Mobility reductions in response to Covid-19 in India: Comparing voluntary, state and central responses[1]

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In response to the surge of Covid-19 cases nations focused on reducing mobility to contain transmission of the virus. This change in mobility patterns can be achieved through two channels; (1) voluntary reductions in mobility due to rising public awareness and (2) explicit social distancing policies imposed by governments. In India, two weeks prior to the national lockdown imposed by the central government on 24th March, state governments had started independently enacting social distancing measures. However, there is little empirical evidence on the efficacy of the initial state-level restrictions, in comparison to the national lockdown. Even fewer studies have commented on the role of public awareness in reducing mobility. This paper contributes by comparing the impact of two policy events on mobility: the first Covid-19 social distancing policy imposed by each state and the imposition of the lockdown. We further explore how the news of the first reported case in a state impacted public awareness. The above effects were estimated by using an event study Difference-in-Differences model with time-varying treatment. Results show that while people did seek information in response to the perception that Covid-19 had 'reached' their state, they did not reduce out-of-home mobility significantly. However, starting from the second day after the lockdown, time spent in residence increased significantly for each day by 3-4% for the next 21 days. This is in sharp contrast to the insignificant

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effect of states' own first policy on mobility. The intervention of the central government had a much larger and persistent impact on mobility than the initial state-level policies, indicating that a unified, coordinated policy intervention is more effective than isolated, subnational efforts.

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1. Introduction

In response to the Covid-19 pandemic, state and central governments in India imposed social distancing policies, which have drastically reduced population mobility levels. The rationale for these non-pharmaceutical interventions (NPIs) is to slow down the rate of infections by reducing contact between individuals. By restricting non-essential economic and social activities, increasing numbers of people are forced to stay in their residences. Growing information and awareness about the disease also leads people to reduce their mobility, even in the absence of explicit restrictions.

In past epidemics of contagious, influenza-like diseases, countries have imposed human mobility restrictions to control transmission. Epidemiological studies have expressed mixed support for their effectiveness (Bajardi et al 2011; Bootsma and Ferguson 2007). Several empirical studies have examined the effects of Covid-19 social distancing policies around the world (Fang et al, 2020; Dahlberg et al 2020; Kurita et al 2020). The variation in timing of Covid-related restrictions among US states has been exploited by several studies to test their effects on mobility.[4] Using event study regressions on mobility data, Gupta et al (2020) found that state-level 'stay-at-home' orders produced smaller mobility reductions than closure orders or emergency declarations. Using aggregated Google mobility data, Wellenius et al (2020) found that emergency declarations led to a 10% increase in time spent inside residences, compared to 29% in response to stay-at-home orders. A subset of studies examined the interaction of political affiliation in US states with adherence to social distancing restrictions (Adolph et al. 2020; Andersen 2020; Painter and Qiu 2020). Studies also showed that with the rising risks of infection, people self-regulate their mobility resulting in higher compliance with government directives (Fang et al, 2020; Suwanprasert 2020).

On 11 March, the Indian Central government advised states to enact mobility restrictions authorized by the Epidemic Diseases Act (1897). The Act empowers state governments to impose sweeping social distancing policies; and states independently used this Act to implement varying policies in response to rising COVID-19 cases till 22nd March. These policies ranged from emergency declarations to complete lockdowns (equivalent to stay-at-home orders). However, India has an 'asymmetric' federal structure where the national government can exercise overarching authority (Tillin, L. 2007). The national government overruled the states, and imposed a nationwide lockdown on 24th March. This ordered a complete halt on all non-essential activities, and was recognized as the most 'stringent' lockdown in the world (Hale 2020).[5]

Indian studies of the restrictions' impact on mobility have focused exclusively on the effects of the national lockdown. Mukhopadhyay and Roy (2020) found that the lockdown disrupted usual migration patterns and initiated a reverse migration from cities to rural regions.[6] Lee and Sahai (2020) found that after the national lockdown intra-city mobility in Delhi reduced by 80%, working days by 73% and income by 53%. However, inter-state portability of food security benefits reduced within-state mobility by 12% (Choudhury et al 2020). As mentioned above, India's states had started enacting social distancing policies two weeks before the national lockdown. However, there is little empirical evidence on the efficacy of the initial

[4] Unlike India, the US federal government did not institute mandatory restrictions and allowed states to decide their own policies, with wide variation.
[5] This was implemented through the National Disaster Management Act, 2005
[6] Using Facebook's mobile users' data from the company's 'Data for Good' platform

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state-level restrictions, in comparison to the national lockdown. This paper adds to the literature by comparing the impact of two time-varying events on state-level mobility: the first Covid-19 policy imposed by each state, and the imposition of lockdown in each state. Even fewer studies have commented on the role of public awareness in reducing mobility. We further explore how the news of the first reported case in a state impacted public awareness about Covid-19, and the extent to which it was translated into mobility reductions. This analysis was conducted by constructing a dataset on state government policies, combined with newly available data on mobility patterns (see section 3).

2. Analytical framework

People move out of their residences mainly to supply labour and participate in consumption of goods and services (Gupta et al, 2020). Mobility patterns can be captured by visits to grocery stores, pharmacies, workplaces, malls and parks. A rise in mobility leads to a negative change in time spent in residences. Conversely, a fall in mobility leads to a positive change in time spent in residences. Hence, the time spent in residences can be a convenient indicator of changes in mobility patterns.

The surge in Covid-19 cases is expected to reduce mobility through two channels, the 'information channel' and the 'policy channel':

(i) *Information channel*: People voluntarily reduce mobility in response to information about the pandemic, independent of government policies. As the number of cases and risk of infection rises, they start limiting movement to essential purposes only (Fang et al, 2020). In India, the online, print and TV media rapidly spread news of detected cases, escalating fear as well as compliance among people (Choudhury et al 2020; Suwanprasert 2020).[7] Recent statistics indicate that a majority of Indian smartphone users access news primarily online (Aneez et al 2019). The aggregated volume of searches on issues related to COVID-19, as a proportion of total searches in a region, could be a proxy for the relative rise in awareness.

(ii) *Policy channel*: State governments imposed social distancing policies to minimise chances for the virus to spread from infected to uninfected patients. These restrictions were legally enforceable with violators being penalised. These measures 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. In India, these policies were classified into the following categories:

a. Restrictions on public gatherings
b. Closures: schools, recreational services (movie theatres, gyms, parks), bars and restaurants, all non-essential services
c. Internal travel restrictions: closure/reduction of public transport, closing state borders
d. Declaration of an epidemic/emergency
e. Lockdown: equivalent to 'stay-at-home' orders, where all the above restrictions are in effect

[7] This includes the number of cases, risks, symptoms, prevention and government policies.

3. Data and variables

3.1 Change in time spent in residences

We compiled a dataset at the state-day level, recording observations for 30 states from 15th February to 26th April, 2020. Google open-source Community Mobility data at the state level was used to capture the changes in mobility.[8] The data records changes in mobility trends for six categories of locations: grocery and pharmacy stores, parks, transit stations, retail and recreational establishments, workplaces and residences. In 2018, there were an estimated 390.9 million mobile internet users in India (Agnihotri and Chetan, 2019). Around 77% of the smartphones have Google search engines pre-installed. This implies that changes in movement patterns detected should be representative of the overall population. Our primary variable of interest is percentage rise in time spent in residences relative to baseline, which conversely indicates 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 Jan 3 – Feb 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 deal with this high seasonality, the time series is smoothed using an exponential window function. A moving window of observations is used to calculate a new, 'smoothed' variable. The original variable (x_t) is averaged to generate a new variable (Y_t) such that each observation gives more weightage to the present day's fluctuation (equations 1 and 2).

$$Y_0 = x_0 \quad (1)$$

$$Y_t = \alpha x_t + (1 - \alpha) x_{t-1}, t > 0 \quad (2)$$

Where α is the smoothing factor, and $0 < \alpha < 1$. The smoothing factor is optimised to minimize the forecast error for each individual state.

3.2 Social distancing policies and cases

Information on Covid-19 mobility restrictions in Indian states were compiled from news reports and state government executive orders. The state-wise dates of each policy announced is given in appendix A2. Data on the first case in each state was taken from covid19india.org.

3.3 Google Search trends

We include Google Trends data on the relative frequency of online searches related to Covid-19. The data is based on a sample of the total searches for the topic COVID-19[9] in a state within the time range of our study, expressed as an index of relative popularity. A higher value of the index means that searches related to the topic increased, as a proportion of all searches (Rogers, 2016).

[8] The data was gathered by Google from users who have enabled GPS location history on their personal devices.
[9] This includes searches for different words associated with COVID-19 like "coronavirus" and "corona".

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4. Empirical model

Researchers note that disentangling the effect of any specific policy is difficult, as several states imposed multiple policies on the same day (Wellenius et al 2020). As states imposed several restrictions in quick succession or simultaneously, later actions were possibly influenced by public awareness. However, early actions were plausibly exogenous with respect to their impact on mobility (Gupta et al, 2020). This analysis focuses on the first response policy of each state and compares its effectiveness with the declaration of lockdown.

The specification aims to the estimate dynamic effect of a time-varying treatment which is gradually absorbed over time by the treatment unit. The popular strategy to estimate the effect of a treatment on the outcome variable is the two-way linear fixed effect regression, which accounts for unobserved unit-specific and time-specific confounding effects. The basic Difference in Differences (DID) model consists of a single treatment, two groups (control and treated) and two time periods, pre-treatment and post-treatment (Angrist and Pischke, 2009). The basic DID setup, however, assumes a homogenous impact of the treatment through time. But the effect of a treatment can vary dynamically within pre-treatment and post-treatment time periods. Recent studies have used event study DID regression models to incorporate these aspects. (Athey and Imbens 2018, Borusyak and Jaravel, 2017, Callaway and Sant'Anna, 2018, de Chaisemartin and D'Haultfœuille, 2019 and Goodman-Bacon, 2018). The Goodman-Bacon (2018) variant of the panel-event study extends the DID setup to situations where treatment timing can vary across units. This event study DID regression accounts for two features which are key to the current analysis. First, it reveals the time-heterogeneous impact of a treatment/event on population mobility. Second, the specification accounts for the fact that the treatments/events of interest occur at different time periods for each state.

We considered two treatments that vary in their dates of occurrence across states: the first mobility restriction imposed by the state and the declaration of lockdown. Event windows are defined as a range of 20 days before and 20 days after the date of a particular event. These 20-day windows ensure that the effect of non-event related changes in mobility are kept to a minimum.

The panel event study DID regression is given by equation (3), based on Clarke and Schythe (2020).

$$Y_{it} = \alpha + \sum_{j=-20}^{-2} \beta_j \left(W_{it} = j\right) + \sum_{k=0}^{20} \gamma_k \left(W_{it} = k\right) + \theta_i + \mu_t + \varepsilon_{it} \quad (3)$$

Y_{it} is the percent change in time spent in residences for state *i* at time *t*, which has undergone the single exponential smoothing process described in (1) and (2). W_{it} is the event window dummy for the i^{th} state at the t^{th} time period with $t = j$ for the lag periods with $j = [-20, -2]$ and $t=k$ for the lead periods with $k = [0, 20]$. In the model, θ_i is the set of state fixed effects, which captures the fixed differences in the level of outcomes across states that are time invariant. μ_t is the set of time fixed effects that are common across all states. β_j and γ_k are event study coefficients that captures the deviations from the regular trends that the states experience in the days before and after a given policy treatment respectively. α represents effects which are constant across all states. ε_{it} is the residual error term.

To check whether the first reported case led to a break in parallel trends in people's awareness, we also estimate the above model with search frequencies for Covid-19 as the dependent variable, as shown in equation (4).

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$$S_{it} = \alpha + \sum_{j=-20}^{-2} \beta_j \, (W_{it} = j) + \sum_{k=0}^{20} \gamma_k (W_{it} = k) \; + \theta_i + \mu_t + \; \varepsilon_{it} \quad (4)$$

Here S_{it} is the search volume for state i at the t^{th} time period, and windows are defined around the date of the first reported case in each state. To check whether the information about first case translated into changes in mobility equation (4) was estimated with time spent in residence as the dependent variable.

5. Results

5.1 Descriptive results

Appendix A2 shows that states reported their first cases and instituted the first restrictions on different dates. Kerala reported the first COVID-19 case in India on 31st January. Some states – like Delhi - imposed restrictions more gradually, while others – like Arunachal Pradesh - adopted several policies within a shorter span of time. Kerala became the first state to invoke the EDA (1897), by declaring an epidemic/emergency on 11th March. Most states closed schools as their first policy response. The first state to declare a lockdown was Chattisgarh, on 20th March. It was the only state to impose a lockdown before the '*Janta* Curfew' on 22nd March which was effectively a voluntary nationwide lockdown. Nearly all states had enacted at least two mobility restrictions by 21st March.

As the number of cases and restrictions imposed by states began to increase, public awareness about Covid-19 began to rise. This is seen by the time series plots of state-wise search frequencies for Covid-19 (Appendix A3). However, these search volumes gradually declined with time. The same figures also show that mobility fell during the period of analysis, as the time spent in residences rose in all states. With the imposition of the national lockdown (shown by the dashed vertical line indicating March 24), time spent in residences rose sharply. States took varying amounts of time to elicit the maximum compliance to the national lockdown. Additionally, the maximum *levels* of time spent in residences also varied considerably. States' mobility levels did not stabilize at the maximum levels. The figure also shows roughly similar patterns for search frequencies, which increased till March 24th, followed by a much faster decline.

5.2 Event Study DID regression

The above patterns indicate that the national lockdown had a large impact on mobility levels and search trends, with varying lags. Figure 1 plots the estimated event study coefficients for search frequencies from equation (4), with the regression results shown in Appendix A4. The event is defined as the date on which the first case was reported in the state. There are two large, positive coefficients on the first and second days after the event, indicating a sharp break in parallel trends. One day after the first reported case, average search frequencies for Covid-19 went up by 5 percentage points after controlling for time and state-fixed effects. After the first day, none of the coefficients are significant. This implies that the news of the first confirmed case in a state led to a large number of people seeking information about Covid-19 online, but this heightened awareness did not persist beyond two days.

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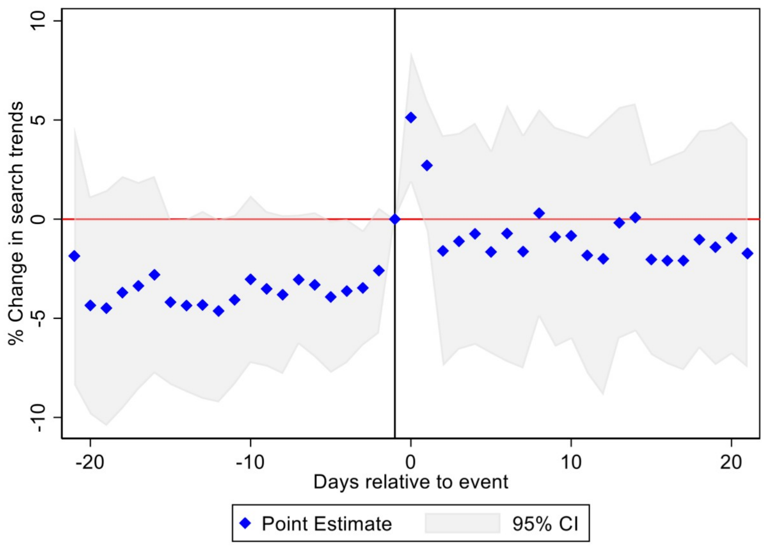
Fig.1 Event study coefficients plot: effect of first reported case on search frequencies



Note: Dependent variable is search frequencies. Regression results included in appendix A4.

As increase in people's information might translate into self-regulated changes in mobility, we estimate the above model with time spent in residences as the dependent variable. However, the report of the first case did not significantly change mobility patterns (as the first column in appendix A7 shows). These results show that while people did seek information in response to the perception that Covid-19 had 'reached' their state, they did not reduce out-of-home mobility significantly. This indicates that the 'information channel' was largely ineffective in reducing mobility. To check the effect of the 'policy channel', equation (3) was estimated with the two policy events mentioned above (section 2).

The second column of appendix A7 reports the coefficients of the event study regression with time spent in residence as the dependent variable. The event is defined as the date of the first Covid-19 related policy in each state. None of the coefficients are significant, reflecting that there was no break in parallel trends in mobility with the imposition of the first state-level policy.

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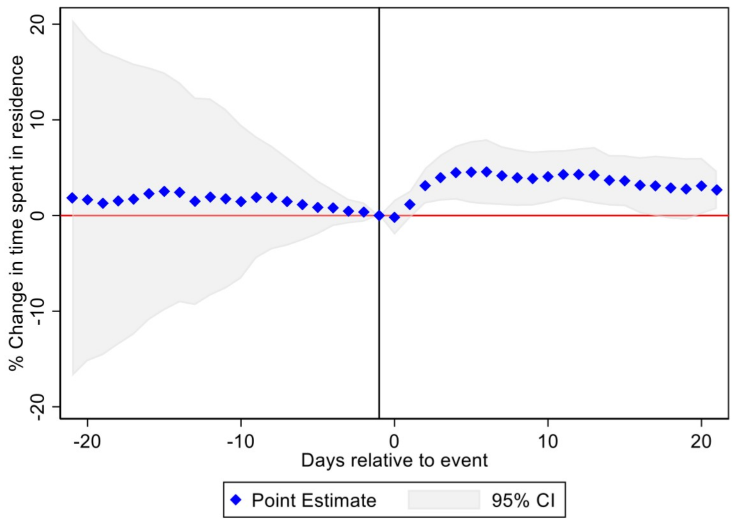
Fig 2. Event study coefficients plot: effect of lockdown on time spent in residences



Note: Dependent variable is time spent in residences. Regression results included in appendix A7, column 3.

The third column of appendix A7 reports the coefficients of the same event study regression model, with the event defined as the date on which a lockdown was imposed in the state. For the majority of states, this was the date of the national lockdown. As mentioned above, for eight states the lockdown was declared one to two days earlier. However, these policies coincided with the '*Janta* Curfew' declared on 22nd March. Hence, although the treatment/event varied over time across states, the impact of the event can be mainly attributed to the national lockdown.

The results show that starting from the second day after the policy, time spent in residence increased significantly for each day by 3-4% for the next 21 days. The cumulative effect of the lockdown was a 74 % rise in people's time spent in their residences from the baseline value, after 21 days. This is in sharp contrast to the insignificant effect of states' own first policy on mobility. We can conclude that the intervention of the central government had a much larger and persistent impact on reducing mobility than the initial state-level policies.

6. Conclusion and Discussion

One reason why heightened awareness about Covid-19 did not translate into voluntary mobility reductions may be related to people's assessment of the relative risks. Different age structures make certain populations more vulnerable to the disease (Suwanprasert, W; 2020). Levels of education and access to the internet vary widely among states, implying possibly high inequalities in how people get and use information.

Citizens' compliance with rules depends on the quality of institutions and level of trust in authority (van Rooj.et al, 2020; Goldstein & Wiedemann, 2020; Liu, N.N, 2015). Societies

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with institutions emphasizing collective decision-making witnessed better compliance with Covid-19 restrictions, than those with individualistic norms and cultures (Jinjarak et al 2020). Some, but not all, Indian states enacted supporting policies to ensure higher compliance with mobility restrictions, most importantly centred around food security (Choudhury et al 2020).

States also varied in how effectively they implemented the initial mobility restrictions, apart from the mere declaration. Enforcement measures like identifying and penalising violators become critical, such that sufficient deterrence fear is created (May, P. J, 2005). States pursued legal action against offenders, such as seizing vehicles and issuing fines. Police forces in several states also resorted to extra-legal violence against violators. Such coercive implementation strategies may be effective, but may create mistrust and antipathy towards authorities due to the disregard for human rights (Ray and Subramaniam 2020). These arguments point towards complex reasons why state-level policies had limited success.

The pandemic has raised questions about the efficacy of varying, state-level public health responses versus uniform, centralised decisions. The intervention of the Indian central government achieved a massive reduction in mobility across states, though it overrode states' autonomy and citizens' rights.[10] Findings from this study indicate that a unified, coordinated policy intervention is more effective than isolated, subnational efforts.

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[10] State government offices and courts were closed under the national lockdown.

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Appendix

A1: Summary Statistics

Variable	Obs	Mean	Std.Dev.	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

A2: State-wise dates of first cases and policy responses

States/UT	First Case Date	Date of restricting public gathering	Date of Declaring Lockdown	Date of School Closure	Date of Recreational Service Closure	Date of Restaurant Closure	Date of Internal Travel Closure	Date of Declaration of Emergency
Andhra Pradesh	12-Mar	24-Mar	24-Mar	20-Mar	20-Mar	24-Mar	24-Mar	Not Taken
Arunachal Pradesh	03-Apr	24-Mar	24-Mar	18-Mar	18-Mar	24-Mar	18-Mar	Not Taken
Assam	01-Apr	24-Mar	24-Mar	16-Mar	16-Mar	24-Mar	22-Mar	Not Taken
Bihar	22-Mar	19-Mar	24-Mar	14-Mar	14-Mar	22-Mar	22-Mar	18-Mar
Chandigarh	19-Mar	17-Mar	23-Mar	14-Mar	17-Mar	23-Mar	14-Mar	16-Mar
Chhattisgarh	19-Mar	16-Mar	20-Mar	14-Mar	14-Mar	20-Mar	14-Mar	Not Taken
Goa	26-Mar	22-Mar	22-Mar	15-Mar	15-Mar	22-Mar	24-Mar	Not Taken
Gujarat	20-Mar	24-Mar	24-Mar	16-Mar	16-Mar	24-Mar	24-Mar	15-Mar
Haryana	04-Mar	16-Mar	24-Mar	16-Mar	16-Mar	24-Mar	24-Mar	18-Mar
Himachal Pradesh	21-Mar	18-Mar	24-Mar	15-Mar	15-Mar	24-Mar	21-Mar	13-Mar
J and K	07-Mar	24-Mar	24-Mar	12-Mar	24-Mar	24-Mar	24-Mar	18-Mar
Jharkhand	01-Apr	24-Mar	24-Mar	17-Mar	17-Mar	24-Mar	22-Mar	17-Mar

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Karnataka	09-Mar	14-Mar	24-Mar	14-Mar	14-Mar	24-Mar	22-Mar	Not Taken
Kerala	31-Jan	22-Mar	24-Mar	11-Mar	14-Mar	24-Mar	24-Mar	11-Mar
Madhya Pradesh	21-Mar	24-Mar	24-Mar	15-Mar	15-Mar	23-Mar	24-Mar	Not Taken
Maharashtra	09-Mar	14-Mar	24-Mar	18-Mar	18-Mar	24-Mar	24-Mar	Not Taken
Manipur	24-Mar	22-Mar	24-Mar	13-Mar	22-Mar	22-Mar	18-Mar	Not Taken
Meghalaya	NA	24-Mar	24-Mar	17-Mar	17-Mar	24-Mar	24-Mar	Not Taken
Mizoram	25-Mar	24-Mar	24-Mar	18-Mar	18-Mar	24-Mar	10-Mar	Not Taken
Nagaland	NA	22-Mar	22-Mar	17-Mar	22-Mar	22-Mar	24-Mar	11-Apr
NCT of Delhi	02-Mar	17-Mar	24-Mar	13-Mar	17-Mar	20-Mar	24-Mar	14-Mar
Odisha	16-Mar	21-Mar	24-Mar	14-Mar	14-Mar	21-Mar	22-Mar	14-Mar
Puducherry	18-Mar	22-Mar	24-Mar	18-Mar	18-Mar	18-Mar	24-Mar	Not Taken
Punjab	09-Mar	17-Mar	22-Mar	14-Mar	14-Mar	14-Mar	19-Mar	Not Taken
Rajasthan	03-Mar	17-Mar	23-Mar	14-Mar	14-Mar	14-Mar	23-Mar	Not Taken
Tamil Nadu	07-Mar	24-Mar	24-Mar	17-Mar	17-Mar	24-Mar	17-Mar	Not Taken
Telangana	02-Mar	23-Mar	23-Mar	15-Mar	15-Mar	23-Mar	20-Mar	Not Taken
Tripura	07-Apr	24-Mar	24-Mar	16-Mar	16-Mar	24-Mar	24-Mar	Not Taken
Uttar Pradesh	04-Mar	24-Mar	24-Mar	14-Mar	17-Mar	24-Mar	24-Mar	Not Taken
Uttarakhand	15-Mar	23-Mar	23-Mar	15-Mar	15-Mar	23-Mar	24-Mar	15-Mar
West Bengal	18-Mar	24-Mar	24-Mar	16-Mar	17-Mar	22-Mar	22-Mar	Not Taken

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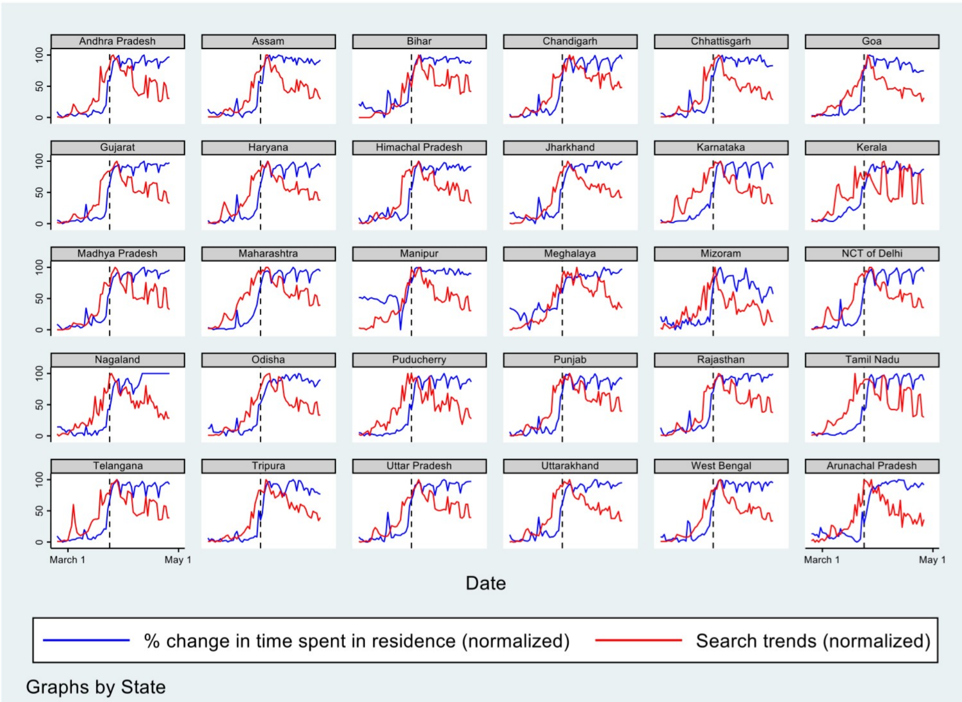
A3: State-wise time series plots of Percentage Change in time spent in residence and Search volume trends



Note: Values are normalised between 0 and 100. Vertical dashed line indicates the date of declaration of national lockdown.

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A4: Event study regression results corresponding to Figure 1(a)

Dependent Variable: Search frequencies for Covid-19

Regressors	First Case
Days Before Event=21	-1.857
	(3.19)
Days Before Event=20	-4.348
	(2.69)
Days Before Event=19	-4.485
	(2.91)
Days Before Event=18	-3.702
	(2.87)
Days Before Event=17	-3.364
	(2.56)
Days Before Event=16	-2.804
	(2.44)
Days Before Event=15	-4.184*
	(2.04)
Days Before Event=14	-4.356
	(2.14)
Days Before Event=13	-4.325
	(2.32)
Days Before Event=12	-4.630*
	(2.26)
Days Before Event=11	-4.068
	(2.09)
Days Before Event=10	-3.034
	(2.07)
Days Before Event=9	-3.515
	(1.92)

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Days Before Event=8	-3.809
	(1.96)
Days Before Event=7	-3.048
	(1.60)
Days Before Event=6	-3.311
	(1.79)
Days Before Event=5	-3.921*
	(1.88)
Days Before Event=4	-3.625
	(1.78)
Days Before Event=3	-3.466*
	(1.42)
Days Before Event=2	-2.591
	(1.55)
Days After Event=0	5.129**
	(1.62)
Days After Event=1	2.711
	(1.63)
Days After Event=2	-1.599
	(2.85)
Days After Event=3	-1.114
	(2.67)
Days After Event=4	-0.738
	(2.74)
Days After Event=5	-1.650
	(2.51)
Days After Event=6	-0.720
	(3.18)
Days After Event=7	-1.633

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	(2.89)
Days After Event=8	0.301
	(2.57)
Days After Event=9	-0.894
	(2.71)
Days After Event=10	-0.837
	(2.55)
Days After Event=11	-1.826
	(2.92)
Days After Event=12	-1.998
	(3.38)
Days After Event=13	-0.183
	(2.86)
Days After Event=14	0.085
	(2.81)
Days After Event=15	-2.034
	(2.36)
Days After Event=16	-2.091
	(2.55)
Days After Event=17	-2.089
	(2.71)
Days After Event=18	-1.029
	(2.69)
Days After Event=19	-1.410
	(2.91)
Days After Event=20	-0.948
	(2.87)
Days After Event=21	-1.724
	(2.82)

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Constant	6.230*
	(2.81)
N	2232
Date Fixed Effects	Yes
State Fixed Effects	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Clustered standard errors in parentheses

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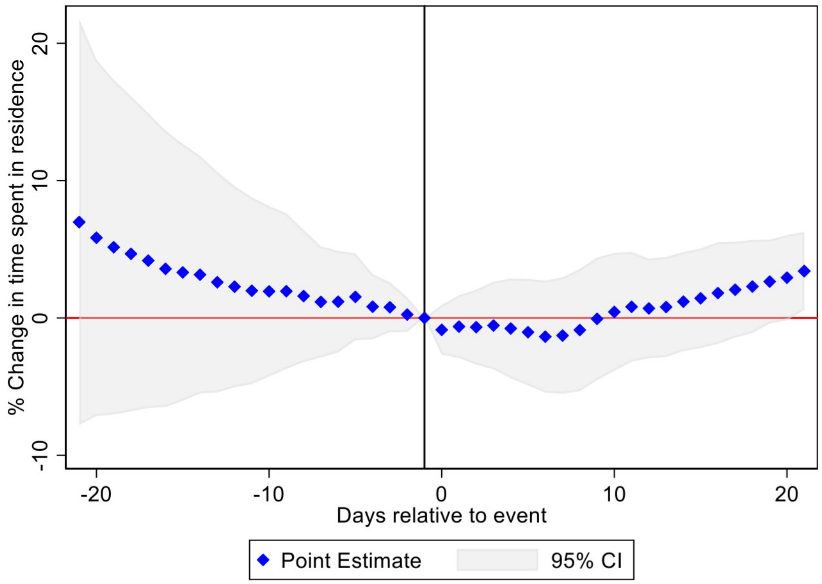
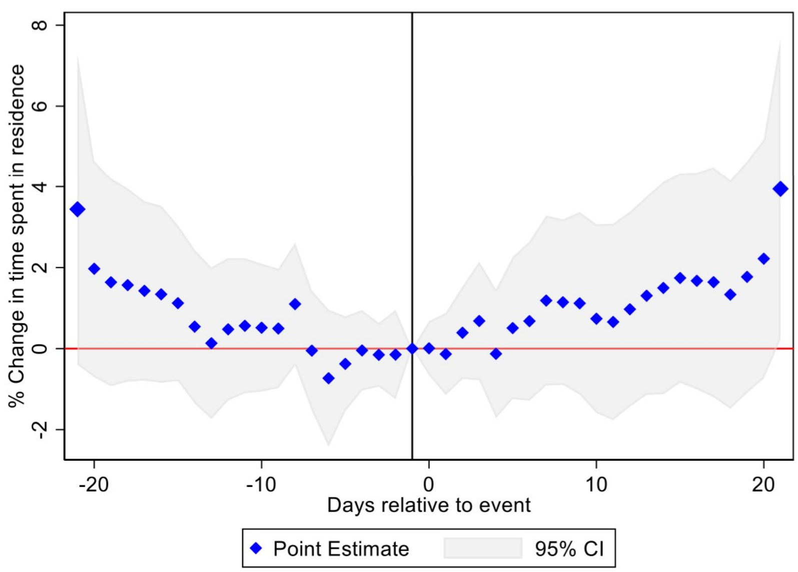
A5: Event study coefficients: Dependent Variable-Change in Mobility, Event-First policy enacted by each state



A6: Event study coefficients: Dependent variable-Change in Mobility, Event-First reported case in each state



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A7: Event study regression results corresponding to Figure 1, A5 and A6

Dependent Variable: Change in time spent in residence

Regressors	First Case	First Policy Implemented	Lockdown
Days Before Event=21	3.440	6.980	1.844
	(1.88)	(7.23)	(9.13)
Days Before Event=20	1.971	5.841	1.650
	(1.31)	(6.35)	(8.26)
Days Before Event=19	1.638	5.153	1.279
	(1.26)	(5.96)	(7.77)
Days Before Event=18	1.568	4.673	1.532
	(1.17)	(5.62)	(7.35)
Days Before Event=17	1.427	4.179	1.712
	(1.08)	(5.26)	(6.94)
Days Before Event=16	1.341	3.578	2.285
	(1.07)	(4.93)	(6.47)
Days Before Event=15	1.122	3.318	2.528
	(0.94)	(4.57)	(6.09)
Days Before Event=14	0.544	3.155	2.421
	(0.93)	(4.24)	(5.63)
Days Before Event=13	0.134	2.601	1.487
	(0.92)	(3.93)	(5.31)
Days Before Event=12	0.477	2.278	1.938
	(0.86)	(3.58)	(5.04)
Days Before Event=11	0.564	1.984	1.752
	(0.82)	(3.33)	(4.59)
Days Before Event=10	0.516	1.939	1.456
	(0.77)	(3.04)	(3.94)
Days Before Event=9	0.496	1.950	1.900
	(0.72)	(2.77)	(3.11)

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Days Before Event=8	1.100	1.597	1.877
	(0.74)	(2.35)	(2.65)
Days Before Event=7	-0.050	1.172	1.464
	(0.73)	(1.98)	(2.26)
Days Before Event=6	-0.731	1.185	1.143
	(0.83)	(1.81)	(1.83)
Days Before Event=5	-0.375	1.537	0.851
	(0.57)	(1.55)	(1.38)
Days Before Event=4	-0.044	0.820	0.804
	(0.49)	(1.16)	(0.93)
Days Before Event=3	-0.152	0.783	0.457
	(0.39)	(0.89)	(0.62)
Days Before Event=2	-0.147	0.249	0.363
	(0.54)	(0.62)	(0.49)
Days After Event=0	0.009	-0.864	-0.188
	(0.33)	(0.89)	(0.90)
Days After Event=1	-0.134	-0.626	1.155
	(0.50)	(1.11)	(0.70)
Days After Event=2	0.392	-0.670	3.122**
	(0.56)	(1.34)	(0.92)
Days After Event=3	0.683	-0.549	3.964**
	(0.72)	(1.56)	(1.18)
Days After Event=4	-0.128	-0.763	4.483**
	(0.78)	(1.78)	(1.39)
Days After Event=5	0.508	-1.036	4.539**
	(0.86)	(1.90)	(1.59)
Days After Event=6	0.679	-1.361	4.571*
	(0.96)	(2.00)	(1.67)
Days After Event=7	1.186	-1.281	4.164**

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	(1.03)	(2.07)	(1.51)
Days After Event=8	1.146	-0.879	3.956*
	(1.00)	(2.18)	(1.44)
Days After Event=9	1.118	-0.064	3.859**
	(1.10)	(2.19)	(1.38)
Days After Event=10	0.739	0.438	4.066**
	(1.14)	(2.10)	(1.34)
Days After Event=11	0.658	0.813	4.284**
	(1.19)	(1.95)	(1.24)
Days After Event=12	0.972	0.696	4.289**
	(1.18)	(1.77)	(1.34)
Days After Event=13	1.306	0.798	4.214**
	(1.20)	(1.78)	(1.45)
Days After Event=14	1.498	1.191	3.684**
	(1.28)	(1.76)	(1.29)
Days After Event=15	1.744	1.435	3.635**
	(1.27)	(1.77)	(1.30)
Days After Event=16	1.673	1.815	3.164*
	(1.31)	(1.81)	(1.44)
Days After Event=17	1.642	2.057	3.107
	(1.39)	(1.71)	(1.54)
Days After Event=18	1.334	2.293	2.890
	(1.38)	(1.66)	(1.58)
Days After Event=19	1.771	2.650	2.775
	(1.40)	(1.49)	(1.58)
Days After Event=20	2.219	2.937	3.100*
	(1.45)	(1.52)	(1.44)
Days After Event=21	3.944*	3.414*	2.678**
	(1.82)	(1.39)	(0.97)

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Constant	-1.676	-5.814	-0.677
	(1.57)	(7.09)	(9.00)
N	2232	2232	2232
Date Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Clustered standard errors in parentheses

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