COVID-19 Containment, Coordinated Compliance, and Collective Cooperation: How EDM Centralisation Asymmetrically Affected India's Urban and Rural Districts

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1. Introduction

As the COVID-19 pandemic acceleratingly encroached on the health and wellbeing of both individuals and countries around the world in early 2020, governments sought to put measures in place in order to stop or slow the spread of the disease. Primary among these preventive measures were 'social-distancing policies': policies that placed and enforced limitations on people's mobility with the purpose of reducing the number of personal encounters during which COVID-19 transmission could take place. Although virtually all efforts by governments to combat COVID-19 incorporated a social-distancing aspect, the precise political and social contexts as well as the success rates of these policies varied substantially between countries across the world (Nicola et al, 2020).

One dimension of containment strategies that has been discussed by various authors is the centralisation of decision-making: the level of government at which strategic decisions are made. Some find that centralisation benefits public compliance with preventive measures because it expedites decision-making (Biase & Dougherty, 2021; Bouckaert et al, 2020; Haffajee & Mello, 2020). Others are positively predisposed to local governance as facilitated by decentralised approaches (Hattke & Martin, 2020; Hegel & Schnabel, 2021; Waugh & Streib, 2006). Another topic of research is how the urban-rural differences affect compliance (Callaghan et al, 2021; Kumar et al, 2022).

To the best of my knowledge, no author has yet combined the dimensions of centralisation and urbanisation to predict compliance. In this paper, I make the argument that decentralised and centralised strategies each have their advantages and disadvantages. Overall, centralised strategies are better at fostering compliance with preventive measures, but their appeal is more apparent in urban areas than in rural areas. Urban areas are more compliant than rural areas, creating an 'urban-rural compliance gap'. This compliance gap is greater under centralised strategies than under decentralised strategies.

First, I theoretically substantiate this line of argumentation. Then, using India as my single case study, I run three regression analyses to bolster it: two to assess the direct effect of centralisation and urbanisation on compliance, and thirdly a difference-of-differences regression analysis to assess how urbanisation mediates the effect of centralisation on compliance. My findings largely corroborate my theory: centralisation indeed positively influences compliance, but does so more significantly in urban areas than rural areas. This research contributes to the existing corpus of academic literature regarding effective health governance and emergency disease management. Notwithstanding inherent limitations and the evident need for further research in this field, it offers valuable insight into what sorts of strategies do or do not work in various circumstances.

The resulting research question is:

How does the level of centralisation of an EDM strategy during a pandemic affect public compliance with preventive social-distancing measures?

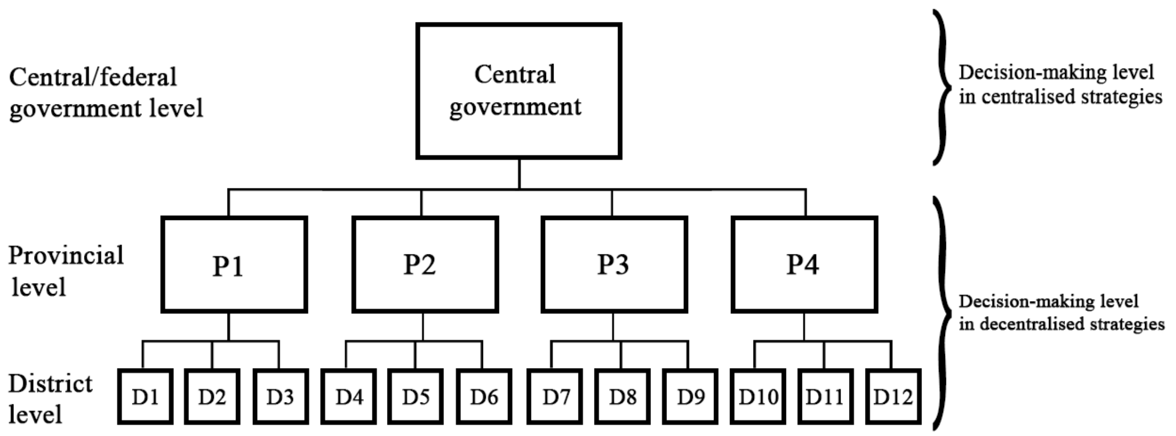
2. Theory

The paradox of (de)centralised EDM strategies

Because pandemics pose an extraordinary threat to the health and wellbeing of societies at large, governments resort to Emergency and Disaster Management (EDM) strategies to deal with them (Hattke & Martin, 2020). EDM strategies can be classified as occurring in one of two forms: centralised or decentralised, where the level of centralisation refers to the level of the organisational and bureaucratic hierarchy of the state at which decisions regarding the containment of the disease are made. A strategy is centralised when "the [central] government decides on the introduction, amendment or abolition of a policy measure by proposing legislation or by adopting regulations and executive orders" (Hegele & Schnabel, 2021, p. 1054). In this kind of strategy, decision-making power is centrally vested at the top of the bureaucratic hierarchy. On the other hand, a decentralised strategy devolves this decision-making power to smaller, subnational governments of local constituent units. This occurs less frequently than centralised strategies, but its occurrence is most commonly seen in federal states where decisions are generally already devolved to the municipal or provincial level, especially in the field of healthcare (Kumar et al, 2022).

Figure 1

(De)centralised Decision-Making



Most states adopt centralised EDM strategies during health crises because the nature of the crisis often demands fast and decisive action to be taken before the situation spins out of control. Especially when dealing with communicable diseases, preventive measures need to be put in place that can potentially interfere with individual rights and freedoms (Biase & Dougherty, 2021). For example, highly transmissible diseases might necessitate the right of free movement or association to be compromised in order to stop or slow the transmission of the disease between people. Such intrusive measures are most effectively passed when legislated by a single, powerful, centralised institution that is not swayed or delayed by the fragmented preferences and incentives that are common among institutions lower in the bureaucratic hierarchy (Haffajee & Mello, 2020; Hegele & Schnabel, 2021).

Especially in earlier stages of the pandemic, swift and decisive legislation and implementation of preventive measures is necessary to stimulate compliance with these measures because it mobilises people quickly. States where power and authority are centralised enjoy the legitimacy needed to implement harsh measures and expect people to comply (Bouckaert et al, 2020). On top of this, they are able to communicate clearly and directly with the people, which is necessary to convince people of the gravity of the situation. An exemplary illustration of this is Greece. Thanks to an early, unitary approach, the Greek government was able to declare a national state of emergency and implore people to comply through regular press conferences in which preventive measures were announced, relevant statistics were reported, fake news was debunked, etc. This resulted in early compliance levels exceeding those of surrounding European countries (Ladi et al, 2021).

Decentralised EDM strategies, on the other hand, are relatively common among federal states, especially during the early stages of the pandemic, when preventive measures are simply filed under already devolved 'regular' healthcare policy. Federal states are generally keen to devolve healthcare policy to the subnational level for several reasons, the most prominent being the fact that local governments are better able to deliver healthcare services that are specifically tailored to local needs and circumstances. Additionally, local governments are better connected with essential interorganisational networks and are more cost-efficient than federal governments (Banting & Corbett, 2002; Waugh & Streib, 2006). However, this comparative advantage of devolving 'regular' healthcare policy only partially translates to the context of EDM strategies. The relevant distinction with EDM strategies is namely that the latter beg for a certain level of urgency and swiftness to deal with a rapidly developing threat, and centralised strategies are simply superior in providing this.

That is not to say that decentralised EDM strategies are worthless. They retain the advantage that they are closer to the people, facilitating state-society communication and adaptation to local needs and practices (Hegele & Schnabel, 2021). By virtue of the fact that centralised strategies are orchestrated high in the bureaucratic hierarchy, they inevitably cause a certain state-society disconnect. This difference is most clearly felt in peripheral regions where disenchantment with the central government already compromises compliance:

centralised strategies achieve a relatively low level of compliance there (Wasserfallen, 2015). Local governments with devolved EDM powers are more effective at fostering compliance with these measures in peripheral regions because they are better at mitigating collective actions problems that hinder compliance (Hattke & Martin, 2020). The appeal, therefore, of decentralised EDM strategies is that their scope of reach is more extensive than that of centralised EDM strategies, despite the latter admittedly being more effective in fostering compliance in aggregate.

We arrive at what Moynihan (2008) calls "a crisis management paradox: crises not only require an interorganizational response but also require traits unusual in networks: rapid and decisive coordinated action" (p. 206). An unforgiving dichotomy exists between top-down, authoritative, hierarchically decisive approaches and bottom-up, network-based, interorganisationally coordinated approaches. Ideally, an effective EDM strategy would have both elements, but centralised EDM strategies can offer only the former and decentralised EDM strategies can offer only the latter. Crucially, states can only choose one. Therefore, a state's ability to foster high aggregate compliance with preventive measures through swift, decisive action inherently goes at the expense of its ability to enforce these measures homogeneously across society in a coordinated manner, suppressing compliance in peripheral contexts with a state-society disconnect - and vice versa.

The urban-rural compliance gap

No matter whether a strategy is centralised or decentralised, a divergence in compliance with preventive measures can be observed between urban and rural areas. Urban areas see more compliance than rural areas across the board (Asnakew et al, 2020; Callaghan et al, 2021; Haischer et al, 2020; Kumar et al, 2022). Various factors are at play here, but they can all be bundled into a single determinant of compliance: *risk perception*. According to the *Health Belief Model* introduced by Champion and Skinner (2008), people are more likely to comply with preventive measures if they perceive a high enough risk of being compromised - in any way or form - by not complying, and vice versa. This risk perception is the product of two processes: first, one assesses the outcomes - costs and benefits - associated with (non-)compliance, and second, they assign utility to these perceived costs and benefits. Consequently, people choose to comply when the perceived utility associated with the outcomes of compliance is greater than the perceived utility associated with the outcomes of not complying (Allcott et al, 2020).

It seems appropriate to approach this decision-making process from a rational choice theory perspective because either consciously or subconsciously, people generally employ cost-benefit analyses to substantiate decisions regarding their behaviour. As people decide whether or not to comply with preventive measures, they are faced with choice X: compliance (*C*) or non-compliance (*NC*). Both options result in perceived outcomes (Z_X): benefits and costs. The most obvious outcome of compliance (Z_C) is the *reduced risk of infection* with the disease, provided that the measures are in principle effective. Additionally, there might be legal or social incentives for someone to comply: one might not want to run the *risk of getting fined* or *shamed* for not following the rules. However, there are also costs associated with complying, such as *social isolation* (in case of social distancing measures) or the *nuisance* of having to frequently and thoroughly wash one's hands (in case of hygiene measures), among others.

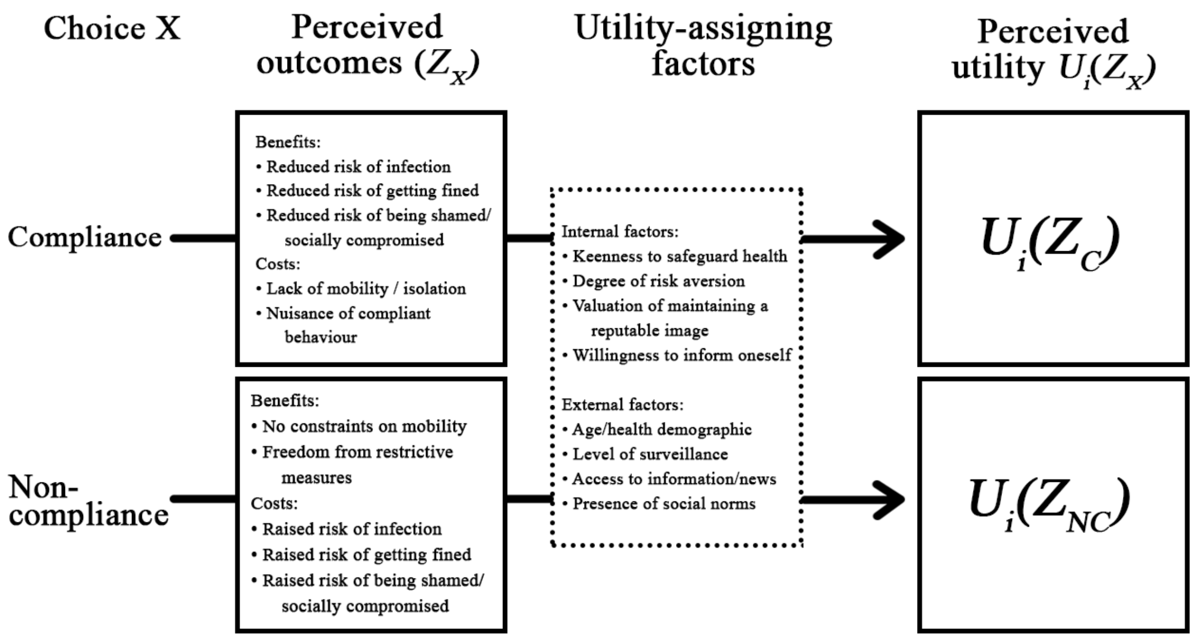
On the other hand, non-compliance also leads to certain outcomes (Z_{NC}). Primarily, it exposes one to the *risk of infection*, which is inherently costly. Additionally, one runs the *risk of getting fined* if caught by law enforcement as well as the risk of being *socially compromised* by members of a community who expect fellow members to comply with the preventive measures in order to safeguard the health of the community. However, the beneficial outcomes of non-compliance include a lack of constraints on *mobility* (in case of social distancing measures) or a sense of *freedom from limitations* of the measures, again among others.

The perceived utility assigned to these outcomes ($U_i(Z_X)$, where *i* denotes the *i*th individual) varies per individual because the costs and benefits are experienced differently from one person to another, depending on several internal and external *utility-assigning factors*. Internal factors are inherent to the person, their personality, or the values that they hold. For example, not all people are equally keen on *protecting their health*, meaning some might be more willing to risk an infection than others. Also, people differ in their level of *risk aversion*: a risk-averse person might go out of their way to avoid risk, meaning they attribute less utility to stochastic choices such as running the risk of infection or getting caught by the police. Alternatively, one might not attach as much utility to *keeping up a compliant reputation* if it means they can - illicitly - spend time with their peers, in which case a person is less likely to comply. Another hugely influential internal factor is how *informed* an individual is: an individual who chooses not to inform themselves on the spread, severity, or susceptibility of the disease is more likely to underestimate its gravity, therefore deem compliance less utile.

External utility-assigning factors that shape compliance incentives are not subject to an individual's influence as much as they are simply the result of the circumstances one finds themselves in. For example, the *demographic* one belongs to might have a significant bearing on the severity of the disease once they catch it - a young and healthy individual might place less utility on compliance than an older individual. In a similar vein, someone with a low *socioeconomic status* may simply not have the resources to afford to comply because they have to go out and work. Alternatively, the level of *surveillance* of (non-)compliant behaviour might incentivise compliance: an individual residing in a heavily policed area might find compliance very utile. Irrelevant of whether one chooses to inform themselves, the amount of *information available* to them can also vary substantially, which can shape perceptions of utility. Similarly, irrelevant of whether one places high or low utility on conforming to communal expectations, there might or might not exist the relevant *social norms* that dictate compliance to exert such pressure in the first place.

Figure 2

The Rationalisation of Compliance



After having assessed - consciously or subconsciously - perceived outcomes Z_C and Z_{NC} and assigned to them perceived utility $U_i(Z_C)$ and $U_i(Z_{NC})$, individual *i* decides whether or not to comply. If $U_i(Z_C) > U_i(Z_{NC})$, they will comply. If $U_i(Z_C) < U_i(Z_{NC})$, they will not comply. This process is heavily influenced by the weight of the relevant utility-assigning factors.

These vary largely throughout society, but a split can be seen between urban and rural areas: some utility-assigning factors for Z_C are consistently stronger in urban areas than in rural areas. One example is the level of *surveillance*: urban areas, being densely populated, see much more policing than rural areas, which are much more sparsely populated. Urban people are also better informed than rural people: they are more *educated*, meaning they are more aware of personal hygiene and health hazards (Young, 2013). Additionally, they have more access to *accurate news outlets* to stay updated about the spread and danger of the disease (Geana, 2020; Uddin et al, 2021). Because these utility-assigning factors are stronger in urban areas, the perceived utility of compliance in urban areas $U_{urban}(Z_C)$ frequently exceeds that in rural areas $U_{rural}(Z_C)$. Therefore, urban areas see higher compliance than rural areas, resulting in the aforementioned 'urban-rural compliance gap'.

Collective action and government intervention

Government intervention reduces this compliance gap. In itself, compliance with preventive measures constitutes a collective action problem because perceived individual interests are generally not aligned with the collective interest, as visualised in Figure 3 (Bicalho et al, 2021; Ostrom 1990). The risk of infection would be lowest - i.e. society as a whole would be better off - if everyone complied, but each individual i would be even better off if all other individuals i' complied and individual i themselves did not comply (Hattke & Martin, 2020). In such a scenario, individual i enjoys a free ride: the risk of being infected is minimised thanks to the compliance of individuals i', and on top of that individual i enjoys the benefits of non-compliance Z_{NC}. For each individual i, the optimal outcome can only be attained if individuals i' cooperate, but cooperation is inhibited by a lack of coordination and trust. This reduces the perceived utility of compliance $U_i(Z_C)$, universally lowering incentives to comply (Tsai et al, 2020).

Government intervention can help mitigate this collective action problem by manipulating the *external utility-assigning factors* associated with the beneficial outcomes of compliance, such that each individual i's perceived utility of compliance $U_i(Z_C)$ is raised and the constellation of incentives is rearranged in favour of the collective good. Governments are generally limited to manipulating external factors because they exist and operate completely outside of the agency of individuals, meaning governments can independently use them to shape the conditions and incentives under which individuals make decisions regarding compliance. Internal factors, however, are within the realm of the individual, rendering them generally inaccessible to the government.

Figure 3

Compliance as a Collective Action Problem

Individual i	Individual i'	
	NC	C
NC	$U_i(Z_{NC})$ = moderate $U_{i'}(Z_{NC})$ = moderate	$U_i(Z_{NC})$ = high $U_{i'}(Z_{NC})$ = low
C	$U_i(Z_{NC})$ = low $U_{i'}(Z_{NC})$ = high	$U_i(Z_{NC})$ = high $U_{i'}(Z_{NC})$ = high

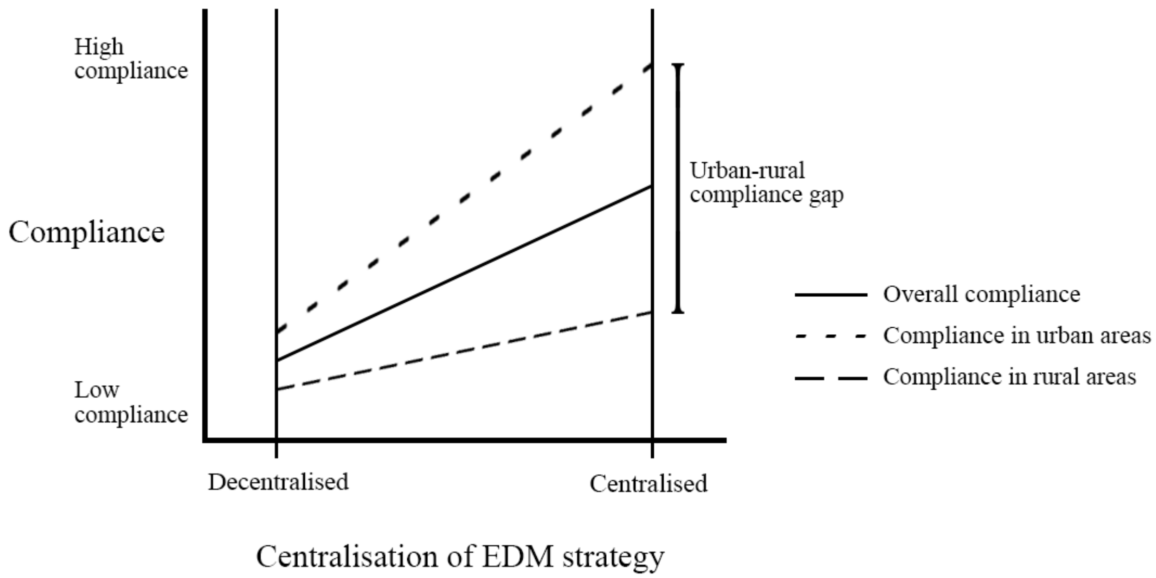
This manipulation can be done in two ways: (1) altering public perceptions of the costs and benefits of compliance, and (2) instilling trust among the population in order to encourage cooperation. Public perceptions are best shifted in favour of compliance through the *provision of information*, for example by institutionalising direct communication channels such as regular press conferences through which the people are kept up to date on the spread of the disease (Ladi et al, 2021). Governments can also engage in *educational campaigns*, educating people on the spread and hazards of the disease (Bouckaert et al, 2020). By instilling a heightened sense of alertness to the disease, people are driven to overestimate the costs of non-compliance $U_i(Z_{NC})$ such that they - perhaps irrationally - shed their private interests in favour of the common interest, instigating collective action.

The second way to manipulate utility-assigning factors in favour of collective action is by instilling trust among the people, so that they are more willing to cooperate and not free-ride because they trust that others will not free-ride either. To this end, governments engage in *norm creation*, so that compliance is the assumed behaviour (Hattke & Martin, 2020; Tsai et al, 2020). This in part also happens in an intertwined fashion with providing information, as a baseline of common knowledge is key to the development of social norms. Then, peer-to-peer communication is facilitated in order to let people assess and criticise non-compliant behaviour (Bicalho et al, 2021). The result is a mechanism of social control, where people police each other, encourage compliance, and punish non-compliant free-riders for not cooperating (Boterman, 2020).

Now, it becomes clear why a locally involved government is beneficial to fostering compliance. In order for people to be maximally informed, communications channels between state and society need to be tight, adjusted to local needs and practices, and locally accessible. In order for people to trust each other, they first need to trust the government that instigates these norms. The disparity between centralised and decentralised EDM strategies in the way they foster compliance in urban and rural areas also becomes clear: centralised strategies see higher levels of compliance overall vis-a-vis decentralised strategies, but this improvement is less significant in rural areas than in urban areas because centralised strategies are not able to engage in local governance as well as decentralised strategies can (Figure 4 provides a visual representation of this relationship).

Figure 4

Hypothesised Plot: Overall, Urban, and Rural Compliance Against EDM Centralisation



Considering the delineated theoretical argumentation, I maintain the following three hypotheses:

H_1: centralised EDM strategies see higher rates of compliance with preventive measures than decentralised EDM strategies;

H_2: urban areas see higher rates of compliance with preventive measures than rural areas;

H_3: the difference in compliance between urban and rural areas is larger under centralised EDM strategies than under decentralised EDM strategies.

3. Methodology

Case selection and timeframe: India during lockdown

To test these hypotheses, I examine the varying levels of compliance with centralised and decentralised COVID-19 social-distancing measures in rural and urban India. A single case study is appropriate for this end because it largely guarantees that the external conditions within which the tested relationships occur are held constant, facilitating reliable *ceteris paribus* analysis. Crucially however, India is specifically suitable because the factors that *are* relevant to this study see substantial variation, allowing for an accurate and reliable analysis of the relationships in question. Quantitative regression analysis is conducted of district-level variation in compliance to preventive measures legislated by state and central governments, with a specific distinction made between urban and rural districts.

The first case of COVID-19 in India was observed on 30 January 2020 in the state of Kerala. The responsibility to deal with this emerging threat to public health was initially left to states themselves, as health policy is generally devolved in India's federal system. In the weeks following the introduction of the virus, these state governments individually began introducing increasingly restrictive social-distancing measures in order to slow the spread of the virus (Choutagunta et al, 2021). India's EDM strategy was consequently centralised in two particular stages: on March 22nd, prime minister Modi announced a national, voluntary '*Janta' curfew*, and on March 24th, a radically and nationally centralised lockdown was announced (Kumar et al, 2022; Singh, 2022). This strict lockdown lasted until May 4th, when first relaxations were introduced. The radical switch on March 24th lends itself remarkably well to capture the effects of EDM centralisation because the pre- and post-March 24th periods can effectively be seen as control and treatment groups, where other factors - except for other time-varying factors - are conveniently held constant.

The timeframe maintained in this analysis spans 79 days from February 15th to May 3rd. Having February 15th as a starting date is due to a lack of rigorous data availability on public social-distancing before this. Although this is after the start of COVID-19 in India, it is before the first social-distancing policy is introduced on March 6th, so it still captures the intended relationship between preventive policy and compliance. It is important that the 'treatment' day (March 24th) occurs somewhat in the middle of the timeframe because there needs to be substantial 'pre-treatment' data in order to make a reliable comparison. The last included day in the timeframe is May 3rd because May 4th is the first day that some states introduced relaxations, indicating the end of the unequivocally centralised strategy that started on March 24th (MHA, 2020).

This analysis includes all 36 states (or union territories) of India except Jammu and Kashmir, of which both the jurisdictional allegiance and data availability is muddy. 629 districts out of 766 districts are included - 126 districts were excluded because they did not exist during the 2011 census from which my *urbanisation* data originate, and 11 were excluded because of lack of *compliance* data. Arguably, this could compromise the representativeness of the district sample, but since the excluded districts were not methodically left out, this is unlikely. The sample size is still large enough to guarantee an admissible level of reliability. Districts are maintained as the primary unit of analysis because although preventive measures were legislated at state level (at least before March 24th), compliance rates saw a lot of local, sub-state-level variation (Kumar et al, 2022). Additionally, these districts are the smallest unit for which rigorous data is readily available.

Variables: conceptualisation and operationalisation

This analysis maintains two independent variables: the level of *centralisation* of the EDM strategy at hand and the level of *urbanisation* of the district in question. *Centralisation* is conceptualised as the level of the bureaucratic hierarchy of government at which preventive measures are legislated (Figure 1 provides a visual representation of the various levels of decision-making in this hierarchy). In centralised EDM strategies, these measures are legislated at the central government level; in decentralised EDM strategies, at the state government level. India maintained a decentralised strategy in the early phase of the pandemic: from its beginning until March 23rd. On March 24th, a centralised strategy was commenced through a severe, nationwide lockdown, which continued until May 3rd. In my data, this translates to a binary 'centralised' variable, coded '0' for the 37 days from February 15th to March 23rd, and coded '1' for the 41 days from March 24th to May 3rd.

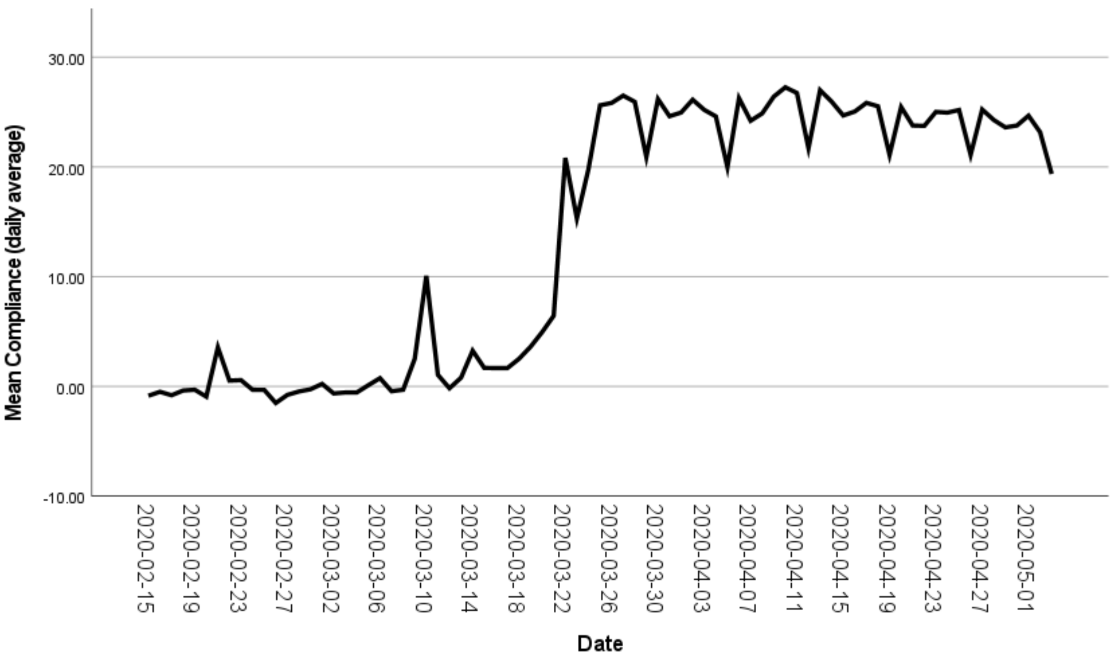
A district's level of *urbanisation* refers to the proportion of the population that resides in an urban area. The conditions for an area to be urban as maintained during the 2011 census are threefold: a minimum population of 5000; a population density of at least 400 people per square kilometre; 75% of the working population is employed in a non-agricultural sector (MHA, 2011). In my data, I again maintain a binary 'urban' variable, coded '0' for all districts that have a majority of rural residents, and '1' for all districts that have a majority of urban residents. Rural districts are far more common with 548 districts (87.1%) as opposed to

81 (12.9%) urban districts, but there are still enough districts in either category that this disparity is not likely to compromise reliability.

In this analysis, these two independent variables predict the level of *compliance* with preventive measures - specifically, social-distancing policies. Social-distancing measures imposed a limitation on mobility through the closure of public spaces, workplaces, schools, supermarkets, recreational areas etc. They also prohibited large public gatherings and visiting family or friends in large numbers, all with the purpose that people stay at home to prevent transmission of the COVID-19 virus (Kumar et al, 2022). It follows that compliance can be conceptualised as the extent to which people adhered to these measures, and operationalised by measuring the amount of 'extra' time that people spend at home as compared to the pre-COVID-19 era. To this end, I employ data from Google's (Google LLC) *Community Mobility Reports* on how much time people spent in residential areas, expressed as the percentage increase from a reference value taken from the baseline 5-week period of January 3rd to February 6th of 2020, during which there was presumably no COVID-19. Figure 5 shows a level of compliance around the baseline during the first weeks of the time frame, with a sharp and sustained increase in compliance from the end of March onwards. The spike around March 11th can likely be attributed to the World Health Organisation (WHO) declaration of COVID-19 as a pandemic.

Figure 5

Mean Compliance During the Analysed Timeframe



Using this data necessarily requires some nuance to be provided. The baseline values are determined individually per day, meaning any Monday will be compared to the average value for the five Mondays in the baseline period. As a result, it is not appropriate to compare between individual weekdays, because the baseline is likely not the same. However, it is possible to compare weeks because the seven baseline values are used on a weekly rotating basis. It is for this reason that Figure 5 shows a weekly ‘dip’ in compliance starting near the end of March: the increase in compliance was not as significant during weekends because people already spent a lot of time at home during the baseline weekends. Additionally, this data will likely underestimate compliance on days that saw an unusual spike in time spent at home during the baseline period - for example due to a national holiday - and vice versa. Arguably, this marginally undermines the precision of the data, but this effect is small enough that it can still be considered a suitable proxy indicator for compliance.

Controlling for confoundment

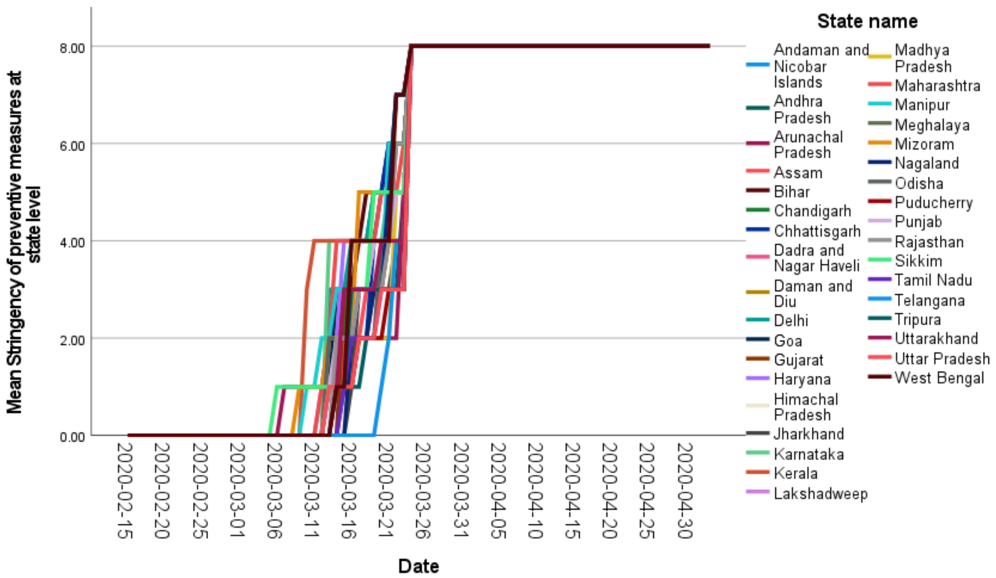
It would be a statistical and conceptual mishap to equate correlation to causation. Variables that are correlated are not necessarily causally linked, and even then the direction of the causal link can only be reasonably inferred using theoretical argumentation. The regression models used in this analysis can only accurately capture the individual effect on compliance of each intended predictor when all other variables that influence compliance are accounted for. Otherwise, if these predicting variables are at all correlated with each other, the real effect of these other variables is wrongly attributed to the intended predictor. For this reason, a theory-grounded selection of control variables is hierarchically introduced in each model besides the intended independent variable to hold these other variables constant and reduce the chance of mistakenly capturing a spurious relationship.

Potential confounders of the effect of *centralisation* predict *compliance* by some other time-varying factor. First among these is *time* itself: the goal of the model is to estimate the binary effect of the centralisation of the EDM strategy, not the incremental change in compliance across time. Therefore, I include a ‘time’ variable in the analysis, coded ‘1’ to ‘79’ for the 79 days from February 15th to May 3rd 2020. Secondly, two important moments during this period - besides the centralisation on March 24th - might have individually prompted compliance: the announcement by the WHO that officially *declared COVID-19 a pandemic* on March 11th and the *voluntary Janta curfew* announced by prime minister Modi on March 22nd (WHO, 2020; PIB, 2020). Though neither of these announcements legally enforced compliance, it can be theoretically presumed that they mobilised the population to comply (Kumar et al, 2022). To account for these effects, two binary variables 'pandemic' and 'curfew' were included, coded '1' for the days after they occurred and otherwise '0'.

These three variables vary solely across time, but there are also potential confounders that vary both across time and districts, potentially confounding the effects of both *centralisation* and *urbanisation* on *compliance*. Most important here is *stringency*: how severe the social-distancing policies were. H_1 pertains only to the *centralisation* of the EDM strategy and H_2 pertains only to the *urbanisation* of the district: both should be assessed independent of differences in stringency. To measure stringency, an adapted version of the Oxford Coronavirus Government Response Tracker (OxCGRT) edited by Kumar et al (2022) is used (Hale et al, 2021). This data assesses the stringency of each state's social-distancing policy based on eight indicators for preventive measures. An additive index then maps these indicators onto a '0' to '8' scale where '0' indicates no measures and '8' the most possible measures. As visualised in Figure 6, stringency varied significantly across states before centralisation took place. It increased heterogeneously from early March onwards until reaching a universal level of '8' on March 24th when the EDM strategy was centralised.

Figure 6

Stringency per State Across Time



Other potential confounders that vary across both time and districts are the number of COVID-19 *cases* and *deaths*. As the pandemic intensified and people saw it taking its toll around them, they might have felt more incentivised to comply, again undermining the individual effects of *centralisation* and *urbanisation*. Both of these indicators are taken from the OxCGRT dataset, measured on the state-level, and quantified as the cumulative number of cases or deaths reported in that state since the beginning of the pandemic. Figures 7 and 8 respectively show the rise of cases and deaths per district. As this time covers the early stage of the pandemic, the growth is exponential and consistently so. Maharashtra saw the highest death and infection rates, followed by Bihar and a relatively tight cluster of the remaining states after that. While it is in no way guaranteed that these six potential confounders account for all confoundment, it is most likely the best that can be done given the known theoretical circumstances in which this analysis takes place.

Figure 7

COVID-19 Cases per State over Time

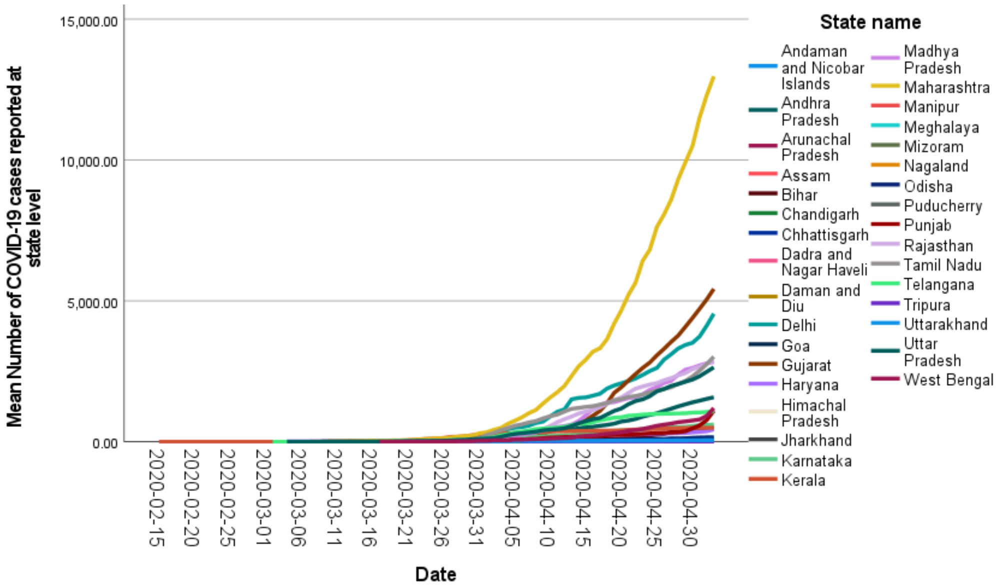
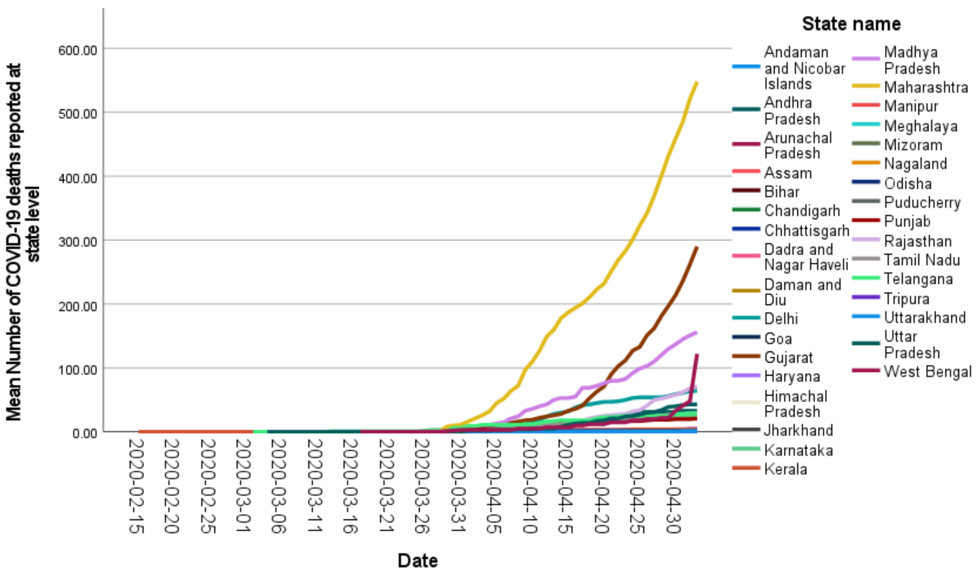


Figure 8

COVID-19 Deaths per State over Time



Research design & models

In order to test H_1 and H_2, OLS regression models are run to assess the individual effects of *centralisation* and *urbanisation* on *compliance*. OLS regression is appropriate here because the aim is to precisely assess the direction, size, and significance of the linear relationships between each relevant independent variable and *compliance*. Furthermore, using an OLS regression model enables the singling out of the intended effect with respect to potential other confounding effects by controlling for them in the model itself. The following two models are yielded:

Model 1: $\boldsymbol{M_t = \alpha_0 + \beta_1 C_t + \beta_j X_t + \varepsilon_t}$

where M_t is the average *compliance* of all districts at the *t*th time; α_0 is the constant term; β_1 is the slope coefficient for C_t, which is the binary *centralisation* indicator at the *t*th time; β_j is the slope coefficient for the *j*th control variable X_t at the *t*th time; ε_t is the error term; and

Model 2: $\boldsymbol{M_k = \alpha_0 + \beta_1 U_k + \beta_j X_k + \varepsilon_k}$

where M_k is the average *compliance* across the analysed timeframe of the *k*th district; α_0 is the constant term; β_1 is the slope coefficient for U_k, which is the binary *urbanisation* indicator of the *k*th district; β_j is the slope coefficient for the *j*th control variable X_k of the *k*th district; *and* ε_k is the error term.

Model 1 tests the veracity of H_1 in that it models the relationship between *centralisation* C_t and *compliance* M_t. It helps answer the research question because it indicates *whether* there is a significant relationship between centralisation and compliance at all. The accuracy of this model is however conditioned on the inclusion of relevant confounders. As such, the previously discussed time-varying potential confounders X_t for model 1 are *time*, *curfew declaration*, *pandemic declaration*, *stringency*, *cases*, and *deaths.*

Model 2 introduces the urban-rural distinction into the analysis, pertaining more to the *how* of the research question. It models the relationship between a district's level of *urbanisation* U_k and its level of *compliance* M_k. Again, relevant confounders need to be included into the analysis in order for its results to be accurate. For model 2, these potential confounders X_t are only *stringency*, *cases*, and *deaths* since they vary across districts - there is no point in including time-varying potential confounders when the relevant predictor *urbanisation* U_k only varies across districts.

In order to test H_3, a simple OLS regression will not suffice because it does not simply pertain to the direct, linear relationship between *centralisation* and *compliance*, but instead seeks to assess this relationship separately for *urban* and *rural* districts. For this purpose, a difference-of-differences regression model is run to simulate an experimental approach where a certain 'treatment' (in this case, *centralisation*) is applied to a 'treatment group' (the time period post-March 24th) while controlling for a 'control group' (the time period pre-March 24th). For each group, the difference in *compliance* between *urban* and *rural* districts (the urban-rural compliance gap) is assessed. The 'treatment effect', then, is the difference in the urban-rural compliance gap between the 'treatment group' and the 'control group', constituting the 'difference of differences'. The following model is yielded:

Model 3: $\boldsymbol{M_{kt} = \alpha_0 + \beta_1 C_t + \beta_2 U_k + \beta_3 C_t U_k + \beta_j X_{kt} + \varepsilon_{kt}}$

where M_{kt} is the *compliance* of the *k*th district at the *t*th time; α_0 is the constant term; β_1 is the slope coefficient for C_t, which is the binary *centralisation* indicator at the *t*th time; β_2 is the slope coefficient for U_k, which is the binary *urbanisation* indicator for the *k*th district; β_3 is the slope coefficient for C_tU_k, which represents the interaction between *centralisation* and *urbanisation* for the *kth* district at the *t*th time; β_j is the slope coefficient for the *j*th control variable X_{kt} of the *k*th district at the *t*th time; and ε_{kt} is the error term.

Model 3 provides the most conclusive answer to the research question as a whole, as it assesses the effect of *centralisation* C_t on *compliance* M_{kt} separately for urban and rural districts. For rural districts, centralisation results in a β_1 increase in compliance. Urban districts see a β_2 increase in compliance compared to rural districts, with an additional $\beta_1 + \beta_3$ increase in compliance when centralisation takes place. This model also rests on the assumption that any relevant confounders are accounted for, and since *compliance* here varies across time and district, all previously mentioned potential confounders were controlled for: *time*, *curfew declaration*, *pandemic declaration*, *stringency*, *cases*, and *deaths.*

Considering both the previously delineated theoretical arguments and the explicated research design, I maintain the following refined, *specific* hypotheses:

$H_{1.2}$: model 1 illustrates a significant, positive slope coefficient β_1 for *centralisation* in predicting *compliance*;

$H_{2.2}$: model 2 illustrates a significant, positive slope coefficient β_1 for *urbanisation* in predicting *compliance*;

$H_{3.2}$: model 3 illustrates a significant, positive slope coefficient β_3 for the interaction between *centralisation* and *urbanisation* in predicting *compliance*.

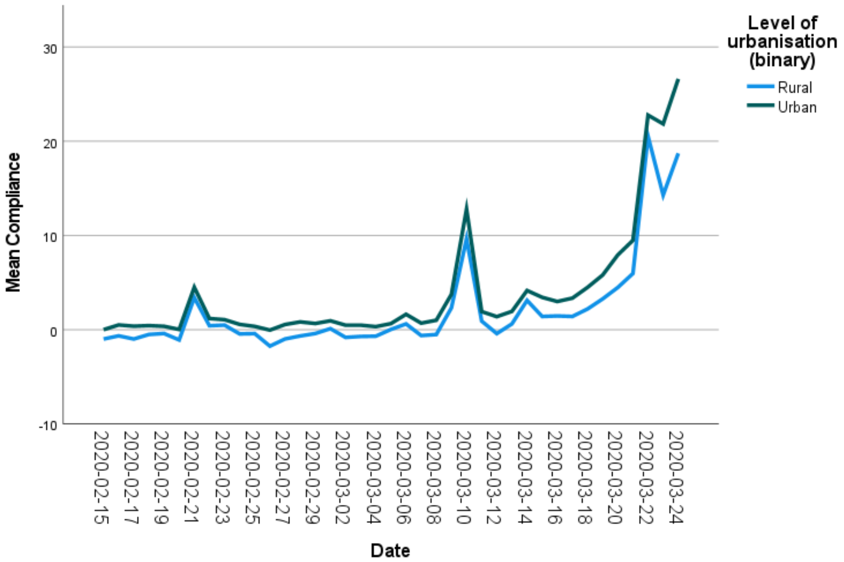
Asserting robustness: parallel trends & multicollinearity

The significance of the difference-of-differences test that is executed by model 3 is contingent on that the 'pre-treatment' difference, i.e. the urban-rural compliance gap before centralisation, is constant. A 'parallel trends' robustness test as displayed in Figure 9 shows that the urban-rural gap is in principle consistent when the EDM strategy was decentralised, even for the minor peaks in compliance before centralisation occurred. However, a minor divergence can be observed after March 22nd, when the Janta curfew was announced. On this day itself, compliance spiked significantly for both urban and rural districts. The day after, however - one day before the centralisation on the 24th - a drop in compliance for rural districts can already be observed while urban districts more or less maintained this high level of compliance. In theory, this undermines the precise effect of the March 24th centralisation on the urban-rural compliance gap because divergence was initiated one day earlier.

However, this does not refute this difference-of-differences test as a whole. First of all, a single day of discrepant data is not enough to conclude a null effect of centralisation in predicting compliance - it might be a fluke in the data. Furthermore, this test does not take into account potential interference of control variables: it is likely that the Janta curfew already raised compliance. Without this interference, centralisation might still explain the divergence from the 24th onwards, but a more rigorous robustness check is necessary to account for confoundment here. Further research in this regard is necessary, but for the sake of this paper, the minor discrepancy will be regarded as tolerable.

Figure 9

Urban and Rural Compliance in the Pre-Centralisation Phase



A second challenge to robustness arises in models 1 and 3 where the *centralisation* predictor is highly collinear with two of the control variables, *curfew declaration* and *stringency* (Model 2: VIF = 10.478, tolerance = 0.095; Model 3: 10.718, tolerance = 0.093). This can, in theory, be problematic because it makes it unclear whether the observed effect should be attributed to *centralisation* or to the control variables. However, a further robustness check indicates that, for both models, leaving the control variables out causes the issue of multicollinearity to disappear and only raises the effect size of *centralisation*. This means that whether or not *centralisation* is a significant predictor of *compliance* does not depend on, nor is it compromised by the inclusion of these control variables. The effect size does change, but it is statistically significant either way ($p < 0.001$). The numerical details regarding this robustness check can be found in the Appendix.

4. Analysis

Results

Tables 1, 2, and 3 display convincing regression results: all three models explain a considerable proportion of the variation observed in the dependent variable, compliance. Having controlled for theoretically plausible confounders, model 1 boasts by far the most impressive results as it explains a generous 94.2% of the variation observed in compliance ($R^2 = 0.942$). Model 2 is less powerful but nonetheless noteworthy at 27.1% ($R^2 = 0.271$), and model 3 is also quite a strong predictor at 74.9% ($R^2 = 0.749$). In model 1 and 2, the intended predictor of compliance is very statistically significant, even exceeding the $\alpha = 0.001$ level (Model 1: $\beta_{centralisation} = 4.87$, $p < 0.001$; Model 2: $\beta_{urbanisation} = 5.37$, $p < 0.001$). This means that the regression analysis finds enough cases in the presented data where the expected effect is indeed observed, so that it can reliably conclude that the chance that the observed effect occurs at random is nihil - smaller than 0.1%. According to the first model, centralisation significantly raises compliance: centralised strategies result in a percentage increase in compliance from the baseline level that is 4.87 percentage points higher than that of decentralised strategies. The second model indicates that urban districts in general see 5.36 more percentage points of time spent in residential areas than rural districts, and this effect is maintained - if anything, slightly raised to 5.37 - by accounting for potential confounders.

In the third model, both centralisation and urbanisation reliably predict compliance ($\beta_{centralisation} = 2.44$, $p < 0.001$; $\beta_{urbanisation} = 4.865$, $p < 0.001$). On top of this, the interaction variable indicates that there is significant moderation going on between centralisation and urbanisation - that is, one affects the size of the effect of the other on compliance ($\beta_{interaction} = 5.96$, $p < 0.001$). What these regression coefficients reveal about the relationship between centralisation, urbanisation, and compliance is that when urbanisation is held constant at 0, - i.e. in rural districts - centralisation raises compliance rates by 2.44 percentage points of the baseline level over decentralised compliance rates. Similarly, the difference in compliance between urban and rural districts - i.e. the urban-rural compliance gap - under decentralised strategies amounts to 4.865 percentage points in favour of the former. Now, crucially, moving from a decentralised to a centralised strategy increases this urban-rural compliance gap by 5.96 percentage points.

Table 1
Model 1: OLS Regression of Compliance (Daily Average) Against Centralisation

	Block 1	Block 2
(Constant)	4.891*** (0.04)	2.29*** (0.054)
Centralisation of EDM strategy (0 = decentralised; 1 = centralised)	19.559*** (0.045)	4.865*** (0.09)
Time (in days since 15-2-2020)		-0.021*** (0.001)
Pandemic declaration (0 = not declared; 1 = declared)		-0.41*** (0.075)
Janta curfew declaration		13.782*** (0.085)
Stringency of preventive measures (0 = no measures; 8 = most stringent measures)		0.657*** (0.019)
COVID-19 cases (cumulative number per state)		< -0.001*** (< 0.001)
COVID-19 deaths (cumulative number per state)		0.003*** (0.001)
R^2	0.85	0.942
N	50320	50320

Note: OLS regression coefficients with standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001.

Table 2
Model 2: OLS Regression of Compliance (District Average) Against Urbanisation

	Block 1	Block 2
(Constant)	12.787*** (0.021)	13.537*** (0.053)
Urbanisation of district (0 = rural; 1 = urban)	5.364*** (0.056)	5.373*** (0.054)
Stringency of preventive measures (0 = no measures; 8 = most stringent measures)		-0.145*** (0.007)
COVID-19 cases (cumulative number per state)		< 0.001*** (< 0.001)
COVID-19 deaths (cumulative number per state)		0.021*** (0.001)
R^2	.225	.271
N	50320	50320

Note: OLS regression coefficients with standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001.

Table 3
Model 3: Difference-of-Differences Regression of Compliance against Centralisation and Urbanisation

	Block 1	Block 2
(Constant)	4.936*** (0.079)	3.316*** (0.141)
Centralisation of EDM strategy (0 = decentralised; 1 = centralised)	18.503*** (0.089)	2.44*** (0.23)
Urbanisation of district (0 = rural; 1 = urban)	1.501*** (0.189)	4.865*** (0.09)
Interaction of centralisation and urbanisation (centralisation * urbanisation)	6.524*** (0.220)	5.96*** (0.19)
Time (in days since 15-2-2020)		-0.077*** (0.003)
Pandemic declaration (0 = not declared; 1 = declared)		-1.079*** (0.187)
Janta curfew declaration		12.85*** (0.214)
Stringency of preventive measures (0 = no measures; 8 = most stringent measures)		1.237*** (0.048)
COVID-19 cases (cumulative number per state)		-7.057e-5 (< 0.001)
COVID-19 deaths (cumulative number per state)		0.024*** (0.002)
R^2	.662	.749
N	50320	50320

Note: OLS regression coefficients with standard errors in brackets.
* p < 0.05, ** p < 0.01, *** p < 0.001.

Discussion

In congruence with the previously delineated theoretical expectations, the tested relationships are positive, sizable, and significant. The level of EDM centralisation and the level of urbanisation of a district positively and significantly influence compliance levels. The urban-rural compliance gap is larger under centralised strategies than under decentralised strategies, indicating that centralisation tends to benefit the urban significantly more than the rural. Figures 10 and 11 provide a visual representation of these relationships through box plots of compliance, separated respectively by decentralised and centralised strategies in Figure 10 and by rural and urban districts in Figure 11. Even a cursory glance at the plots reveals that the differences between these groups are stark: under decentralised strategies, compliance rates lay within about 3 percentage points from the baseline compliance more than 50% of the time, where as compliance rates under centralised strategies consistently lay about 25% higher. The difference in compliance between urban and rural districts is also significant: about 50% of rural areas saw an increase in compliance from the baseline compliance of 10 to 15%, with a large spread ranging from even a 5% drop to a 25% jump - urban areas saw higher levels of compliance, with 50% of districts complying between 17 and 20% more than they did during the baseline period.

However, for centralisation, a close comparison between Figure 10 and the regression results in Table 1 reveals that its effect may not be as large as the visual suggests. Figure 10 seemingly indicates that centralisation leads to an approximate 25% increase in compliance, and Table 1 seemingly indicates a similar effect in Block 1, where it associates centralisation with a 19.559% increase in compliance ($\beta_{centralisation}$ = 19.559; $p < 0.001$), but including the control variables in Block 2 readjusts this effect to a mere 4.865% growth. The effect of centralisation on the 24th is still significant, but the overwhelming majority of explanatory power is shifted to one of the control variables: the Janta curfew declaration on the 22nd (β_{curfew} = 13.782, $p < 0.001$). It seems that people already started complying *en masse* when the voluntary curfew was announed, and not necessarily when the EDM strategy was officially and legally nationalised.

The same phenomenon can be observed in model 3. Figure 12 displays the visual representation of the difference-of-differences test performed in model 3. Urban districts see higher levels of compliance than rural districts across the board, but this difference is larger under centralised strategies than under decentralised ones. Block 1 in table 3 indicates that this growth in urban-rural compliance - i.e. the ‘treatment effect’ - is 6.524% ($\beta_{interaction}$ = 6.524, $p < 0.001$) when centralisation is regressed on its own, but block 2 - having accounted for potential confounders - lowers this to 5.96% ($\beta_{interaction}$ = 5.96, $p < 0.001$). Again, explanatory power is shifted to the Janta curfew declaration (β_{curfew} = 12.85, $p < 0.001$). Although both the direct and moderation effects of centralisation on compliance remain very significant, the fact that model 3, which was theoretically expected to best explain variation in compliance due to its refined design of centralisation being moderated by urbanisation, ‘only’ yields an R^2-value of 0.749, and that model 1, in which centralisation on the 24th and the curfew on the 22nd are on a ‘level playing field’ in predicting compliance, yields an impressive 0.942 R^2-value, might be an indication that the Janta curfew is in fact a better predictor of compliance than the official centralisation on the 24th. However, more research is necessary to precisely assess the explanatory power of the Janta curfew.

Figure 10

Model 1: Box Plots of Compliance (Daily Average) Under (De)Centralised Strategies

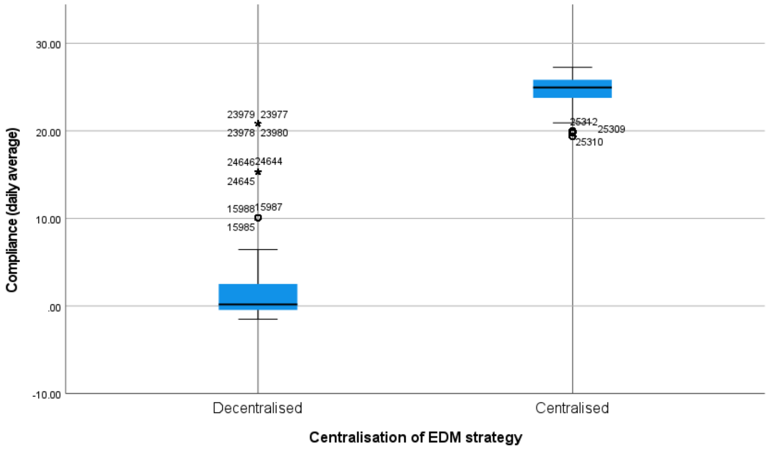


Figure 11

Model 2: Box Plots of Compliance (District Average) for Urban and Rural Districts

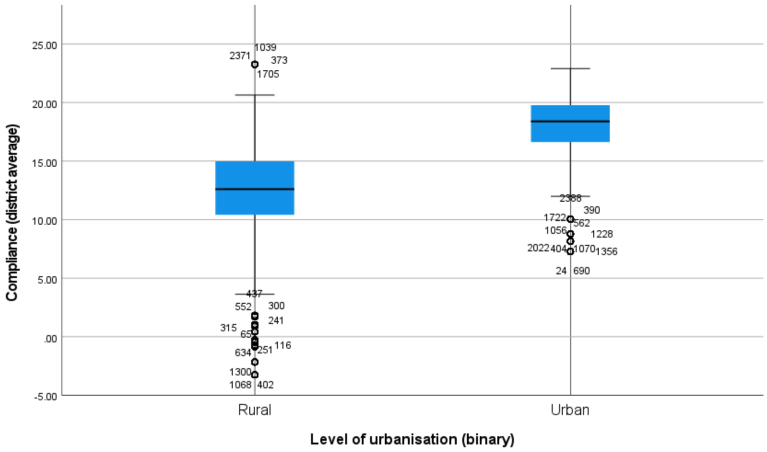
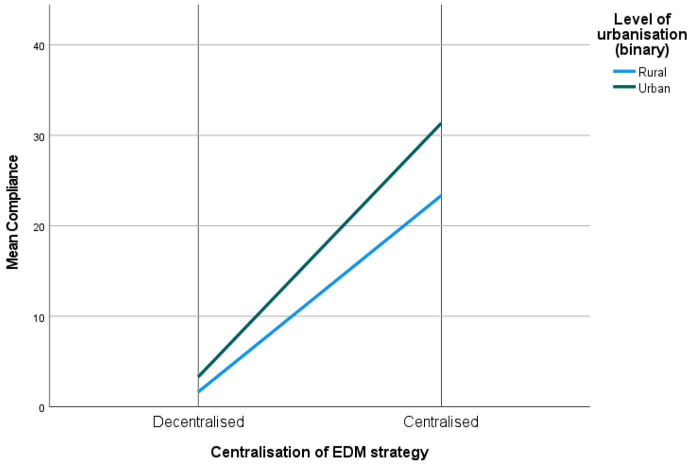


Figure 12

Model 3: Line Graph Plotting Compliance Against Centralisation With Separate Groups for Rural and Urban Districts



6. Conclusion

From the obtained results and consequent analysis, it can be reasonably concluded that all three of the theoretically substantiated hypotheses are valid. The performed regression analyses provide adequate means to successfully capture the effect of centralisation on compliance, and how this is moderated by urbanisation. Centralised EDM strategies see higher levels of compliance than decentralised ones; urban districts see higher levels of compliance than rural districts; the impact of centralisation is larger in urban areas than in rural areas - in other words, the urban-rural compliance gap is larger under centralised strategies than decentralised strategies. All of these observed effects exceed the statistical significance threshold of $\alpha = 0.001$, virtually discarding the probability that they merely occurred at random.

However, there are certain limitations to the findings presented here. First of all, although including the theorised control variables in the analysis consistently raised the explanatory power of each model - indicating that the theoretical substantiation for the inclusion of these control variables held empirical merit - it also reduced the individual effects of the intended predictors *centralisation* and *urbanisation* in favour of an alternative explanatory variable: the Janta curfew announced on March 22nd. It is yet unclear if and how this voluntary curfew exactly affected compliance, but it seems appropriate that more research is done in this regard. In any case, this effect would not conceptually undermine the underlying logic of the research performed here - as the nation-wide Janta curfew can still be framed as a stage in the overarching process of EDM centralisation in India - but it still undermines the specific theoretical premises put forward here.

Furthermore, it is possible that the observed effects are in fact not the result of the theoretical argumentation delineated here, but due to some confounding factor that was missed in the analysis. There is no way to rule out the possibility of ulterior explanations, so one must be careful to decisively attribute the observed effects to the theorised causal mechanism. Another issue with this specific research design is the fact that, by virtue of making use of time-series data, the analysis is heavily subject to problematic levels of autocorrelation. All three models have Durbin-Watson values that are too far from the ideal value of 2 (Model 1: Durbin-Watson = 0.8; model 2: 0.788; model 3: 0.799). The resulting problem is that the regression errors are correlated, while they should be random. Arguably, this reduces the statistical power of the models, but it does not fully discredit its findings. Lastly, by virtue of this research being a single case study analysis, there are no conclusive grounds to assume that this effect extrapolates to settings other than India. Perhaps there are factors that enable this effect that are unique to India, such as the government system, culture, geographic locations, etc.

All things considered, the performed research is sufficiently significant and robust to refute the null hypothesis that there is no relationship between EDM centralisation, district urbanisation, and compliance with preventive measures in the case of COVID-19 containment in India. Further research is necessary to precisely assess (1) the significance of ulterior explanations such as the voluntary Janta curfew in India and (2) the reliability of these findings across different contexts. As it stands now though, this research offers a valuable contribution to the EDM literature and provides a solid point of departure for more thorough research to be done in the future.

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Appendix: multicollinearity robustness check

Table 4

Raw Output Table for Model 1, With Curfew Announcement and Stringency

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	4.891	.040		122.814	.000		
	Centralisation of EDM strategy	19.559	.045	.922	435.026	.000	1.000	1.000
2	(Constant)	2.290	.054		42.404	.000		
	Centralisation of EDM strategy	4.865	.090	.229	53.850	.000	.095	10.478
	Day since 15-2	-.021	.001	-.040	-17.573	.000	.338	2.957
	Pandemic declaration	-.410	.075	-.011	-5.466	.000	.439	2.277
	Janta curfew announcement	13.782	.085	.611	161.779	.000	.122	8.230
	Stringency of preventive measures at state level	.657	.019	.194	34.203	.000	.054	18.492
	Number of COVID-19 cases reported at state level	.000	.000	-.034	-7.466	.000	.084	11.918
	Number of COVID-19 deaths reported at state level	.003	.001	.020	4.503	.000	.089	11.183

a. Dependent Variable: Compliance (daily average)

Table 5

Raw Output Table for Model 1, Without Curfew Announcement and Stringency

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	4.876	.040		122.633	.000		
	Centralisation of EDM strategy	19.575	.045	.922	435.894	.000	1.000	1.000
2	(Constant)	1.712	.083		20.504	.000		
	Centralisation of EDM strategy	18.429	.067	.868	273.066	.000	.413	2.420
	Day since 15-2	.007	.002	.014	3.958	.000	.342	2.925
	Pandemic declaration	4.014	.090	.107	44.528	.000	.727	1.375
	Number of COVID-19 cases reported at state level	.000	.000	-.059	-8.308	.000	.084	11.909
	Number of COVID-19 deaths reported at state level	.005	.001	.032	4.702	.000	.089	11.182

a. Dependent Variable: Compliance (daily average)

Table 6

Raw Output Table for Model 3, With Curfew Announcement and Stringency

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4.936	.079		62.462	.000		
	Centralisation of EDM strategy	18.503	.089	.745	207.254	.000	.833	1.200
	Level of urbanisation	1.501	.189	.051	7.937	.000	.259	3.865
	Interaction of centralisation and urbanisation	6.524	.220	.195	29.694	.000	.250	3.995
2	(Constant)	3.316	.141		23.444	.000		
	Centralisation of EDM strategy	2.440	.230	.098	10.608	.000	.093	10.718
	Level of urbanisation	2.104	.164	.072	12.848	.000	.256	3.901
	Interaction of centralisation and urbanisation	5.960	.190	.178	31.310	.000	.248	4.036
	Day since 15-2	-.077	.003	-.123	-24.798	.000	.326	3.068
	Pandemic declaration	-1.079	.187	-.025	-5.753	.000	.439	2.278
	Janta curfew announcement	12.850	.214	.487	59.910	.000	.121	8.276
	Stringency of preventive measures at state level	1.237	.048	.312	25.730	.000	.054	18.427
	Number of COVID-19 cases reported at state level	-7.057E-5	.000	-.010	-1.036	.300	.082	12.188
	Number of COVID-19 deaths reported at state level	.024	.002	.143	15.036	.000	.088	11.343

a. Dependent Variable: Compliance

Table 7

Raw Output Table for Model 3, Without Curfew Announcement and Stringency

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4.921	.079		62.487	.000		
	Centralisation of EDM strategy	18.518	.089	.745	207.972	.000	.834	1.199
	Level of urbanisation	1.516	.189	.052	8.020	.000	.259	3.861
	Interaction of centralisation and urbanisation	6.510	.220	.194	29.643	.000	.250	3.993
2	(Constant)	2.695	.158		17.078	.000		
	Centralisation of EDM strategy	18.126	.128	.730	142.004	.000	.382	2.621
	Level of urbanisation	1.895	.184	.064	10.299	.000	.257	3.891
	Interaction of centralisation and urbanisation	6.200	.214	.185	28.986	.000	.248	4.029
	Day since 15-2	-.043	.003	-.069	-12.532	.000	.330	3.033
	Pandemic declaration	4.686	.163	.107	28.668	.000	.722	1.386
	Number of COVID-19 cases reported at state level	.000	.000	-.037	-3.312	.001	.082	12.176
	Number of COVID-19 deaths reported at state level	.026	.002	.157	14.648	.000	.088	11.340

a. Dependent Variable: Compliance