly, the lower right quadrant is empty; indicating that there was no state which performed above median during the state-level phase but achieved relatively lower mobility reductions in the national lockdown phase.

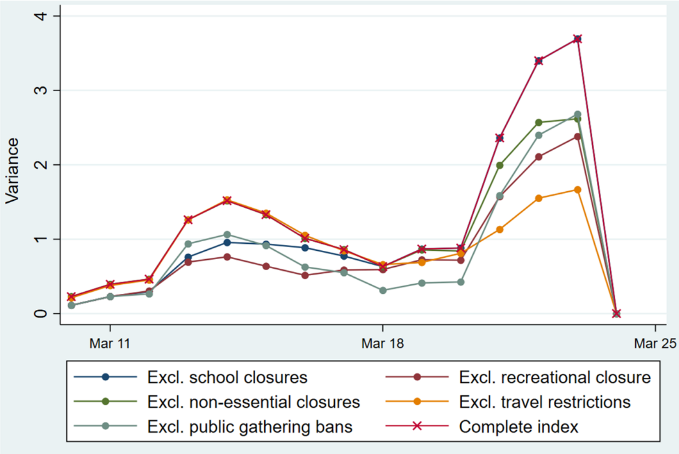


Fig. 7 Variations in SD policy index from March 10–24, by different components

Robustness

Additive Index of Social Distancing

There are concerns that the model results may be sensitive to the construction of the additive index of SD policies. Variations in the index across states are highly sensitive to the inclusion/exclusion of particular components of the SD index. Any component in the index would be redundant if the variance of the index across states and time remains unchanged by its inclusion or exclusion. To check the contribution of each policy, we create six different indices, by excluding one different category of SD policies from the complete index. Figure 7 shows the variance for each of the six indices across states, for each day of the pre- national lockdown period.

The variance remains zero till March 10, when before states started enacting restrictions. The variance drops to zero again from 24th March, as the national lockdown imposed a uniform set of policies across all states. The complete index shows the highest variation across states throughout the period, demonstrating that no component is redundant in the index. This characteristic makes the complete index most suitable for use as an explanatory variable in the regressions. The variance of social-distancing policies increases initially, followed by a period of relative convergence (decreasing variance) among states' restrictions till March 19. After that, divergence in SD policies across states rose rapidly, as a few states rapidly imposed several restrictions.

Checking Consistency of the Results Between the District-Level and the State-Level Model Specification

The outcome variable, viz., mobility varies at the district level, whereas the key independent variables do not differ extensively at the district level. State governments and the Centre imposed targeted measures in relatively few districts before 24 March, which were quickly superseded by statewide containment orders. Also, the index of Google search trends is available at the state level. It is recognized that an extremely large number of observations (N) may artificially inflate statistical significance of coefficients, making it easy to detect trivial differences in the outcome variable (Bruns and Ioannidis 2016). To ensure that the district-level regressions are not reporting false-positive results, we aggregate observations for each state and have re-estimated the model given in Eq. 1 at the state level to check the robustness of our initial results. The estimated results are reported in Appendix A8 (column 1 and 3), which show that district- and state-level results are broadly consistent.

Adjusting for Endogeneity in the Model

The estimated coefficients of the panel FE regression model, considering both the district- and state-level data before the national lockdown period, elaborate the effect of a state's social-distancing policies on its population mobility. The model also addresses the concern about public awareness of the state by taking the 'search' variable as a control in the model that can directly affect its population mobility. However, issue of endogeneity may arise due to omitted factors which can be correlated with the main explanatory variables. An example in this regard can be the number of cases in the state. The reported number of cases will influence the social-distancing policies, as respective states respond to address the rise in cases by escalating their policy response. In order to address this endogeneity, Panel Instrument Variable (IV) FE regression based on Eq. 1 is employed for both the district- and state-level data following Baum et al. (2015) to check the robustness of our analysis. Hence, an appropriate instrument variable is required which is correlated with social-distancing policy but is uncorrelated with the error term, i.e. it affects mobility only through social-distancing policy (Stock and Watson 2011). The average of the social-distancing policies of the states with which the given state shares its land border is considered as an instrument. The neighbouring state's policies will influence the given state to emulate or infuse ideas from them to formulate their own policies (Obinger et al. 2013). Hence, the policy of the neighbouring state can influence the mobility of the given state only through the state's own policy.

Further, since the Google Mobility Data might not incorporate inter-state migration (see "Discussion" section for details), it can be argued that the instrument remains exogenous. The Kleibergen-Paap (2015) LM Test also confirms the average social-distancing policy as a relevant (weak) instrument (See Appendix A8).

However, in case of the district-level data, since the states hold the authority of framing the policies, it is assumed that the social-distancing policies of the neighbouring districts within a state will not be exogenous. Hence, the instruments are constructed at the state level only for both the district- and state-level regression. It should be mentioned that the model is performed for two different time ranges: the pre-Janta Curfew period (column 2) and pre-national lockdown period (column 4). The estimated results are reported in Appendices A6 and A8 for district- and state-level data, respectively. The results show that although coefficients have increased in magnitude in case of panel IV FE model, the order of the coefficients of social-distancing policies of the different states remain broadly similar for both the models with state- and district-level data. However, this concern is not going to arise for Eq. 2, as the sudden imposition of the national lockdown came as an arguably exogenous policy shock for states. Moreover, the implementation guidelines of the national lockdown in the time range from 24 March to 26 April were homogenous across states.

Despite the above approach, endogeneity issues might still remain. For instance, the Google search variable might be endogenous in the model, for which a suitable instrument is required. Further analysis is needed to deal with these concerns.

Discussion

COVID-19 has been an unprecedented experience for the entire world. All the governments, both national and subnational, were forced to experiment with their welfare policies to curtail the spread of the virus and protect citizens. This resulted in a situation of extreme heterogeneity in government responses, especially in federal nations where subnational units have substantial autonomy to formulate policies. India is an example of a highly centralized federation, where the central government is endowed with more power over the state governments. The findings show that India's national lockdown led to large increases in time spent in residences, albeit with considerable variation across states. Before the intervention of the Central government, the effect of state-level policies on mobility was highly heterogeneous. Several states were unable to achieve meaningful reductions in mobility despite enacting multiple SD policies. The results also show that states which were successful in implementing SD policies before 24th March have experienced a larger increase in time spent at home from the national lockdown as well. Prior to the national lockdown, the Janta Curfew had managed to substantially reduce the mobility in states.

The effectiveness of containment policies depends on the state's ability to enforce the new rules, as well as the economic feasibility of such policies (Shiva and Molana 2021). Arguably the highest costs of containment and closure policies are borne by low-income and informal workers, dependent on daily earnings to maintain consumption needs. The vast majority of India's workers are employed in the informal sector without any social security (Kesar and Bhattacharya 2019) and very few of these jobs can be done remotely. Some state governments adopted supporting policies aimed at making it easier for citizens to comply with stay-at-home orders. For example, the government of Kerala arranged for community kitchens to ensure food security. Coercive measures like vehicle seizures, punishment, and fines were commonly exercised. Several instances emerged of law enforcement personnel employing extralegal physical violence to enforce social-distancing policies (The Indian Express 2020). These stringent implementation strategies may be effective, but may hinder compliance in the long run (Ray and Subramanian 2020).

Accounting for Interstate Migration

The abrupt and uncoordinated declaration of the national lockdown by the Prime Minister led to a dramatic migrant exodus from major cities, garnering widespread attention (Ray and Subramanian 2020). The lockdown disrupted usual migration patterns and initiated a reverse migration from cities to rural regions, with an increase in rural population by 7% and a corresponding reduction in urban population by 4–11% (Denis et al 2020). Social policy frameworks among states were critical in influencing migrants' experiences and decisions (Rao et al 2020). An example is that states with inter-state portability of food security benefits ('porf ration card' policy) reduced mobility by 12% (Choudhury et al. 2020).

Migration is a channel through which one state's policy might impact another state's mobility patterns. However, the Google mobility data might not accurately reflect or even define migrant movements because of its design. A person migrating from one district/state (say X) to another (Y) after February 2020 is a part of baseline measurements of X. It might be that any movement outside their residences (including moving outside X) will reduce the time spent in residences for X. However, they would likely not be considered as part of Y's mobility data, as they were not present in Y during the baseline period. The effect of migration on mobility will most likely be captured in the measurements of the source region, as a decrease in the time spent in residence. However, it is difficult to isolate the daily mobility changes caused by migrants as distinct from others. With the extensive use of such device-based mobility data to generate insights about policies, their limitations need to be taken into account while interpreting the results.

Changing Relations Between State and Citizens in India

The policy response to the pandemic illustrates the changing relationship between the State and citizens in India. Although government regulation already overarches several economic and social aspects in India, the pandemic witnessed a massive expansion of State authority. An example was the requirement of permission from district-level bureaucrats, appointed by the Central Government, to travel for medical emergencies or funerals. The abrupt announcement by central executive order of the national lockdown had a similar precedent in the declaration of demonetization in 2016. According to Kapur (2020), although state capacity in India is inadequate to deliver services at the local level, performance is better at time-bound, episodic activities, such as elections and immunization, especially at the higher levels of government. The interaction between the central government and citizens has become associated with somewhat grandiose actions, underpinned by national leaders' mass appeal to citizens, indicating a consolidation of individual authority along with centralization of governance.

The growing centralization of decision-making authority coincides with the increasing repression of dissent among opposition parties, civil society, and the media (Vasquez and McMahon 2020). These new state-citizen relations are fuelled by norms which emphasize patriotism and disapprove contestations of ruling government's policies (Chacko 2018). Religious, caste, and ethnic identity are a crucial lens through which citizens perceive government actions. The national media played an influential role in pushing these identity-based narratives.[6] Political affiliation is also linked with adherence to social-distancing restrictions (Adolph et al. 2020). Compared to nearly 85.1% of Americans who perceived the government response to be inadequate, the majority of Indian respondents approved of the government's actions during the pandemic (Tagat 2020)

Concluding Remarks

The pandemic has raised questions about the efficacy of varying subnational public health responses compared to uniform, centralized decisions. In the devastating second wave of the pandemic in 2021, the central government has left the responsibility of imposing containment policies almost entirely to state governments. This resembles the implementation of SD policies of the states in the period before the national lockdown in 2020. The findings of this study indicate that though centralized, coordinated policies may be necessary, their effectiveness is highly dependent on states' individual capacities.

Appendix: Social-Distancing Policies

Descriptions of the Social-Distancing Policies

Name of the policy	Description of the policy	Remarks
Emergency Declarations	States recognizes a situation as a public health emergency and designates the situation as an 'epidemic' through EDA, 1897	On 11th March, cabinet secretary of the central government allowed the states to implement policies independently to tackle epidemics and pandemics by activating EDA
Restrictions on Public Gatherings	These policies prohibit gatherings above a certain threshold	Some states banned all gatherings regardless of size. Districts-imposed section 144, banning gatherings of more than 4 people. Some states allowed higher thresholds for family or religious gatherings

[6] See https://www.thehindu.com/news/national/supreme-court-seeks-response-of-pci-centre-on-plea-against-media-communalising-tablighi-jamaat-incident/article31686090.ece.

Name of the policy	Description of the policy	Remarks
School Closure	An order to close all public and private schools	Many of the orders extended to 'all educational institutions', including universities. Here, we only consider school closures, which affects a larger proportion of the population than university closures
Closure of Recreational/Gathering Places	These policies ordered closings of recreational services where large crowds gather	This includes movie theatres, stadiums, malls and parks
Closure of Food and Beverage Services	Orders for restaurants and bars to close, with the exception of take away and home delivery	This also included small street shops and local food courts. App-based food delivery services were allowed to remain functional in many states with limitations on working hours
Closure of all Non-Essential Activities	These orders shut down almost all economic activities, except certified 'essential services'	On 24th March, Home Ministry listed the essential services. Before that, state ministers decided on the criteria of essential services
Internal Travel Restrictions	Orders to restrict or close transport services and travel	Three levels of policy were in practice by different states. First was allowed transport with an official health certificate, with mandatory quarantine for 14 days after travel. Second, public transportation services were discontinued. Third, borders were sealed and no private transports allowed on roads
Lockdown	Highest possible restrictions on mobility, ordering people not to venture out of their homes except for essential purposes (medical emergencies or buying groceries)	Punjab and Chhattisgarh imposed lockdowns a few days before the national announcement

Data Collection Process

We consider the earliest date on which services under a particular category were closed. For example, if malls were closed on 13 March, but recreational establishments (cinemas, gyms) were closed on 16th March; then closure of recreational services is assigned a value of 1 from 13th March onwards. The rationale is that any closure of recreational activities may lead to voluntary closures of similar businesses, as owners expect that they are likely to be closed soon. These expectations are also informed by observing similar policies in other states. The date from which a restriction is in effect is assigned as the day on which it was enacted. The first preference to get information about an order is official documents as uploaded on the State government's website. Like most governments around the world, all Indian states had setup websites dedicated to COVID-related information, including advisories, orders, and guidance. If the information was not available—or if it was in a different language which could not be interpreted—information was sourced from national/regional news websites. Media coverage of the orders was comprehensive and rapidly updated. If an order restricting public gatherings is phrased as banning 'any/all' gatherings, the threshold is assigned as 1.

(The sources used to compile information on state-wise policies are available on request.)

Single Exponential Smoothing of Mobility Trends

In this method, the daily mobility values are adjusted with the past days' mobility trends to create a new 'smoothed' variable. A new variable (Y_t) is generated which is an over-time weighted average of the actual values of the variable ($x_t, x_{t-1}, x_{t-2}, \ldots x_0$) (Eqs. 1 and 2).

$$Y_0 = x_0, \tag{1}$$

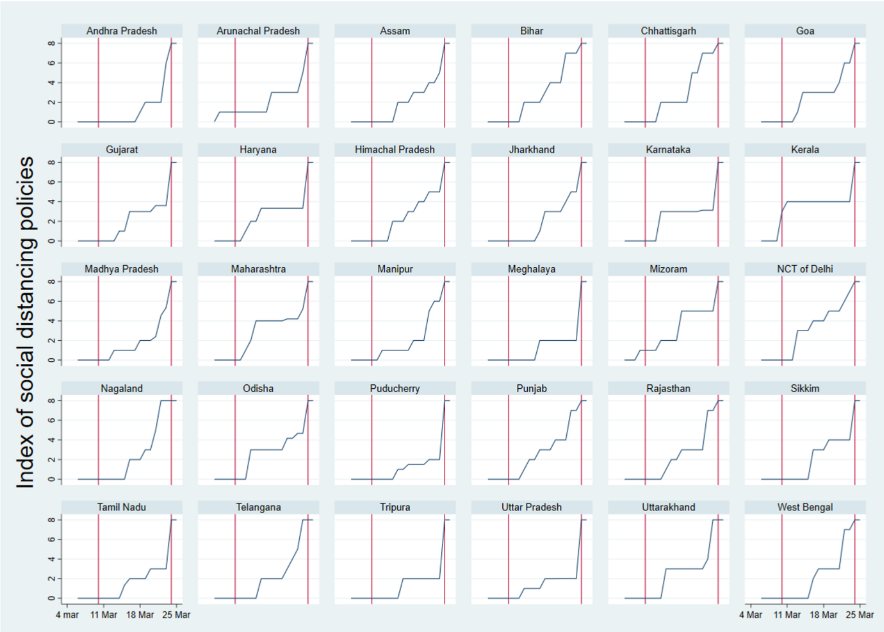
$$Y_t = \alpha x_t + \alpha(1-\alpha)x_{t-1} + \alpha(1-\alpha)^2 x_{t-2} + \cdots + (1-\alpha)^t x_0, \tag{2}$$

where $t > 0$ and α is the smoothing factor with $0 < \alpha < 1$. Its value is obtained by minimizing the forecast errors of each state. The weights are the function of this smoothing factor which decays over time, thus, giving higher weights to the values which are closer to the present day.

Summary Statistics

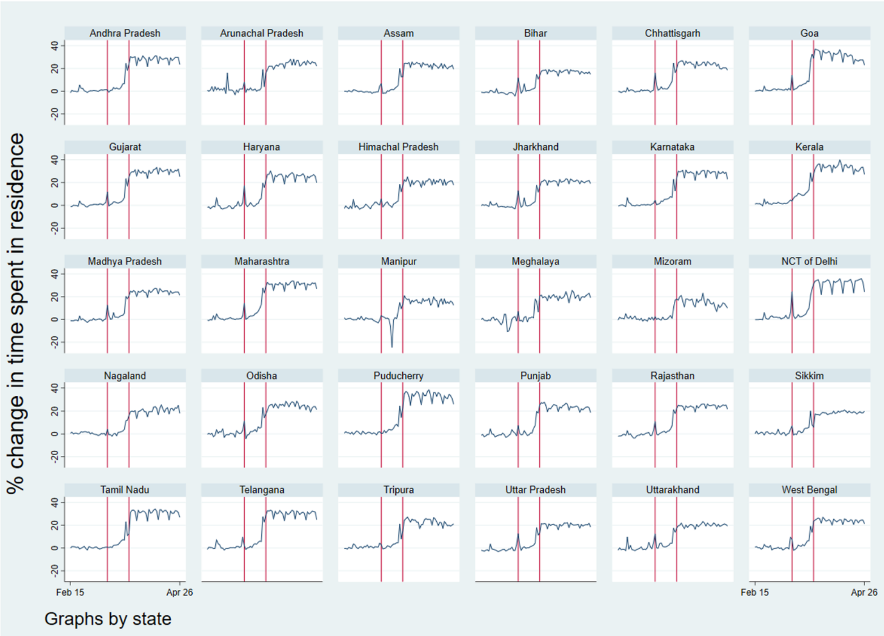
Variable	Obs	Mean	SD	Min	Max
Percent change in out-of-residence mobility	2232	12.476	12.816	– 17	39.057
Search frequency	2232	40.079	30.007	1	100
SD policy index	2232	4.33	3.97	0	8

State-Wise Time Series Plots of SD Policy Index



Note: Figures plot the additive SD policy index for each state from March 4 – March 25. Red vertical dashed lines indicate start of mobility restrictions (10th March) and the declaration of national lockdown (24th March) respectively.

State-Wise Time Series Plots of Percentage Change in Time Spent in Residence



Note: Figures plot the daily average state-level values of the residential mobility metric from Google Community Mobility Reports. Red vertical dashed lines indicate start of mobility restrictions (10th March) and the declaration of national lockdown (24th March) respectively.

Regression Results: Effect of States' SD Policies on Mobility (District-Level Data)

Dependent Variable Time Spent in Residence

	(1) Pre-Janta	(2) Pre-Janta (IV)	(3) Pre-lockdown	(4) Pre-lockdown (IV)
Search	0.037***	0.032***	0.059***	0.008
	(0.00)	(0.00)	(0.00)	(0.00)
Public Gathering	− 0.608**	− 6.269***	− 1.081**	− 10.830***
	(0.19)	(0.92)	(0.42)	(1.39)

	(1) Pre-Janta	(2) Pre-Janta (IV)	(3) Pre-lockdown	(4) Pre-lockdown (IV)
I * Andhra Pradesh	0.336***	0.982***	1.728***	2.680***
	(0.08)	(0.12)	(0.09)	(0.14)
I * Arunachal Pradesh	− 0.780***	− 0.786***	− 0.545***	0.518***
	(0.02)	(0.04)	(0.04)	(0.07)
I * Assam	-0.022	0.298***	0.588***	1.750***
	(0.07)	(0.09)	(0.07)	(0.10)
I * Bihar	0.284***	0.251***	0.302***	0.885***
	(0.03)	(0.04)	(0.04)	(0.05)
I * Chhattisgarh	0.223***	0.463***	0.682***	1.857***
	(0.05)	(0.06)	(0.06)	(0.08)
I * Goa	0.759***	0.879***	1.165***	1.977***
	(0.06)	(0.06)	(0.08)	(0.09)
I * Gujarat	0.064	0.162***	0.318***	1.886***
	(0.04)	(0.05)	(0.06)	(0.10)
I * Haryana	− 0.059	− 0.048	0.073	1.442***
	(0.05)	(0.06)	(0.07)	(0.11)
I * Himachal Pradesh	0.062	1.708***	0.300*	3.909***
	(0.09)	(0.27)	(0.12)	(0.37)
I * Jharkhand	− 0.336***	− 0.129**	− 0.028	0.758***
	(0.04)	(0.05)	(0.06)	(0.07)
I * Karnataka	1.087***	4.383***	1.378***	8.568***
	(0.14)	(0.50)	(0.20)	(0.70)
I * Kerala	1.832***	4.383***	2.125***	7.043***
	(0.11)	(0.32)	(0.14)	(0.46)
I * Madhya Pradesh	0.543***	0.783***	0.937***	1.900***
	(0.06)	(0.08)	(0.07)	(0.09)
I * Maharashtra	0.590***	2.714***	1.218***	5.695***
	(0.10)	(0.33)	(0.13)	(0.43)
I * Manipur	− 2.649***	− 3.093***	− 0.750***	− 0.162
	(0.18)	(0.19)	(0.22)	(0.20)
I * Meghalaya	0.002	0.183	0.653***	2.562***
	(0.08)	(0.10)	(0.13)	(0.17)
I * Mizoram	− 0.218***	1.563***	− 0.158	3.343***
	(0.06)	(0.29)	(0.10)	(0.38)
I * Nagaland	− 0.327***	− 0.415***	0.021	0.530***
	(0.04)	(0.05)	(0.04)	(0.06)
I * NCT of Delhi	− 0.140	0.101	0.298**	1.165***
	(0.12)	(0.13)	(0.10)	(0.13)
I * Odisha	0.061	0.590***	0.226***	2.348***
	(0.05)	(0.07)	(0.06)	(0.11)
I * Puducherry	1.856***	2.548***	2.336***	7.523***
	(0.20)	(0.42)	(0.40)	(1.05)

	(1) Pre-Janta	(2) Pre-Janta (IV)	(3) Pre-lockdown	(4) Pre-lockdown (IV)
I * Punjab	− 0.256***	− 0.042	0.615***	1.342***
	(0.05)	(0.06)	(0.06)	(0.08)
I * Rajasthan	0.403***	0.897***	1.040***	2.080***
	(0.08)	(0.12)	(0.08)	(0.11)
I * Tamil Nadu	0.697***	0.694***	0.979***	2.367***
	(0.08)	(0.10)	(0.10)	(0.14)
I * Telangana	0.340**	0.249	1.278***	2.548***
	(0.12)	(0.13)	(0.07)	(0.15)
I * Tripura	0.170	0.330***	0.411***	1.874***
	(0.09)	(0.10)	(0.11)	(0.14)
I * Uttar Pradesh	0.105	0.293***	0.348***	2.191***
	(0.07)	(0.08)	(0.10)	(0.14)
I * Uttarakhand	0.070	0.075	0.197**	1.814***
	(0.06)	(0.07)	(0.08)	(0.15)
I * West Bengal	0.200***	0.268***	0.556***	1.427***
	(0.05)	(0.06)	(0.06)	(0.08)
Constant	0.045**	0.064**	− 0.268***	− 0.039
	(0.02)	(0.02)	(0.03)	(0.03)
N	22,015	22,015	23,237	23,237
District fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap LM test		203.275***		684.319***

Note Robust standard errors clustered at the district level in parentheses. Dependent variable is the percentage change in time spent in residence from January–February baseline. Independent variables consist of inverse public gathering threshold, state-level search frequencies for COVID-19 and SD policy index (I) interacted with state dummies. Column (1) and column (2) reports results for the period till March 22, and column (3) and column (4) reports results for the period till March 24

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Regression Results: Effect of National Lockdown on Mobility Across States

Dependent Variable: Time Spent in Residence

State	Coefficients			Number of observations
	(1) Constant	(2) National lockdown	(3) Search	
Andhra Pradesh	0.997*** (0.23)	24.359*** (0.55)	0.040*** (0.01)	936
Arunachal Pradesh	3.447*** (0.00)	23.665*** (0.00)	− 0.076*** (0.00)	288

State	Coefficients			Number of observa-tions
	(1) Constant	(2) National lockdown	(3) Search	
Assam	0.080 (0.18)	19.752*** (0.32)	0.040*** (0.00)	1944
Bihar	− 0.411*** (0.11)	13.806*** (0.25)	0.054*** (0.00)	2664
Chhattisgarh	0.911*** (0.23)	18.751*** (0.47)	0.065*** (0.00)	1944
Goa	0.420 (0.60)	23.894* (0.71)	0.131* (0.01)	144
Gujarat	1.125** (0.35)	25.624*** (0.64)	0.036*** (0.00)	2376
Haryana	− 0.335 (0.44)	22.697*** (0.82)	0.043*** (0.00)	1512
Himachal Pradesh	− 0.332 (0.33)	18.27*** (0.52)	0.034*** (0.00)	792
Jharkhand	0.345 (0.24)	18.550*** (0.53)	0.024*** (0.00)	1728
Karnataka	0.893** (0.25)	24.207*** (0.48)	0.041*** (0.00)	2160
Kerala	2.584*** (0.29)	25.363*** (0.57)	0.077*** (0.00)	1080
Madhya Pradesh	0.503** (0.17)	20.339*** (0.41)	0.048*** (0.00)	3672
Maharashtra	0.722** (0.28)	24.851*** (0.41)	0.072*** (0.00)	2592
Meghalaya	− 0.251 (0.32)	17.901*** (0.99)	0.026*** (0.00)	577
Mizoram	0.172 (0.13)	13.303*** (0.24)	0.043*** (0.00)	335
NCT of Delhi	2.076*** (0.30)	26.822*** (0.39)	0.047*** (0.00)	792
Nagaland	1.266** (0.28)	19.949*** (0.44)	− 0.018*** (0.00)	231
Odisha	1.071*** (0.15)	21.247*** (0.38)	0.026*** (0.00)	2160
Puducherry	1.174 (1.41)	28.597 (2.32)	0.044 (0.01)	144
Punjab	− 0.849** (0.27)	19.512*** (0.59)	0.072*** (0.00)	1584
Rajasthan	− 0.192 (0.27)	20.364*** (0.52)	0.058*** (0.00)	2376
Tamil Nadu	0.782* (0.36)	27.177*** (0.56)	0.028*** (0.00)	2304
Telangana	0.746** (0.47)	25.979*** (0.83)	0.056*** (0.00)	720
Tripura	0.762** (0.18)	17.528*** (0.73)	0.058*** (0.01)	576

State	Coefficients			Number of observa-tions
	(1) Constant	(2) National lockdown	(3) Search	
Uttar Pradesh	-0.724*** (0.20)	17.686*** (0.35)	0.042*** (0.00)	5400
Uttarakhand	0.852 (0.65)	17.382*** (1.13)	0.022*** (0.00)	936
West Bengal	0.641* (0.29)	19.856*** (0.67)	0.052*** (0.00)	1440

Note Robust standard errors clustered at the district level in parentheses. Dependent variable is the percentage change in time spent in residence from January–February baseline. Columns (2) and (3) represent independent variables—dummy variable for national lockdown, and state-level search frequencies for COVID-19. Each row represents estimates for each state

*p < 0.05, **p < 0.01, ***p < 0.001

Robustness Test: Effect of States' SD policies on Mobility (State Level)

Dependent Variable: Time Spent in Residence

	(1) Pre-Janta	(2) Pre-Janta (IV)	(3) Pre-lockdown	(4) Pre-lockdown (IV)
Search	0.027***	0.020*	0.038**	0.002
	(0.01)	(0.01)	(0.01)	(0.01)
Public Gathering	− 0.749	− 5.333*	0.210	− 6.153*
	(0.53)	(2.26)	(1.43)	(2.83)
I * Andhra Pradesh	0.618**	1.402*	1.974***	2.603***
	(0.18)	(0.61)	(0.20)	(0.45)
I * Arunachal Pradesh	− 0.633***	− 0.594**	− 0.245	0.580
	(0.10)	(0.21)	(0.18)	(0.67)
I * Assam	0.148	0.492*	0.936***	1.793**
	(0.11)	(0.22)	(0.20)	(0.64)
I * Bihar	0.341***	0.338*	0.470***	0.823**
	(0.06)	(0.15)	(0.11)	(0.31)
I * Chhattisgarh	0.291**	0.510*	0.775***	1.498**
	(0.09)	(0.21)	(0.13)	(0.53)
I * Goa	0.881***	1.009***	1.399***	1.831***
	(0.08)	(0.28)	(0.13)	(0.52)
I * Gujarat	0.216*	0.339	0.718**	1.850*
	(0.10)	(0.20)	(0.21)	(0.90)
I * Haryana	0.092	0.132	0.422*	1.547
	(0.10)	(0.29)	(0.20)	(0.82)
I * Himachal Pradesh	0.280	1.655*	0.359	2.808**
	(0.19)	(0.69)	(0.30)	(1.00)
I * Jharkhand	− 0.207*	0.041	0.255	0.850
	(0.08)	(0.25)	(0.17)	(0.46)

	(1) Pre-Janta	(2) Pre-Janta (IV)	(3) Pre-lockdown	(4) Pre-lockdown (IV)
I * Karnataka	1.388***	4.151***	1.280*	6.222**
	(0.31)	(1.20)	(0.58)	(1.99)
I * Kerala	2.019***	4.246***	2.000***	5.613***
	(0.21)	(0.86)	(0.41)	(1.38)
I * Madhya Pradesh	0.754***	1.029**	1.283***	1.803***
	(0.16)	(0.38)	(0.21)	(0.51)
I * Maharashtra	0.821***	2.564**	1.224**	4.248***
	(0.21)	(0.87)	(0.35)	(1.25)
I * Manipur	− 2.085***	− 2.680*	− 0.229	− 0.156
	(0.11)	(1.26)	(0.17)	(0.95)
I * Meghalaya	0.190	0.418	1.101***	2.686*
	(0.14)	(0.34)	(0.28)	(1.15)
I * Mizoram	− 0.094	1.402	− 0.249	2.124*
	(0.16)	(0.72)	(0.30)	(0.91)
I * Nagaland	− 0.184	− 0.272	0.222	0.496
	(0.09)	(0.24)	(0.12)	(0.29)
I * NCT of Delhi	0.028	0.224	0.540***	0.989*
	(0.09)	(0.28)	(0.15)	(0.41)
I * Odisha	0.184*	0.714**	0.538***	2.044**
	(0.07)	(0.28)	(0.14)	(0.78)
I * Puducherry	1.756***	2.242***	2.534***	5.296**
	(0.21)	(0.61)	(0.43)	(1.97)
I * Punjab	− 0.060	0.161	0.920***	1.395**
	(0.13)	(0.32)	(0.18)	(0.53)
I * Rajasthan	0.613***	1.093**	1.273***	1.965***
	(0.14)	(0.37)	(0.14)	(0.53)
I * Tamil Nadu	0.917***	1.005***	1.442***	2.510**
	(0.15)	(0.30)	(0.28)	(0.86)
I * Telangana	0.498***	0.461	1.404***	2.202**
	(0.10)	(0.30)	(0.14)	(0.73)
I * Tripura	0.329**	0.536*	0.843**	2.024*
	(0.10)	(0.25)	(0.25)	(0.92)
I * Uttar Pradesh	0.328*	0.553	0.862**	2.348*
	(0.15)	(0.34)	(0.30)	(1.09)
I * Uttarakhand	0.215*	0.266	0.475***	1.389**
	(0.09)	(0.22)	(0.14)	(0.51)
I * West Bengal	0.351**	0.461	0.805***	1.320**
	(0.10)	(0.29)	(0.14)	(0.42)
Constant	0.365***	0.400***	0.104	0.291***
	(0.06)	(0.095)	(0.11)	(0.145)
N	1044	1044	1102	1102
State fixed effects	Yes	Yes	Yes	Yes

	(1) Pre-Janta	(2) Pre-Janta (IV)	(3) Pre-lockdown	(4) Pre-lockdown (IV)
Kleibergen-Paap LM test		16.41***		48.797***

Note Robust standard errors clustered at the state level in parentheses. Dependent variable is the percentage change in time spent in residence from January–February baseline. Independent variables consist of inverse public gathering threshold, state-level search frequencies for COVID-19 and SD policy index (I) interacted with state dummies. Column (1) and Column (2) report results for the period till March 22, and column (3) and column (4) report results for the period till March 24

*$p<0.05$, **$p<0.01$, ***$p<0.001$

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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