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10 May 2020

Online at <https://mpra.ub.uni-muenchen.de/100325/>
MPRA Paper No. 100325, posted 12 May 2020 12:44 UTC

The Impact of COVID-19 Mobility Restrictions in India: Comparing State and Central Responses

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Abstract

Indian central and state governments have imposed restrictions on human mobility to slow the spread of COVID-19. Based on state government directives and mobility data from Google, we find that similar restrictions did not lead to equal reductions in mobility across states before the national lockdown. Maharashtra's restrictions were the most effective in reducing mobility by a large margin. The national lockdown had a larger and more uniform effect for most states.

Regional Variation in the spread of COVID-19

The COVID-19 pandemic has spread unequally across regions within India, with five states accounting for more than 70 percent of active cases till [5th May](#). Restrictions on human mobility and social distancing measures are found to slow the spread of infectious diseases, by reducing contact among people ([Bajardi et al, 2011](#)). Supporting empirical evidence also exists for the ongoing coronavirus pandemic ([Fang et al, 2020](#)). Indian state governments imposed such restrictions up to 24th March, until the Central government finally declared a national lockdown. The restrictions were [recognized as among the most stringent in the world](#), laying down a uniform policy and overriding state governments. The national lockdown ended on [3rd May](#). States were then given back the authority to manage their own outbreaks, with a few central directives.¹

In the initial weeks of March, states reacted with differing speed and stringency to the rising number of infections, with different outcomes in terms of reducing mobility. Using data on state-wise restrictions and mobility changes for 31 Indian States and UTs from February 15 to April 26, we try to understand if all states performed equally in reducing mobility. We also compare the mobility-reducing effects of stringency in the phase before the national lockdown,

¹State governments could relax restrictions in districts reporting no new infections for 28 days. (Source: <https://ndma.gov.in/images/covid/MoHFW-Letter-States-reg-containment-of-Hotspots.pdf>)

with the subsequent period. As India’s current containment strategy is again based on state-level decisions, evidence from the pre-lockdown experience is illustrative.

Measuring stringency of government restrictions

Mobility restrictions imposed by states included one or more of the following measures: bans on public gatherings, declaration of a health emergency, internal travel restrictions, closure of services, and finally declaration of a ‘lockdown’. Based on state-wise government orders and news reports, we categorize these restrictions into eight indicators (Figure 1). This is similar, but not identical, to the OxCGRT classification of containment and closure measures ([Hale et al, 2020](#)).²

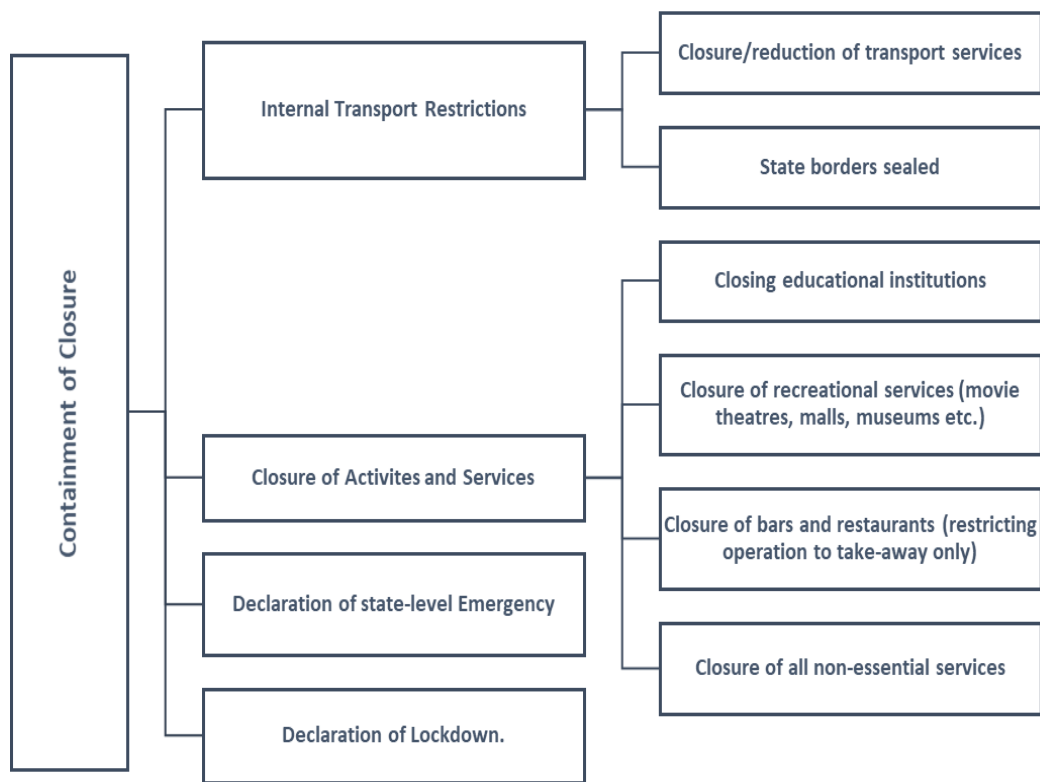


Figure 1: Categories of Government Restrictions³

We record these measures using binary variables which equal 1 for days on which the policy is in effect. These variables are added to generate a daily stringency score for each state. The value of the stringency score represents the relative intensity of restrictions in effect, with zero

² The [OxCGRT](#) (Oxford COVID-19 Government Response Tracker) collects data on policy responses to COVID-19 at the national level. In contrast, our dataset compiles government responses at the state level. It will be shared on request.

³ A Lockdown imposes a complete ban of non-essential services, transportation and effectively imposes curfew.

as the minimum. The maximum value of the stringency score is 8. Every state attains its maximum value by 24th March, with the commencement of the national lockdown.

Table 1: State-wise dates of first cases and stringency of responses

States/UT	First Date of any Case	First Date of any Response	Date of Declaring Lockdown	Maximum Stringency score (Before 24th March)
<i>Early Affected States: restrictions came after first case</i>				
Kerala	31-Jan-20	11-Mar-20	24-Mar-20	3
NCT of Delhi	02-Mar-20	13-Mar-20	24-Mar-20	4
Telangana	02-Mar-20	15-Mar-20	23-Mar-20	2
Rajasthan	03-Mar-20	14-Mar-20	23-Mar-20	3
Haryana	04-Mar-20	16-Mar-20	24-Mar-20	3
Uttar Pradesh	04-Mar-20	14-Mar-20	24-Mar-20	2
Tamil Nadu	07-Mar-20	17-Mar-20	24-Mar-20	3
Karnataka	09-Mar-20	14-Mar-20	24-Mar-20	2
Maharashtra	09-Mar-20	18-Mar-20	24-Mar-20	2
Punjab	09-Mar-20	14-Mar-20	22-Mar-20	7
Andhra Pradesh	12-Mar-20	20-Mar-20	24-Mar-20	2
<i>Late Affected States: restrictions came before first case</i>				
Uttarakhand	15-Mar-20	15-Mar-20	23-Mar-20	3
Odisha	16-Mar-20	14-Mar-20	24-Mar-20	5
Puducherry	18-Mar-20	18-Mar-20	24-Mar-20	3
West Bengal	18-Mar-20	16-Mar-20	24-Mar-20	4
Chandigarh	19-Mar-20	14-Mar-20	23-Mar-20	3
Chhattisgarh	19-Mar-20	14-Mar-20	20-Mar-20	4
Gujarat	20-Mar-20	16-Mar-20	24-Mar-20	3
Himachal Pradesh	21-Mar-20	15-Mar-20	24-Mar-20	4
Madhya Pradesh	21-Mar-20	15-Mar-20	24-Mar-20	2
Bihar	22-Mar-20	14-Mar-20	24-Mar-20	6
Manipur	24-Mar-20	13-Mar-20	24-Mar-20	4
Mizoram	25-Mar-20	10-Mar-20	24-Mar-20	3
Goa	26-Mar-20	15-Mar-20	22-Mar-20	3
Assam	01-Apr-20	16-Mar-20	24-Mar-20	2
Jharkhand	01-Apr-20	17-Mar-20	24-Mar-20	5
Arunachal Pradesh	03-Apr-20	18-Mar-20	24-Mar-20	3
Tripura	07-Apr-20	16-Mar-20	24-Mar-20	2
Meghalaya	13-Apr-20	17-Mar-20	24-Mar-20	2
Nagaland	12-Apr-20	17-Mar-20	22-Mar-20	5

(Note: Data for cases taken from covid19india.org)

Table 1 shows that states had varied delays between reporting their first cases, and instituting their first measures. By 11 March, [Kerala](#) was the only state which had enacted any measure in response to COVID-19. Andhra Pradesh was the last state to implement any restrictions.

Measuring changes in mobility

Google provides [Community Mobility Report](#) data at the state level, recording changes in mobility trends for six categories⁴ of locations. It provides the change in mobility for each day of the week, relative to its baseline level (median during Jan 3 – Feb 6, 2020). We calculate a weekly mobility index, averaging across categories.⁵ This index represents relative mobility for each state, ranging from 0 to 1. The maximum value of 1 represents the baseline mobility. A value of 0.5 means that mobility was at 50% of baseline level, for that state.

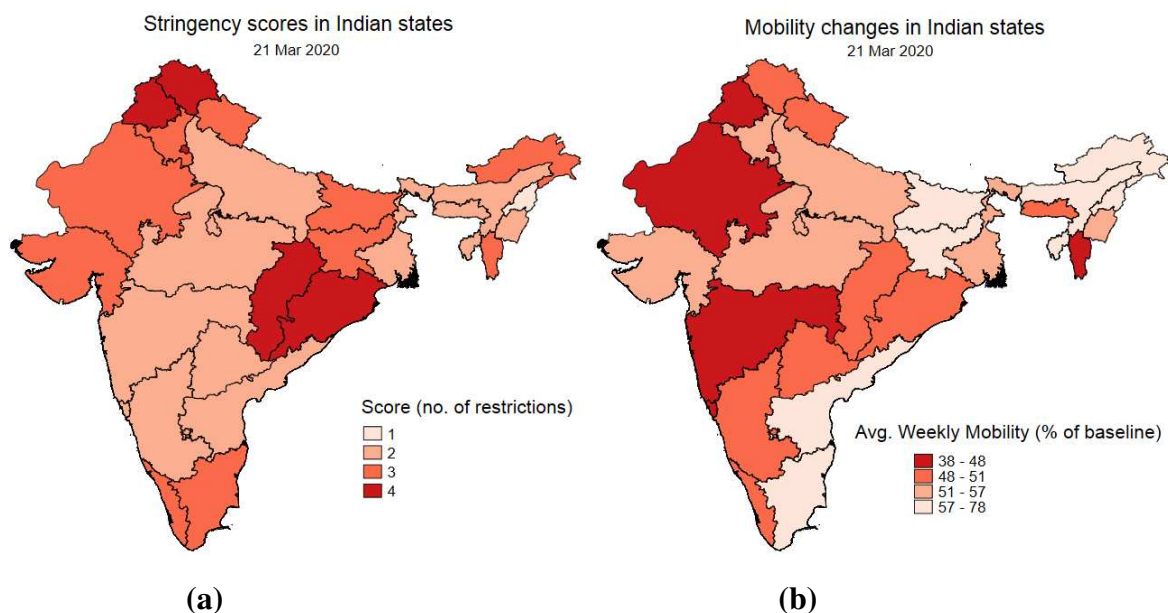


Figure 2: Chloropleth maps of mobility and stringency on 21 March, (a) Stringency score. Darker is more stringent. (b) Avg. mobility level. Darker means lower level of mobility. Note: Jammu and Kashmir was recently split into two UTs - J&K and Ladakh. Mobility data and updated shapefiles are not available for the new UTs. Hence J&K has not been included in the map.

As figure 2a shows, every state had enacted at least one mobility restriction by 21st March. Mobility had reduced from baseline levels in all states (figure 2b), with darker shade

⁴ These are grocery and pharmacy stores, parks, transit stations, retail and recreational establishments (including restaurants and malls) workplaces and residences.

⁵ A normalized weekly mobility index was calculated by the following steps:

- a. We generate weekly averages for mobility in of the five location categories (excluding residences).
- b. We construct a composite weekly mobility index by taking the mean of the above variables.
- c. We normalize the index to take a value of 1 at the maximum and 0 at the minimum mobility value for each state.

representing a lower level of (a higher *reduction in*) mobility. If a state has the same shade in both maps, its stringency score was proportionate to its mobility reduction. With a stringency score of 2, Maharashtra saw the highest fall in mobility, to 38% of its baseline level. In contrast, Arunachal Pradesh’s mobility was at 78% of baseline, despite a higher stringency score of 3.

We plot the changes in mobility and stringency with time for six states (three early affected and three late affected) in figure 3. The blue line shows (normalized) stringency score, which changes sharply with new government restrictions. The red line represents weekly mobility levels. Some states raised stringency more gradually (like Delhi), while others (like Arunachal Pradesh) imposed several restrictions simultaneously. The relative ‘effectiveness’ of restrictions can be inferred from the drops in average mobility.

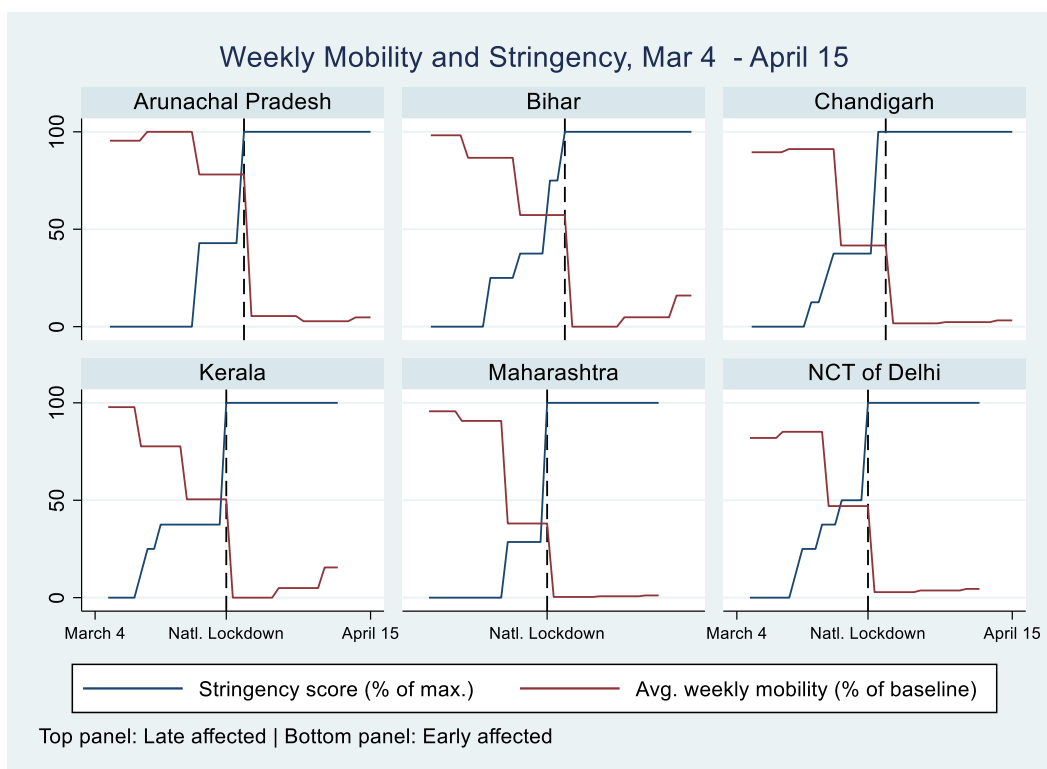


Figure 3: Time series plots of average weekly mobility and stringency score, for six Indian states (March 4–April 15). Values are scaled to between 0 and 100. The vertical axis represents each quantity as a percentage of its maximum. Dashed vertical line represents 24th March.

With the lockdown, stringency hits its maximum value for each state and does not change for the duration the plot. Weekly mobility falls drastically, in most cases reaching the minimum value (zero) compared to baseline. Exceptions like Arunachal Pradesh and Delhi did not reach their respective minimum values in the first week of the lockdown (Mar 24–Mar 31), settling at 5% and 3% of baselines respectively. By the second week of the lockdown, state-wise

mobility had stabilized at higher, but different levels (e.g. to 15% of baseline in Kerala and Bihar). Clearly, similar rises in stringency reduced mobility by different levels for each state.

Quantifying the impact of state-wise restrictions on mobility

To estimate the effect of stringency of restrictions on mobility, we employ a panel regression model with different effects sizes for each state. The model accounts for two additional features. First, there are systematic differences *across* states. Second, *within* states mobility depends on its own past values.⁶ We estimate two separate regressions, one for the time period before the lockdown (15 Feb – 22 March), and the other for the lockdown period (22 March – 26 Apr).

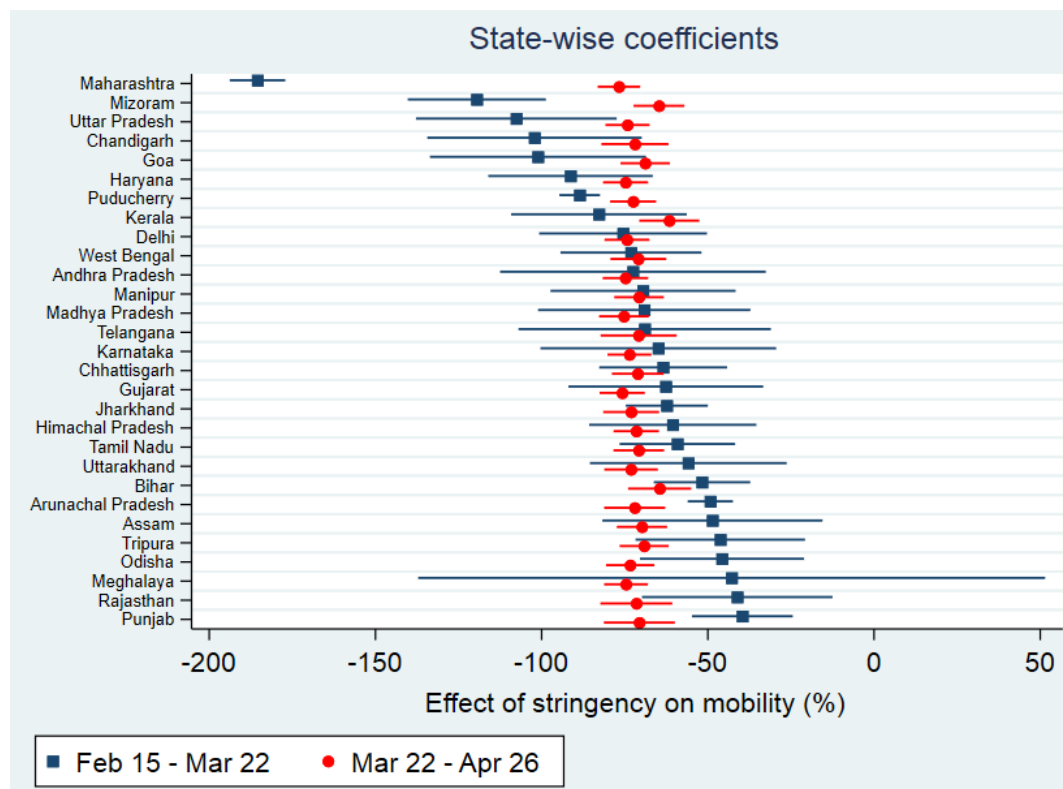


Figure 4: Coefficient plot of panel regression. The value of the coefficient represents the percentage change in weekly mobility associated with a 100% increase in the stringency score, individually for each state. Blue squares represents estimates pre-lockdown period (February 15 – March 22). Red circles represent estimates for lockdown period (March 22 – April 26). Spikes are 95% confidence intervals.

⁶ Our dataset consists of 31 states from February 15 to April 26, for a total of 2,160 state-day observations. We fit a linear panel data model of mobility using feasible generalized least squares (FGLS), with state-specific coefficients for stringency. Residuals do not have constant variance *across states*, due to differences in state-specific characteristics other than stringency. These residuals are also likely to be dependent on their own past values, i.e. they are autocorrelated *within states*. We deal with this by specifying a heteroskedastic error structure across panels, and a panel-specific AR(1) autocorrelation of the residuals.

Increases in stringency had a negative effect on weekly mobility for all states in the pre-lockdown period, (blue squares in figure 4). But effect sizes varied widely across states. Maharashtra saw the highest decline in mobility in response to restrictions.⁷ Each 100% rise in stringency score reduced average weekly mobility by around 200%. On the other extreme, Punjab, Rajasthan and Telangana's restrictions were less effective, causing less than 40% declines in weekly mobility for similar rise in stringency

In the national lockdown period, the impact of restrictions were much higher for most states (red circles in figure 4). Except the few states which already saw reductions of more than 100%, a rise in stringency by 100% reduced mobility by more than 75% (on average). The variation in the impact is also lesser, both across and within states. The national lockdown was able to elicit higher and more uniform mobility reductions across states.

Conclusion

States varied in their ability to reduce mobility through restrictions due to a number of possible reasons. Many of the worst affected districts (like Mumbai, Delhi, Indore) are among the country's most densely [urbanized clusters](#). [The 'Red Zone' districts consist of 53% of economic output](#). There were also instances of [mass reverse migration](#) from cities to villages after restrictions began to be imposed, which might have led to spikes in mobility. Thirdly, people's levels of awareness about COVID-19 leads to falls in [mobility](#), as they curtail movement to avoid exposure.⁸ Finally, states with [weaker institutions](#) might lack the ability to effectively implement mobility restrictions. Some variations in mobility changes are thus related to systematic features of states (urbanization or level of awareness). Other variations stem from more random sources. For instance, major religious gatherings occurred in [Kerala](#) and [New Delhi](#) in the days before the national lockdown.

The pandemic has raised difficult questions about [decentralised](#) public health responses versus uniform, [centralised](#) decisions. COVID-19 is projected to have a trajectory of ['rolling waves' of infection](#), and is unlikely to see a permanent decline within the next few months. [Until a vaccine](#) or cure is developed, governments will have to constantly monitor trends in the number of cases, and adjust or relax restrictions accordingly. India is now entering a period likely to be characterized by high state-wise heterogeneity in restrictions; extending to the district and

⁷ J&K had a higher coefficient, but the confidence interval was too wide.

⁸ Fang et al (2020) split this effect into a 'virus effect' and 'panic effect'

[intra-city levels](#). Our empirical analysis shows that in the initial phase of mobility restrictions, equal actions did not lead to equal effects for all states. Moreover, the national lockdown had a more uniform negative impact on mobility across states. The current decentralised approach should be informed based on these previous experiences.

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Acknowledgements

We are grateful to Dr. Srikanta Kundu and Dr. Ritika Jain for their comments.