India's Vaccination Response to COVID-19

Working Draft

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The Covid-19 pandemic has brought about immense suffering and has exacerbated the weaknesses of the Indian healthcare system. As of November 6th 2021, India is the second worst affected country with 34.3M reported cases and 460K deaths. According to epidemiologists, vaccines are an essential tool to prevent the spread of the pandemic [CITATION]. India's vaccination drive began on January 16th, 2021. The concerned authorities maintained statistics and underlying data readily available through various government and third party websites. Through the course of the vaccination drive, multiple policies were implemented by the government to ensure that vaccines are readily available. In this report, we analyze the inequities that existed in India's vaccination policies, and also compute the effect of the inequity due to introduction of new policies. We analyze the potential inequities that might have been introduced through the implementation of these policies not only qualitatively but also quantitatively by leveraging the data that was made available through the portals. Specifically, we discover (a) inequities that might exist in the policies, (b) we quantify the effect of new policies introduced to increase vaccination coverage, and lastly, we also point the data discrepancies that might exist across different data sources.

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1 Introduction

The Coronavirus pandemic has had a devastating effect across the world, resulting in 255,324,963 cases and 5,127,696 deaths until date. Though the numbers have been high, some sections of society have been disproportionately been affected. In the US, black people have been affected more than others [11]. Even in other parts of the world, the number and severity of COVID-19 cases has been higher amongst minorities and the economically weak .

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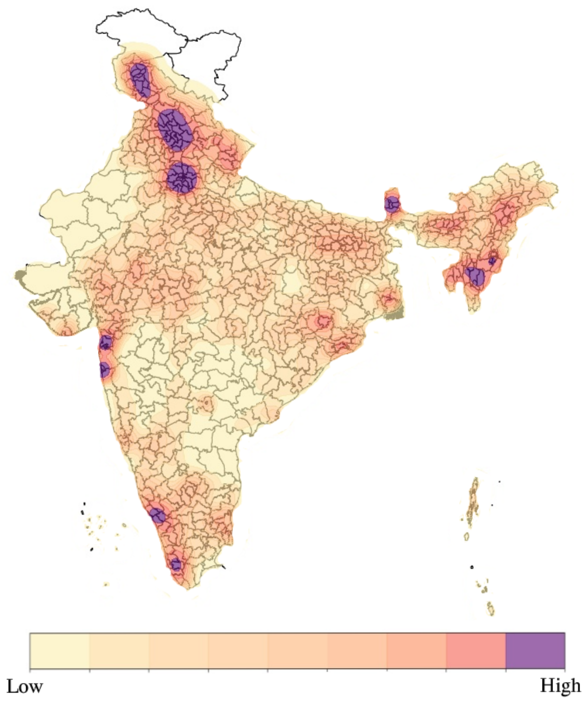


Fig. 1. Distribution of vaccines administered normalised by population in India

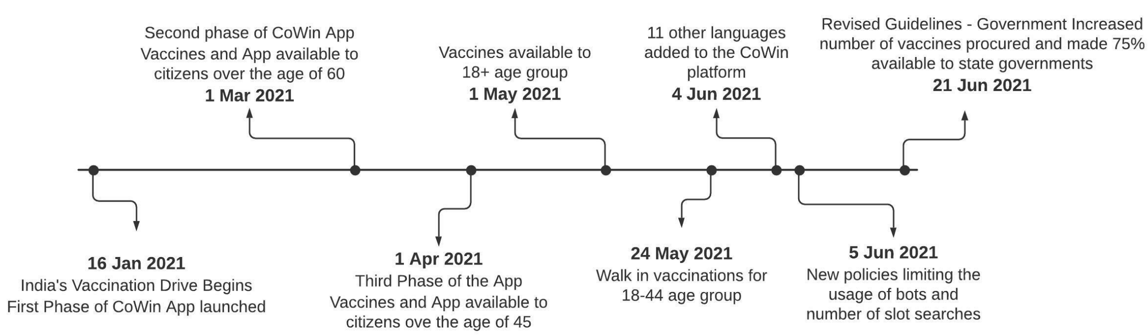


Fig. 2. Distribution of vaccines administered normalised by population in India

A report by the US Center for Disease Control [1] states how those sections of society with essential occupations in places like healthcare facilities and grocery stores coupled with lower access to high-quality education and lower income and wealth are at an increased risk of getting the disease. With the virus exacerbating the effect of

[1]https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/race-ethnicity.html

existing inequalities, it is essential that the distribution of vaccines is equitable as per the requirements of the population.

The Director-General of the World Health Organisation said "Vaccine inequity is the world's biggest obstacle to ending this pandemic and recovering from COVID-19."[2]. Most manufactured vaccines are being supplied to affluent countries, with poorer nations struggling to vaccinate their population. As per the Global Dashboard for COVID-19 Vaccine Equity[3] (a joint initiative from UNDP, WHO and the University of Oxford's Blavatnik School of Government), as of Nov 12 2021, 64.99% of the population has been vaccinated with at least one dose in high income countries, while the same number stands at 6.48% for low income countries. Be it rich or poor, many nations are struggling to make equitable distribution of vaccines possible within their borders [13]. People residing in slums, marginalised and migratory population have difficulty getting access to vaccination facilities [3].

In this report, we study inequity in India's vaccination drive from multiple angles – through the lens of qualitative evaluation of policies as well as quantitative evaluation of data. India's Covid-19 vaccination drive began on January 16^{th} 2021, opening up to different sections of the population in phases. To facilitate the booking of vaccines, the government developed the CoWIN platform[4]. For reporting purposes, the government also maintained a dashboard[5] that made all the statistics related to the number of vaccines administered available to the general public. As of June 2nd, India had provided as many vaccinations to 9 urban cities as they had to 114 of the least developed districts having double the combined population.[6] With only 39.9% of the Indian population fully vaccinated as of November 6^{th} 2021, it is all the more important that the vaccinations being administered should be equitable according to the needs and demands of the population and that the policies implemented should be effective.

Past work studying the unfairness of the vaccination drive in India is limited. While [17] has explored unfairness in the vaccination drive in Maharashtra with respect to gender, it limits itself to only one variable– gender and one state– Maharashtra. Our work aims to bridge this gap.

In this report, we analyse the data made public by the government to detect inequities in the vaccination drive. In particular, we answer the following questions:

(1) Is India's distribution of vaccines skewed in favour of any section of society?
(2) Were there any state-level policies declared that were unfair against a group of people?
(3) How effective were the government policies in the vaccination drive towards increasing vaccination response and mitigating inequities?
(4) Are the data sources made available by the government consistent?

In Section 4, we analyse the number of vaccines administered and the distribution of centers in districts around the country to detect skew against the rural population in a district (if any). We found that while vaccination centers are distributed evenly overall, districts with more urban people had a higher percentage of vaccines administered to their population. We also demonstrate how some states in India are more skewed against the distribution of vaccines to the rural population.

Throughout the vaccination drive, the government of India has been implementing many policies to ensure that the vaccinations are made available to as many people as possible, and that the distribution is fair and efficient. It is thus vital to study the effectiveness of these policies. Thayer et al. [23] analysed the effectiveness of different lockdown policies on the daily Covid-19 cases and public behavior in India using interrupted time

[2]https://www.who.int/news/item/22-07-2021-vaccine-inequity-undermining-global-economic-recovery
[3]https://data.undp.org/vaccine-equity/
[4]https://www.cowin.gov.in/
[5]https://dashboard.cowin.gov.in/
[6]https://www.reuters.com/world/india/indias-vaccine-inequity-worsens-countryside-languishes-2021-06-04/

series analysis. To the best of our knowledge, there have been no previous works which study the effectiveness of policies implemented during the vaccination drive. We present such an analysis in Section 6.

In Section 6, we carry out regression discontinuity analysis on two significant policies. First, we analyse the change made on June 4^{th} 2021, which added 10 regional languages to the CoWIN platform. Second, we analyse the 'Revised Guidelines for implementation of National Covid-19 Vaccination Program' policy implemented on June 21^{st} 2021 by which the government increased the number of vaccines procured by them and made available for free to the state governments from 50% to 75%. We find that both these policies had a greater positive impact (number of vaccines being administered) on rural districts than urban districts. Another observation was that even though there was a noticeable spike in the number of vaccines administered on June 21^{st}, there was a downward trend afterward, which brings into question the long-term benefits of the 'Revised Guidelines for implementation of National Covid-19 Vaccination Program' policy.

To ensure transparency and effective policy making it is critical that the data reported on vaccinations administered is accurate and granular. In Section 7, we identify inconsistencies within the data sources. We found that the CoWIN portal API, which gives us the number of vaccines available for any query date, did not return consistent data for past dates (Sec. 7.1). The CoWIN dashboard API breaks down the number of vaccines administered using different criteria (Sec. 7.2), which it returns as different fields. We find that these different fields in the API are not consistent, giving error margins of not accounting for up to 5.9 crore people on a single day (Sec. 3.1).

2 Related Work

Our related work flows from three different directions - (a) studies related to inequity in how COVID affected minority populations, (b) studies related to inequity in vaccine policies, and (c) quality of vaccination data.

While not much work has been done on the quality of vaccination data, previous works have looked at the quality of other reported statistics regarding COVID-19 in India (number of cases, deaths reported, resource availability etc.). Vasudevan et al. [25] studied the quality of reporting of COVID-19 data in over one hundred government platforms from India. They found a lack of granularity in the reporting of COVID-19 cases, vaccinations and vacant bed availability. They also found that age, gender and comorbidity was available for less than 30% of cases and deaths. There was no reporting of adverse events following immunization by vaccine and event type. Zimmermann et al. [27] found that the number of cases in India was under-reported by a factor of 10 to 20, and the number of deaths were under-reported by a factor of 2 to 5.

»> More importantly, most of the work centered around Covid-19 vaccination drive misses mentioning or taking into account any inequities the policies might have introduced.

No previous work has studied the consistency between the various data sources made available by the government on the vaccination drive.

The inequitable distribution of vaccines on a global scale was studied by Moosa et al. [22]. They used Lorenz Curves and Gini Coefficients [19] to illustrate the unequal distribution of vaccine stockpiles due to hoarding by the wealthier countries. They found that 80% of the population had only 5% of the total COVID-19 vaccines in the world. The value of the Gini coefficient , which ranges from 0 to 1 with 1 representing perfect unequal distribution , was found to be 0.88 for COVID-19 vaccines around the world. Bolcato et al. analyze how the worldwide distribution of vaccines applies or even disregards the principle of equity [7]. To the best of our knowledge, no work has been done to study the inequity of vaccine distribution in India, and we aim to bridge this gap in our work.

Inequity in Effects of COVID

Gray et al. [10] studied the vulnerabilities and health inequities of different populations in the US. They talk about how certain marginalized populations in the US experience a inordinate amount of COVID-19 related infections and deaths. They found that in such areas, Social Determinants of Health (SDOH) like limited education

, unemployment and structural racism contribute to health conditions like cancer and cardiovascular diseases which unfairly predisposes them to worse outcomes on acquiring COVID-19. Similar work focusing on role of racial,economic and ethnic inequities in the imbalanced vulnerability of populations in the US [14] has been done by Lee et al. They used a Social-Ecological model which predicted 280,000 deaths if the country opened up fully or a loss of 18 million jobs in the case of a country-wide lockdown, mainly affecting the minority groups.

Inequity in COVID mitigation policies
Benfer et al. [6] studied how eviction and uncertainty in housing policies during the pandemic subverted COVID-19 mitigation policies. Eviction increases the risk of contracting COVID-19 due to crowding of people and bad living conditions especially in the neglected and economically under developed areas, thus making mitigation policies such as social distancing impractical to implement. They showed a correlation between COVID mortality and lifting of eviction prohibition. Emmanuel et al. [18] used the Indian context and examined the effect of a lockdown and social distancing government guidelines on urban slums and migrant workers. The sudden and unplanned nature of the lockdown caused migrant workers and people working in the informal sector (over 80% in india) to be stranded in their current working locations as they were forced to leave. The physical distancing and work from home regulations were inequitable towards slum settlements as they are unclear and almost impossible to follow in such areas.

» summarise, tell what is lacking and what gap we fill

3 Data Sources

The government authorities made data available related to covid vaccinations through 2 different APIs - (a) CoWIN Dashboard API and (b) CoWIN Portal API. We review each of these APIs and then describe the data we leverage for our quantitative analysis.

3.1 CoWIN dashboard APIs

The Government of India reports the number of vaccines administered in each district via the CoWIN dashboard, updating the website every few minutes.[7] Through the underlying APIs, we are able to obtain information about the number of vaccines administered and the different sub-groups (age, gender, economic class) to which they were given. However, as discussed by Vasudevan et al [25], these sub-fields are not present for all past dates and districts, thus not allowing for granular study on the same.

Though the data is relatively consistent, we did identify certain discrepancies that exist in the data collected this way, which we report in Section 7.2.

3.2 CoWIN portal API

The CoWIN platform made a set of APIs[8] public, with a rate limit of 100 calls every five minutes. A query can be made for a district in India to get the upcoming vaccination appointment slots available in that district. For our study we queried all the 93 districts in Delhi, Maharashtra, Kerala and Assam [9]. We queried once every five minutes for each district, thus staying well within the rate limits. Henceforth, we refer to data collected this way as *CoWIN portal data.*

Querying the CoWIN API for a particular district gives information about each center in that district. Each vaccination center makes *sessions* available for administering vaccines. A session can be formally considered as the entire full-day event of that center as it makes vaccination slots available for booking. Such a session then contains time slots starting from morning till night which one can book. The API gives details for each such

[7]https://dashboard.cowin.gov.in
[8]https://apisetu.gov.in/public/marketplace/api/cowin
[9]While we could have queried all districts of all states, we chose a random subset of states to avoid putting excessive load on the infrastructure. We randomly selected one state each from the North, South, East and West of the country.

upcoming vaccination session available for every center in a district. For each session it provides the capacity of dose1 and dose2 vaccines which are remaining (i.e. available to book), the qualifying age limit and the brand of vaccine available.

The data provided by the CoWIN dashboard APIs is different from the data presented through the CoWIN app APIs since dashboard numbers indicate the number of vaccines *administered* (as opposed to the number of vaccination appointments made available shown by the app) . That is, the two data sources are distinct.

The advantage of using the CoWIN portal data is that we can scrape the data real-time and observe the availability of slots in the CoWIN app. However, there are some caveats to using this data source:

- Due to the rate limit of one call per 5 minutes, we cannot capture changes within those 5 minutes
- We cannot query for all the districts in India without decreasing the overall amount of data collected per district

While many popular apps and bots have emerged which have found ways to circumvent the rate limit , we felt it is best to stick to the rate limits stipulated by the government so as to avoid disrupting the vaccine booking process. As this data source is not sufficiently granular, we do not use it for analysis of inequities. We discuss issues with the data source in Section 7.1.

4 Distribution of Administered Vaccines and Centers

As described in Sec. 3.1 we leverage the d_{cT} data to get the number of centers, and number of vaccines administered by each center. Using the same, we found that the number of vaccines administered correlates with the fraction of urban people residing in that district. To identify the number of rural and urban people staying in a district, we used the demographic data from the 2011 Census of India. We define rural ratio as the fraction of people living in that district that belong to the rural population. A higher rural ratio for a particular district indicates a higher number of rural people in that district.

To understand the difference between the distribution of vaccines, we used two target variables: the total number of vaccines administered weekly in a district and the total number of centers present in that district. We normalise both these variables by the population of that district (per 1000 population). [10] We obtain values for these two target variables for each district on July 22$^{\text{nd}}$ via d_{ct}. The total number of vaccines administered in a district is the total number of vaccines administered by each center in that district. We present analysis of these two target variables using two methodologies: Pearson's correlation and spatial regression.

4.1 Pearson's Correlation

Each state consists of several districts. We calculate the correlation between the rural ratio and the target variables for each state by taking into account the values for all the districts in that state. The Pearson's correlation coefficient for each state is shown in Table 1. Correlation coefficients closer to zero in magnitude means that the target variable is less dependent on the rural-urban ratio, indicating the distribution is not skewed in favor of rural or urban population. On the other hand, a coefficient that is higher in magnitude (i.e. closer to one) indicates the presence of some skew. A higher positive coefficient for a state means that the target variable is higher when the rural ratio is higher, i.e. it is biased to favor rural districts. On the other hand, a more negative value means that the distribution is in the favor of districts having more urban population.

We show the overall correlation for the entire country by taking all districts as data points In Table 1 (row 1). In this general case, we observe that the correlation value is significantly negative for vaccines administered indicating a skew in the favor of districts having less rural people. However, the correlation value for the number of centers is close to zero, indicating that the center availability seems to be distributed uniformly across the

[10] Because the division of districts within each state has changed since the last census, we formed a mapping of old districts to new, merging the values of districts which had been split to obtain data for our study. We release this mapping publicly for future work .

State	C_{vacc}	C_{cent}
All-India	-0.290	0.058
Andhra Pradesh	-0.76	-0.329
Arunanchal Pradesh	0.138	0.265
Assam	-0.503	-0.489
Bihar	-0.472	-0.054
Chhattisgarh	-0.007	0.383
Gujarat	0.399	0.064
Haryana	-0.708	-0.287
Himachal Pradesh	0.052	0.538
Jammu & Kashmir	0.212	0.442
Jharkhand	-0.355	0.123
Karnataka	0.385	0.38
Kerala	0.489	0.394
Madhya Pradesh	-0.792	-0.36
Maharashtra	-0.671	-0.001
Manipur	0.001	-0.041
Meghalaya	-0.45	-0.278
Mizoram	0.022	0.202
NCT of Delhi	0.235	0.314
Nagaland	-0.718	0.355
Odisha	-0.26	-0.043
Puducherry	-0.542	-0.579
Punjab	-0.401	0.118
Rajasthan	0.028	-0.291
Sikkim	-0.946	0.484
Tamil Nadu	-0.489	-0.264
Tripura	0.231	0.541
Uttar Pradesh	-0.563	-0.189
Uttarakhand	0.046	0.555
West Bengal	-0.819	-0.68

Table 1. Pearson's correlation between Rural Ratio of a State and the Vaccines Administered/Center availability in the state. C_{vacc} : Correlation between Rural Ratio and Avg. Weekly Vaccines Administered per 1000 population. C_{cent} : Correlation between Rural Ratio and Number of Vaccination Centers per 1000 population. The trend across all states roughly reflects the overall correlation values: Indicating that while the distribution of centers may vary significantly across rural and urban districts, that of the vaccinations administered seems to be skewed in the favor of districts having more urban people.

country. However, at the state-level, we see that some states are more skewed than others. For example, states like Maharashtra, West Bengal, Bihar, Haryana and Uttar Pradesh show significant negative correlation between vaccines administered and the rural ratio, i.e., the number of vaccines administered per 1000 people in districts with a higher rural population is lower. States like Rajasthan, Uttrakhand, Manipur, Mizoram, Himachal Pradesh, Gujarat have a relatively lower but positive correlation with the number of vaccines, indicating the absence of the negative impact discussed above. Note that the states themselves show varying correlation values.

Feature	Coefficient	Std. Error
Rural_Ratio	-8.8	1.631
Area (in m^2)	-6.0781	4.726
w_Rural_Ratio	-9.6726	1.997
w_Area	3.1705	3.359

Table 2. Spatial regression on number of vaccines administered. Features with the prefix w_ are the spatial lag of the corresponding feature

4.2 Spatial Regression

We perform spatial regression by taking the districts of all states in India as our data points for both the target variables. The input features used for the model are the district's area and the district's rural ratio. Each feature's *spatial lag* is also used as an input to the model. The spatial lag is the spillover of the value of the feature on the surrounding districts (i.e. change in value for the particular district for unit change in the neighbour's value). Each district's neighbouring districts are found through the Queen-move algorithm . The results of the regression analysis are shown in Tables 2 and 3. The spatial lag of each of the features are indicated by the prefix **w_**. While we see that the regression coefficients are close to zero when the target variable is the number of centers, the distribution seems to be skewed when the target variable is number of vaccines administered. When the target variable is vaccines rural ratio has a high negative coefficient. This indicates that districts with a high rural ratio have less vaccines administered per 1000 population than the ones with more urban districts. Thus the trend observed is similar to the results obtained in Section 4.1. Note that the spatial lag of rural ratio (w_Rural_Ratio) had a negative coefficient. This means that the rural ratio of the surrounding districts for a district also negatively impacts the number of vaccines administered. The area, even though having a significant coefficient, is observed to have little effect and less correlation. The p-value of the same is also high indicating it does not affect the model results by much. When the target variable is number of centers, the coefficient of rural ratio is small in magnitude, but positive instead of negative, indicating that more rural districts might have slightly more centers per 1000 people.

Feature	Coefficient	Std. Error
Rural_Ratio	0.063	0.033
Area (in m^2)	-0.0997	0.097
w_Rural_Ratio	-0.1349	0.041
w_Area	0.0634	0.069

Table 3. Spatial regression on number of centers. Features with the prefix w_ are the spatial lag of the corresponding feature

5 Inequities in Government Policies

When it comes to handling the Covid-19 pandemic, the response of the government is critical. Policies must be implemented quickly to effectively contain the spread of the virus. However, the policies themselves may introduce disparities or lead to amplification of existing ones. In this section, we analyse some of the major steps taken by the government in this regard.

5.1 CoWIN App: Rural Areas and Women

The first phase of the CoWIN app was launched on January 16th 2021. The app was made available only for about thirty million front line healthcare workers (~ 2.2% of the total population) in the first phase. In the second phase, which began on March 1st 2021, the app was made available to all residents over the age of 60 and residents between 45 and 60 having one or more comorbidities. The third phase, which began on April 1st 2021, made the app accessible for residents above 45 years of age. In the final phase, which began on May 1st 2021, the app was available for 18+ residents.

The number of Internet users in India as of 2021 stands at 761.29M [1] which accounts for just above 50% of the population. Since the CoWIN app requires Internet, people who do not have access to the Internet are at a significant disadvantage. Moreover, the distribution of people without access to the Internet is not uniform across demographics.

According to the IAMAI-Kantar ICUBE 2020 report [12], 67% of the urban population and 31% of the rural population are active internet users. This digital divide is present across genders as well. 58% of the active internet users in India are men and the remaining are women . Given that India's rural population stands at 66% [5], the introduction of an online-based registration system of vaccination slot booking has the potential to exacerbate the existing inequities between different sections of society .

5.2 CoWIN App: API and Bots

Another factor that makes the CoWIN booking system unfair in terms of who can access and maximally utilise the system is the presence of bots. A bot is simply any software application that runs automated tasks over the Internet [9]. The aim of a bot is to perform simple tasks much faster and more efficiently than a human.

The purpose of the CoWIN API released by the government is stated as [2]-

The intent is to enable various stakeholders such as States/UT Governments, Private Service Providers, Software Developers and any Other agencies who wishes to provide vaccination related services to develop and rollout software solutions around and compatible with Co-WIN (collectively described as "Application Service Providers" (ASPs) on behalf of State/ UT Governments or other approved Vaccination Service Providers to enhance the diversity and functionality complementing Co-WIN, offer better user experience and choice to people, including for improving access to Covid-19 vaccination.

The API makes the following functionalities available-

(1) Discover vaccination centers and related information.
(2) Schedule appointments.
(3) Manage the scheduling and logging of vaccination administration (mainly for Covid-19 Vaccination Centers).
(4) Generate/download certificates.
(5) Report any adverse events after vaccination as per AEFI guidelines.

These services are intended to be advantageous to the society. Developers, however, facilitate prompt booking of freshly opened slots using bots that exploit the API. In some cases, developers even charge for these services [4]. As of May 27th 2021, there were 1,764 public Github repositories with code for tools which give notifications for available slots or even directly book slots [4].

The negative effects of such bots were felt most in rural areas. There is no restriction on the location in which a person can book a slot. This makes the effect of bots more significant because slots in rural districts are being taken by urban residents. Even if a person does not know how to code, as long as they are capable of using the Internet, they can use one of the many bots to get instant updates on vaccine availability. In Bangalore, the tech-savvy coders used bots to find available centers in neighbouring rural districts of Chikkaballapur, Ramanagara, and Tumkur [24]. A resident in one of the above districts claimed only about 4-5 locals could get vaccinated on any given day, the rest of the people arrived from Banglore.

5.3 CoWIN App: Curbing bots and walk-in vaccinations

The government of India seems to have taken some steps in reducing the disparities explained in Sec. 5.2. The user is now required to enter an OTP every 15 minutes to continue using the CoWIN app. However, this did not seem to affect the functioning of the bots [15]. On May 24^{th} 2021, the government allowed walk-in vaccinations for the 18-44 age group at government-run Covid-19 vaccinations centers (CVCs) [8]. The official reason for this, as mentioned in a press release is as follows-

In case of sessions exclusively organized with online slots, towards the end of the day, some doses may still be left unutilized in case the online appointee beneficiaries do not turn up on day of vaccination due to any reason. In such cases, on-site registration of a few beneficiaries may be necessary to minimize the vaccine wastage.

This policy change has benefited many people who don't earn enough money to afford vaccinations at private hospitals and are not technologically literate enough to use the CoWIN website or rely on bots for availability information [8].

The government has also introduced some new policies regarding CoWIN on June 5^{th} 2021, limiting the functionalities of bots [15]. To prevent bots from constantly searching for slots, the government reduced the number of searches for a slot per user to 15-20 after which the user will get logged out. Whether or not this has actually reduced the efficacy of bots is not known. Berty Thomas, the founder of under45.in, said that even though this policy might temporarily affect bots, these are not strong enough restrictions and can be overcome [15].

5.4 Revised Guidelines for implementation of National Covid-19 Vaccination Program

From the beginning of the vaccination program (January 16^{th} 2021) till April 30^{th} 2021, 100% of the vaccines were procured by the Government of India and provided free of cost to the state governments [16]. On May 1^{st} 2021, the government of India implemented the 'Liberalised Pricing and Accelerated National Covid-19 Vaccination Strategy'. This strategy aimed to liberalize and scale up vaccine coverage. The claim was that this would incentivise vaccine manufacturers to rapidly scale-up their production. Under this scheme, 50% of the vaccines would be procured by the government of India and provided for free to the states. States or hospitals could buy the other 50%. However, many states communicated that this policy negatively impacted the pace of the vaccination program [16]. So, a new policy was announced: the 'Revised Guidelines for implementation of National Covid-19 Vaccination Program', which was to be put into effect from June 21^{st} 2021 onwards. Under this policy, the government of India would procure 75% of the vaccines. These vaccines would be provided for free to states/UTs. The remaining 25% could be bought by private hospitals [16]. This policy was expected to boost the pace of the vaccination program. Thus, the goverment procured 100% of the vaccines till 1^{st} May, 2021, 50% of the vaccines till 21^{st} June, 2021 and 75% of the vaccines 21^{st} June, 2021 onwards. We study the effectiveness of this policy in Section 6.

5.5 CoWIN App: Language Support

Since its release to the general public on March 1^{st} 2021 up until June 4^{th} 2021, CoWIN was only available in English. According to the 2011 census data, only 10.67% of Indians speak English as their first, second or third language [26]. Moreover, this is not equally distributed in rural and urban areas and between the rich and the poor. According to a Lok Foundation Survey [21], only about 3% of the rural population could speak English as opposed to the 12% in the urban population. This is also a clear class separation – 41% of the rich could read/understand English whereas only less than 2% of the poor could read/understand English . On June 4^{th} 2021, CoWIN expanded to support 11 other languages which include Hindi, Marathi, Malayalam, Punjabi, Telugu, Gujarati, Assamese, Bengali, Kannada, and Odia [20]. The inclusion of the new languages should have helped in making the CoWIN app more accessible. We analyse the effectiveness of this policy in Sec. 6.

6 Effectiveness of Government Policies

This section presents an analysis of the effect of select policies on the vaccination drive. In particular, we analyse the effect of adding more languages (Sec. 5.5) and the government's policy providing 75% of vaccines for free (Sec. 5.4). We perform our analysis on a subset of the policies due to constraints of space and resources.

In order to attribute the change in the number of vaccines administered to a particular policy, there must be a measurable difference in the values pre-policy decision and post-policy roll-out. The value we look at is the percentage of the population getting vaccinated per day. To model this, we look at two particular aspects – absolute value (i.e. what the current state is) and trend (i.e. moving upwards or downwards). We fit a simple straight line to this property. The y-intercept of the line gives us the absolute value, while the slope of the line gives us the trend. We perform a regression discontinuity analysis [**?**] to understand how the percentage of the population being vaccinated each day changed due to the policy. We use two linear models:

$$y_t = \alpha_0 + \beta_0 t \quad (t < 0) \tag{1}$$

$$y_t = \alpha_1 + \beta_1 t \quad (t > 0) \tag{2}$$

where t ranges from a negative value to a positive value. Negative values represent dates before the policy roll-out, and positive values represent dates after the policy roll-out. While choosing the range, we ensure that $t > 0$ does not overlap with any other policies. We also ensure the number of days taken into consideration before and after the policy are equal. y_t represents the statistic we are modelling (the percentage of the population getting vaccinated per day). Equation 1 gives us the equation of the line pre-policy, and equation 2 gives us the equation of the line post-policy. These models assume that we can approximate the various data points as a straight line defined by α_0 and β_0 pre-policy roll-out and α_1 and β_1 post-policy roll-out.

Since we are interested in studying the change in the number of vaccines administered after the date of the policy, we define two additional terms: α and β to represent this change. α is the change in the y-intercept post-policy (i.e. $\alpha = \alpha_1 - \alpha_0$) and β is the change in the slope post-policy (i.e. $\beta = \beta_1 - \beta_0$). α represents the dip or rise in the absolute value caused, while β represents the change in the long-term trend. We also study the percentage change in the MVBP (the mean value of the percentage of the population getting vaccinated before the policy date). We further exclude data from a grace period before and after the policy to account for bursty behaviour.

6.1 Rural vs Urban

In this section, we look at the effect of the June 4th and June 21st policies on rural and urban districts in India. We used the demographic data from the 2011 Census of India to obtain the number of rural and urban people in each district. We classify a district as rural if the number of rural people staying in that district outnumbers the number of urban people and vice-versa for urban districts.

6.1.1 June 21st Policy: Here, t = 0 is June 21st 2021 (the date of the policy). We consider 34 days before and after the policy to study the effect of the policy. We ensure that the 34 days after the policy does not overlap with any other major policy roll-outs. We observe that there is a major spike on June 21st i.e. the day after the policy was put into place (see Fig. 3). Still, after that, the number of vaccinations falls once again for both rural and urban districts, which questions the efficacy of the policy implemented. To study this formally, we study the α values for the urban and rural districts. We see that the percentage of people vaccinated in rural districts increased by 0.15% (α = 0.153563) and by 0.12% (α = 0.128349) in urban districts immediately after the policy. The percentage change in the MVBP is 84.5% in rural districts and 43.6% in urban districts. The higher increase in the MVBP and the higher increase in the α value for rural districts shows that the policy was more effective in increasing the number the vaccinations taken in rural districts.

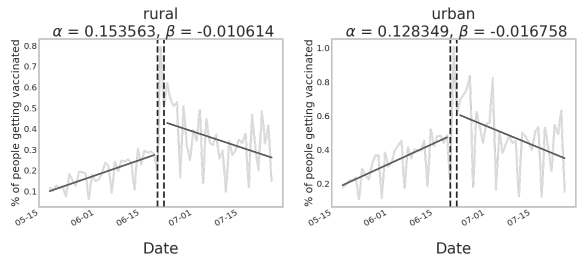


Fig. 3. Effect of the June 21st policy on the percentage of the population getting vaccinated in rural and urban districts. Here, the dates vary from May 18th 2021 to July 25th 2021 to ensure that $t > 0$ does not overlap with other policies. The α and β values are higher for the rural case, indicating it benefitted rural areas more. However, a negative β in both cases indicates that the policy as a whole seems to have decreased the pace of the drive.

To study the long-term effect of the policy, we study the change in slope (β). We observe that the change in slope is negative in both cases (-0.010614 for rural and -0.016758 for urban), which shows the policy was not effective in the long run for both rural and urban districts. However, this negative value is lower in rural districts, showing that the policy had a more positive impact.

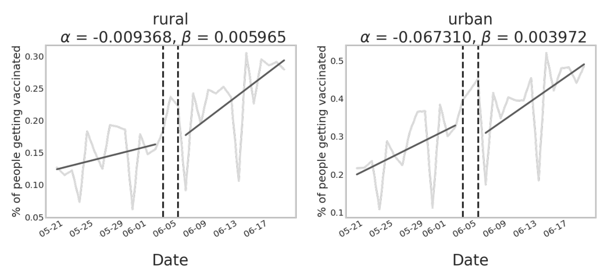


Fig. 4. Effect of the June 4th (language) policy on the percentage of the population getting vaccinated in rural and urban districts. Here, the dates vary from May 20th 2021 to June 19th 2021 to ensure that $t > 0$ does not overlap with other policies. The α and β values are higher for the rural case, indicating it benefitted rural areas more. As both the α values are close to zero, the policy appears to not have had much of an effect.

6.1.2 June 4th Policy (Language): Here, t = 0 is June 4th 2021 (the date of the policy). We consider 15 days before and after the policy to study the effect of the policy. We choose 15 days so that $t > 0$ does not overlap with the June 21st policy (see Fig. 4). We see that the percentage of people getting vaccinated in rural districts decreased by -0.009% (α = 0.009368) and by -0.06% (α = -0.067310) in urban districts immediately after the policy. However, the percentage change in the MVBP changed by 64.0% in rural districts and by 51.1% in urban districts. This shows that introducing the 10 new languages was more effective in getting more people to use the app in rural districts than urban districts.

To examine the long-term effect of the policy, we study the β value. We observe that the change in slope is 0.005 for rural and 0.003 for urban, which shows the policy had more of a long-term positive effect on rural districts. However, the values mentioned above are not very high, which shows that the language policy was not very effective in enabling more people to get vaccines.

6.2 State wise

6.2.1 June 21st Policy: We now analyse the effect of the policy on the percentage of population getting vaccinated per day statewise. We observe that the policy did not have a uniform effect on all the states. On observing Table 4, we find that some states have a high percentage change in the MVBP, which indicates that the number of vaccines being administered increased post policy. However, for states/ union territories like Daman Diu, Ladakh, Lakshwadeep and Telangana the percentage change in the MVBP is either negative or very low which questions the efficacy of the policy in these regions.

However, the β value (long term effect) for all the states is negative (with the exception of Manipur, which has a value close to 0), which shows that the policy was not very effective in increasing the number of vaccines administered in the long term across all states.

6.2.2 June 4th Policy We analyse the effect of adding 10 new languages on the number of vaccinations administered in various states. To analyse the effect of adding Telugu as a language to COWIN, we study the states of Telangana and Andhra Pradesh, where Telugu is the main language. In Andhra Pradesh, we find that α, β and % change in MVBP are negative, which interestingly indicates that the inclusion of Telugu had a negative effect on the number of vaccines being administered, i.e. the number of vaccines administered is lower than it would have been if the policy wasn't implemented. Telangana, on the other hand, has a high % change in MVBP, indicating that the policy did infact have a positive impact. For the languages of Malayalam, Gujarati, Marathi, Punjabi, Bengali, and Kannada, we study Kerala, Gujurat, Maharashtra, Punjab, West Bengal and Karnataka. We find that all these states have a positive percentage change in MVBP, but the values vary between states, indicating that the policy has not been equally effective. However, the β value is negative for all states, which shows that policy was not that effective in the long run. For the languages of Assamese and Odia, we look at the states of Assam and Odisha. We find that both these states have a positive percentage change in MVBP and a positive β value, which shows that the policy was effective in the long run as well.

7 Quality Issues with Data Sources

This section provides preliminary analysis of the raw CoWIN portal data and CoWIN dashboard data using simple visualisations to understand data space and quality.

7.1 CoWIN portal Data

We observed the trends of vaccine availability on the CoWIN app as per the CoWIN portal data. There were two key takeaways from the same:

7.1.1 Difference in trends for 18+ and 45+: For a given center, we plot the total available capacity returned by the API at every 5 minutes for the entire month of May. There is a distinct difference in the behaviour of bookings between slots made available for the 18+ and 45+ age groups. Vaccine slots made available for the 18+ age group appear to get almost instantaneously booked. At the same time, the case of 45+ seems to follow a more gradual booking trend and in most cases does not even reach 0 availability, as shown in Fig. 5.

Two possible explanations for this are:

(1) Various bots and twitter accounts have been providing instantaneous notifications as soon as a slot opens up. The younger generation (being more tech-savvy) might be using these bots to get instant notifications .
(2) The 45+ plot seldom reaches 0 available capacity. This means that there are vaccines available for the 45+ age groups at any given instant in time. This could be because the age group of 45+ was not using bots to book their slots, vaccine hesitancy, or discrepancy in the API itself.

7.1.2 Reliability for past data We attempted to query the CoWIN API by specifying a date in the past. We found that querying the API for past dates does not return any information regarding the number of vaccinations on

State	α	β	% change in MVBP
Andaman and Nicobar Islands	1.1607	-0.0205	666.422
Andhra Pradesh	0.1295	-0.0038	11.2555
Arunachal Pradesh	0.0144	-0.0258	47.0831
Assam	0.2021	-0.0077	125.018
Bihar	-0.0507	-0.0009	79.5216
Chandigarh	0.0155	0.0011	73.8783
Chhattisgarh	0.6083	-0.0178	1285.13
Dadra and Nagar Haveli	1.2673	-0.0603	102.914
Daman and Diu	1.1616	-0.0559	-16.5346
Delhi	0.361	-0.0176	114.004
Goa	0.1644	-0.0426	56.4075
Gujarat	-0.0064	-0.0146	49.4623
Haryana	0.1376	-0.0093	27.7482
Himachal Pradesh	1.0438	-0.0456	202.792
Jammu and Kashmir	0.2289	-0.0094	91.9426
Jharkhand	-0.0019	-0.0074	32.5843
Karnataka	0.0891	-0.0118	34.2092
Kerala	-0.1053	-0.0018	66.6933
Ladakh	0.2226	-0.0248	-50.012
Lakshadweep	-0.5878	-0.0132	-34.5178
Madhya Pradesh	0.3459	-0.0103	112.36
Maharashtra	0.2196	-0.0081	74.2996
Manipur	0.0489	0.0008	281.567
Meghalaya	-0.083	-0.0059	58.2982
Mizoram	0.4409	-0.0384	192.513
Nagaland	0.1962	-0.0139	112.981
Odisha	0.1509	-0.0106	55.3495
Puducherry	-0.3472	-0.0318	37.783
Punjab	0.2534	-0.007	132.125
Rajasthan	0.0244	-0.008	58.2069
Sikkim	0.0343	-0.1308	62.7136
Tamil Nadu	0.0171	-0.0064	51.4482
Telangana	-0.5607	-0.0743	-8.69373
Tripura	0.2329	-0.0536	83.7637
Uttar Pradesh	0.0282	-0.0053	65.4547
Uttarakhand	0.3389	-0.0232	97.0014
West Bengal	0.001	-0.0045	32.0436

Table 4. Regression discontinuity results for policy implemented on June 21st

that particular day. Rather, it just returns how many vaccines were leftover (i.e. appointments not booked) on that day. Recall that the CoWIN portal API returns data about the upcoming sessions. We found that on querying for past dates, the number of dose 1 and dose 2 vaccines shown to be available did not add up to what was returned as the total available capacity. In some cases, the API response is completely empty when queried for

State	α	β	% change in MVBP
Andaman and Nicobar Islands	-0.138	0.035	41.5772
Andhra Pradesh	-0.2228	-0.0436	-30.1893
Arunachal Pradesh	0.3913	0.0282	357.401
Assam	-0.0085	0.0183	51.6042
Bihar	0.0232	0.0194	113.07
Chandigarh	-0.4667	0.0399	15.1123
Chhattisgarh	-0.0196	0.0001	-30.4179
Dadra and Nagar Haveli	-0.1657	0.0811	25.9128
Daman and Diu	-0.0988	0.0336	-28.5922
Delhi	0.0411	0.0218	130.159
Goa	0.0627	0.0837	137.411
Gujarat	0.1175	-0.0014	120.851
Haryana	0.0043	0.018	21.5286
Himachal Pradesh	-0.2761	0.0488	55.376
Jammu and Kashmir	-0.1888	0.0176	10.3675
Jharkhand	0.0973	0.0103	117.665
Karnataka	0.0015	-0.0155	43.0725
Kerala	-0.1391	-0.0489	49.0011
Ladakh	-0.8153	-0.0289	-37.2071
Lakshadweep	0.6199	-0.0706	88.6001
Madhya Pradesh	0.068	-0.017	14.1224
Maharashtra	-0.057	-0.0046	3.90622
Manipur	-0.027	0.001	-31.4521
Meghalaya	-0.1261	0.0536	114.337
Mizoram	-0.131	0.0719	518.371
Nagaland	0.1564	-0.014	150.292
Odisha	-0.0651	0.0024	41.0622
Puducherry	-0.178	0.0823	207.282
Punjab	0.0651	-0.0064	13.655
Rajasthan	0.1412	-0.0025	99.7844
Sikkim	-0.2397	0.2217	1821.1
Tamil Nadu	-0.2766	0.0155	17.6633
Telangana	0.3497	-0.0797	260.454
Tripura	-0.5034	0.099	463.152
Uttar Pradesh	-0.0148	0.0001	69.6394
Uttarakhand	0.3533	0.0007	156.298
West Bengal	-0.0602	-0.0147	28.2393

Table 5. Regression discontinuity results for policy implemented on June 4^{th}

past dates, while the portal had shown some available capacity on that day. The CoWIN portal APIs thus seem to be unreliable for obtaining data for past dates.

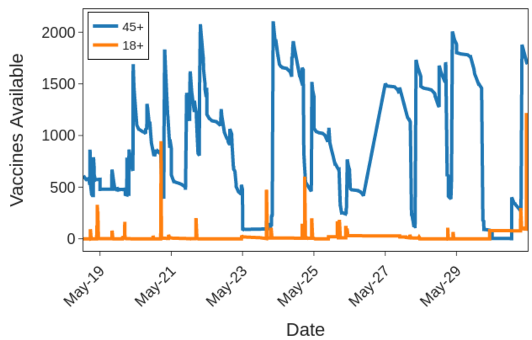


Fig. 5. Number of vaccines made available for the two age-group divisions during a one-week period in May for the district of South Delhi. We observed similar trends in data for other districts collected via the CoWIN portal Data.

7.2 CoWIN dashboard APIs

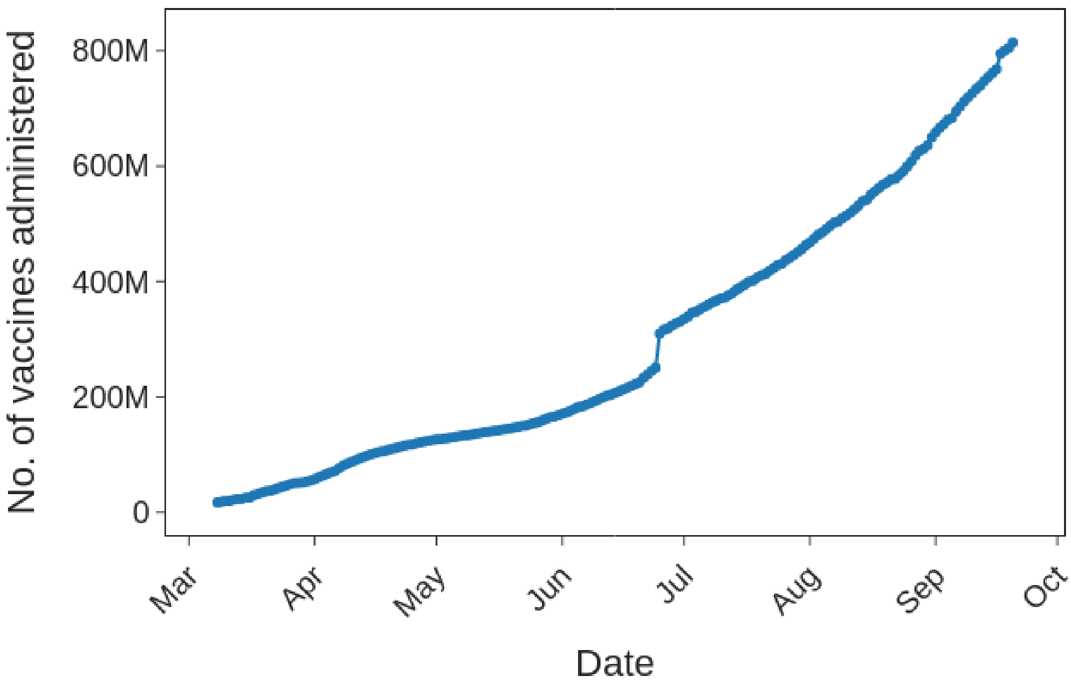
As discussed in Section 3.1, the CoWIN dashboard API returns data on number of vaccines administered in different sub-fields of the API response. We consider three variations here:

(1) *vaccination* field: This gives the total number of people vaccinated uptil the query, and is displayed on the dashboard as a raw figure. We refer to this data as the total number of vaccinations as d_{vT}.
(2) *vaccinationDoneByTime* field: gives the number of people vaccinated hour-wise on a given day. It is displayed on the dashboard as a line graph, showing hourly vaccinations done for that day. We add up all these values to get the total number of people vaccinated on that day. We refer to this data as d_{vbt}.
(3) *vaccinationByAge* field: gives the total number of people vaccinated so far in three age groups (18-44, 45-60, Above 60). It is displayed on the dashboard as a pie chart. We add up all these values to get the total number of people vaccinated on that day. We refer to this data as d_{vba}.

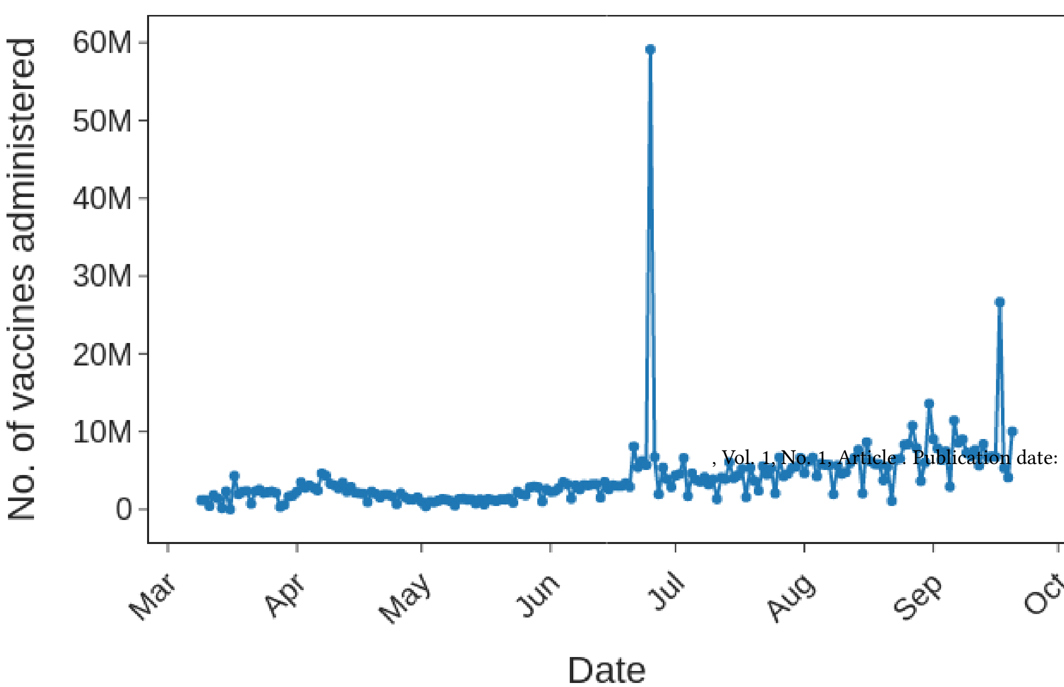
It is expected that the total number of people vaccinated in a given day when calculated using any of the three sources should remain the same. However, we find this not to be the case. We compared these sources and found that upon calculating the total number of vaccinations administered per day from each field, we seem to get different values for the total number of vaccinations administered for a given day. To understand which of the three sources give us "correct" data, we need a baseline for comparison. To this end, we use the data that is displayed in the form of a graph on the CoWIN dashboard. This displayed graph gives us week-wise vaccination statistics from January 16$^{\text{th}}$ onwards. We queried this data on September 8$^{\text{th}}$ to obtain week-wise data for all past weeks as displayed on the dashboard, and call this d_{weekly}. To compare the d_{weekly} data with the day-wise data obtained in the d_{vT}, d_{vbt} and d_{vba}, we aggregate the day-wise data into weeks.

7.2.1 Total Vaccinations field: Here, we analyse d_{vT}. This is the data that is displayed on the dashboard as the total number of vaccines administered up to a particular date. In Fig. 6, we show the raw d_{vT} data. Because the raw data is cumulative (Fig. 6a), we perform day-wise subtractions to get the graph on the right (Fig. 6b). Thus Fig. 6b represents the number of people vaccinated per day according to d_{vT}. For comparison with d_{weekly} data, we aggregate the data in Fig. 6b week-wise and compare it with d_{weekly} displayed on the CoWIN dashboard.

Fig. 7 demonstrates how the week-wise aggregation from d_{vT} compares with the weekly data shown on the website (d_{weekly}). The most notable mismatch is in the week of June 19$^{\text{th}}$ to June 25$^{\text{th}}$. According to the API,



(a) Returned by API



(b) Day-wise difference

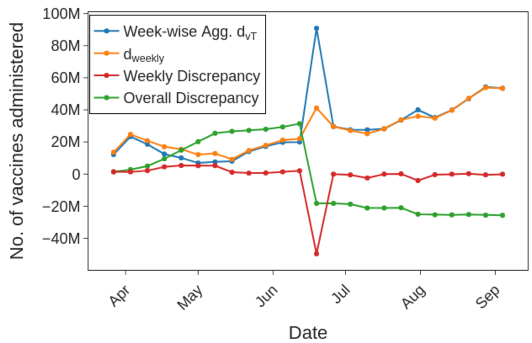


Fig. 7. Comparison of the week-wise aggregated d_{vT} with the d_{weekly} data displayed on the CoWIN dashboard. Here, Weekly Discrepancy is d_{weekly} - d_{vT}. We also display the cumulative difference between the

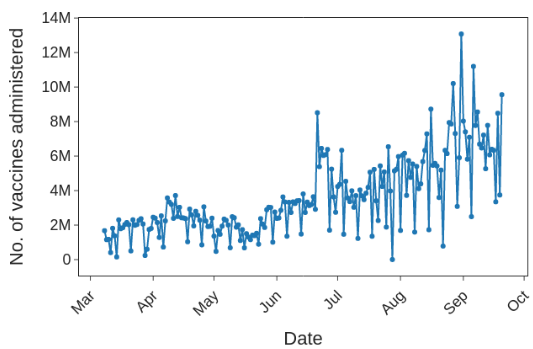


Fig. 8. Total number of people vaccinated according to d_{vbt}. Unlike like Fig. 6, the data here is not cumulative. Thus, we do not need to get the day-wise differences. Here, the dates range from March 8^{th} 2021 to September 14^{th} 2021.

90.84 million were vaccinated that week, however, the dashboard displays 41.20 million. That is a difference of precisely 49,642,682 people just for that week. The cumulative difference between the data returned by the API and the data shown on the website also takes a sharply negative turn in that week. National Covid-19 Vaccination Program' hospitals [16] (discussed in Section 5.4).

7.2.2 Vaccinations By Time Slots: The VaccinationDoneByTime field of the API gives the number of people vaccinated in hour-wise slots (d_{vbt}). We add up all these slots for a given day to get the number of people vaccinated for a given day. The number of people vaccinated day-wise is displayed in Fig. 8. Notice how Fig. 8 and Fig. 6b depict significantly significantly different distributions for the same statistic. This shows that adding up hour-wise slots for a day from d_{vbt} does not give the same total number of vaccines administered per day as obtained from d_{vT} field for the same day.

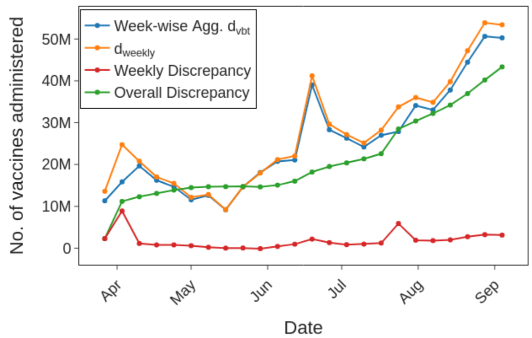


Fig. 9. Comparison of the week-wise aggregated data obtained from d_{vbt} with the week-wise data displayed on the CoWIN dashboard (d_{weekly}). Here, discrepancy is the difference between d_{weekly} and d_{vbt}. We also display the cumulative difference between the data returned by the API and the data displayed on the website.

We aggregate the d_{vbt} field week-wise and compare with d_{weekly} displayed in the CoWIN dashboard in Fig. 9. Observe how the aggregation closely follows d_{weekly}. This is in contrast to what we observed with d_{vT} data (Fig. 7). Also, note how the cumulative difference stays close to 0 for most points as one would expect, unlike Fig. 7. We note that there are some discrepancies nonetheless. The highest week-wise discrepancy in this case is 8,891,282 in the week of April 3^{rd}-9^{th}.

7.2.3 Vaccinations By Age Group: We find that the data returned by the VaccinationByAge field (d_{vba}), i.e. the breakdown into subgroups by age, adds up to be exactly the same as d_{vT} as explained in Sec. 7.2.1. Hence, the same discrepancies follow in this source.

Thus, the data displayed within the dashboard is not consistent. The CoWIN dashboard showed that 793 million people were vaccinated in India as of September 18^{th} 2021. This number is close to the final value in Fig 6a. However, as detailed in Sec. 7.2.1, and shown in Fig. 7 the values that were displayed on the dashboard in the past do not match with the week-wise values displayed on the CoWIN dashboard. The number shown as the total number of people vaccinated so far appears to be coming from a different source than the one used for the historical week-wise data being displayed on the dashboard.

As observed in the various analyses earlier in this section, different end-points of the API give different values. Moreover, these values are not consistent with the numbers being displayed on the CoWIN dashboard. This leads to the questions – what are the accurate numbers? Which data do researchers use to perform analysis or policy makers rely on to make decisions?

After studying this data source carefully, we carried out our analyses in Sec. 6 by using d_{vbt} to obtain the total number of vaccines administered per day as it most closely matches with d_{weekly} (Fig. 9), and provides day-wise distribution which is the granularity useful for obtaining insights.

8 Discussion

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