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Effect of COVID-19 pandemic on Prevalence of other diseases

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Keywords:

Covid-19, Hypertension, Diabetes, Anaemia, Obesity, Immunity.

Abstract:

Multiple researchers posited the impact of Covid-19 on hypertension, diabetes, and obesity. This project compares the spread of diseases before and during the Covid-19 pandemic. Data from NFHS 4 and NFHS 5 from the states affected by COVID were considered to compare the prevalence of different diseases before and during the pandemic.

Analysis is done using the standard statistical procedure as well as Bayesian method.

After comparing the time and age-adjusted rates using standard statistical procedures, we observe that there are significant differences in the rates for immunity and severe anaemia in children, severe anaemia in men, severe hypertension in adults, and severe obesity in adults.

We use the Bayesian method to compute the probability of increase of spread of diseases during COVID-19.

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Introduction:

Diabetes, Hypertension, and Anaemia are a few of the prevalent diseases in India. The estimates in 2019 showed that 77 million individuals had diabetes in India, and approximately 57% of these individuals remain undiagnosed. [1] Similarly, for hypertension, about 33% of urban and 25% of rural Indians are hypertensive. [2]

Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. [3] India, as of 1st May 2021, reported 1,95,49,772 cases and 2,15,524 deaths due to COVID-19. [4] COVID-19 impacted the economy, health facilities, and, in general, the population.

In health, research stated that COVID-19 may severely impact people suffering from different diseases. For example, people with diabetes are more likely to have serious complications from COVID-19. [5] Not only this but conversely, the proportion of adults suffering from hypertension, obesity and diabetes increased during COVID-19. [6]

This paper focuses on the question in general, have people become more prone to diseases such as diabetes, and hypertension during COVID-19?

To answer these questions, we collected the rates of different diseases in the population for the states from NFHS-4 and NFHS-5 reports. The NFHS-4 fieldwork was conducted during the period 2015-2016. The purpose to consider NFHS-4 is to understand the rates of different diseases before COVID-19.

The NFHS-5 fieldwork was conducted in two phases, phase-I from 17 June 2019 to 30 January 2020 covering 17 states and 5 UTs, and Phase-II from 2 January 2020 to 30 April 2021 covering 11 states and 3 UTs. [7]

The period of NFHS-5 Phase II is considered as the COVID period. For comparison of rates of different diseases, we only select those states from NFHS phase II which are highly affected by the COVID-19 pandemic. We use NFHS-5 Phase I rates to account for the effect of time in the NFHS-5 Phase II states. This is done to make a direct comparison of time-independent rates of prevalent diseases in the population for the same states from NFHS-4 and NFHS-5 Phase-II data to examine if there is any significant increment. The test of the significance of the differences in the rates was carried out using the Wilcoxon-signed-rank test.

In the Bayesian analysis we use the beta-binomial model to compute the probability of increase of spread of particular disease during COVID-19. We also construct a 95% confidence interval for the differences of the sample rates for different diseases during and before COVID-19. The purpose is to observe how significant are the differences for the sample rates of the disease during and before COVID-19.

Methods:

To examine the impact of COVID-19 on the spread of prevalent diseases, the percentage of the population affected due to different diseases is collected from the NFHS 4 (2015-2016) and NFHS 5 (2019-2021) report.

The following studies were done where the rates of respective diseases of 2015-16 were compared with their adjusted rates of 2019-21 Phase-II on the respective population within the mentioned age bracket as given in the table below.

Population	Age	Study
Children	Under 5 years	Acute Respiratory Infection (ARI) rates
	6-23 months	Milk feeding rates to non-breastfed children
	6-59 months	Severe anaemia rates
Men	15-49 years	Diabetes rates
	15-49 years	Heart disease rates
	15-49 years	Severe hypertension rates
	15-49 years	Severe obesity rates
	15-49 years	Severe anaemia rates
Women	15-49 years	Diabetes rates
	15-49 years	Heart disease rates
	15-49 years	Severe hypertension rates
	15-49 years	Thyroid rates
	15-49 years	Severe anaemia rates
	15-49 years	Asthma rates
	15-49 years	Severe obesity rates

Table 2.1: Table showing Population and the respective age brackets under different studies

In order to capture the proper effect of COVID-19 on the aforementioned studies, several adjustments are made as mentioned below.

1. Time Factor Adjustment:

The NFHS-5 data was collected in two different phases viz, Phase-I (from 17 June 2019 to 30 January 2020 covering 17 states and 5 UTs) and Phase-II (from 2 January 2020 to 30 April 2021 covering 11 states and 3 UTs).

Now, to have a clear distinction between the pre-COVID and post-COVID periods and also to account for the change in rates of different health parameters due to time following adjustments have been carried out.

Phase-I reflects the pre-COVID stage while Phase II reflects the post-COVID stage. But, the states in those phases were completely different.

Thus, we compare the states in Phase-I of the NFHS-5 study to exactly those states in the NFHS-4 report to get an idea about the changes in the rates due to time. These changes happened over 4 years (2015 to 2019). Considering these changes to be uniform across time we multiplied the median over all the Phase-I states of these changes by $\frac{5}{4}$ (as the period from NFHS-4 to Phase-II of NFHS-5 was 5 years) and subtract these from the rates in the states of Phase-II. Thus, these rates are completely independent of the time factor.

Finally, after these adjustments, we compare the adjusted rates in Phase II of NFHS-5 to the rates in NFHS-4, for the states which were heavily affected by the COVID-19 pandemic.

2. <u>Age Adjustments</u>:

(Only in case of Hypertension rates)

We are given the hypertension rates for states aged 15 and above in the NFHS-5 report. But, in the NFHS-4 report, we are given the rates for the states in the age 15-49.

We are also given average rates for the country for the ages 15-49 in the NFHS-5 report.

Now, to calculate rates for each state for each gender in the age group 15-49, we first calculate the rates for the age group 50 and above and using these rates we calculate the weighted rates for the age group 50 and above, then subtract these weighted rates from the 15 and above group.

Let, $N_{50} = Total\ number\ of\ people\ 50\ and\ above$

$D_{50} = Number\ of\ people\ who\ are\ hypertensive\ in\ the\ age\ group\ 50\ and\ above.$

$\therefore\ Rates\ for\ 50\ and\ above\ = \left(\frac{D_{50}}{N_{50}}\right) *\ 100 ...(1)$

Now, D_{50} can be obtained from the country rates for hypertension in NFHS 5.

We have the rates of hypertensive patients for the age 15-49 and 15 and above. We also know the number of people in the age group 15-49 and 15 and above.

Hence,

$$Rates\ (for\ that\ age\ group) *\ Population\ of\ that\ age\ group\ =$$
$$Number\ of\ people\ who\ are\ hypertensive\ (for\ that\ age\ group)$$

Thus, D_{50}

$= Number\ of\ people\ who\ are\ hypertensive\ in\ the\ age\ group\ 50\ and\ above$

$$= (Number\ of\ people\ who\ are\ hypertensive\ in\ the\ age\ group\ 15\ and\ above) -$$
$$(Number\ of\ people\ who\ are\ hypertensive\ in\ the\ age\ group\ 15\ -\ 49)$$

Hence, after obtaining the above quantities, we can substitute the values in equation (1) and obtain the rates for the population of 50 and above.

Now,

$Weighted\ Rates\ for\ hypertensive\ population\ in\ the\ age\ 50\ \&\ above\ \left(WD_{50}\right) =$

$(Rates\ of\ Hypertension\ for\ the\ age\ 50\ and\ above)$
$*\ (Population\ Proportion\ for\ the\ age\ group\ 50\ and\ above)$

Now, we subtract WD_{50} from all the states and get the average rates for the age group 15-49.

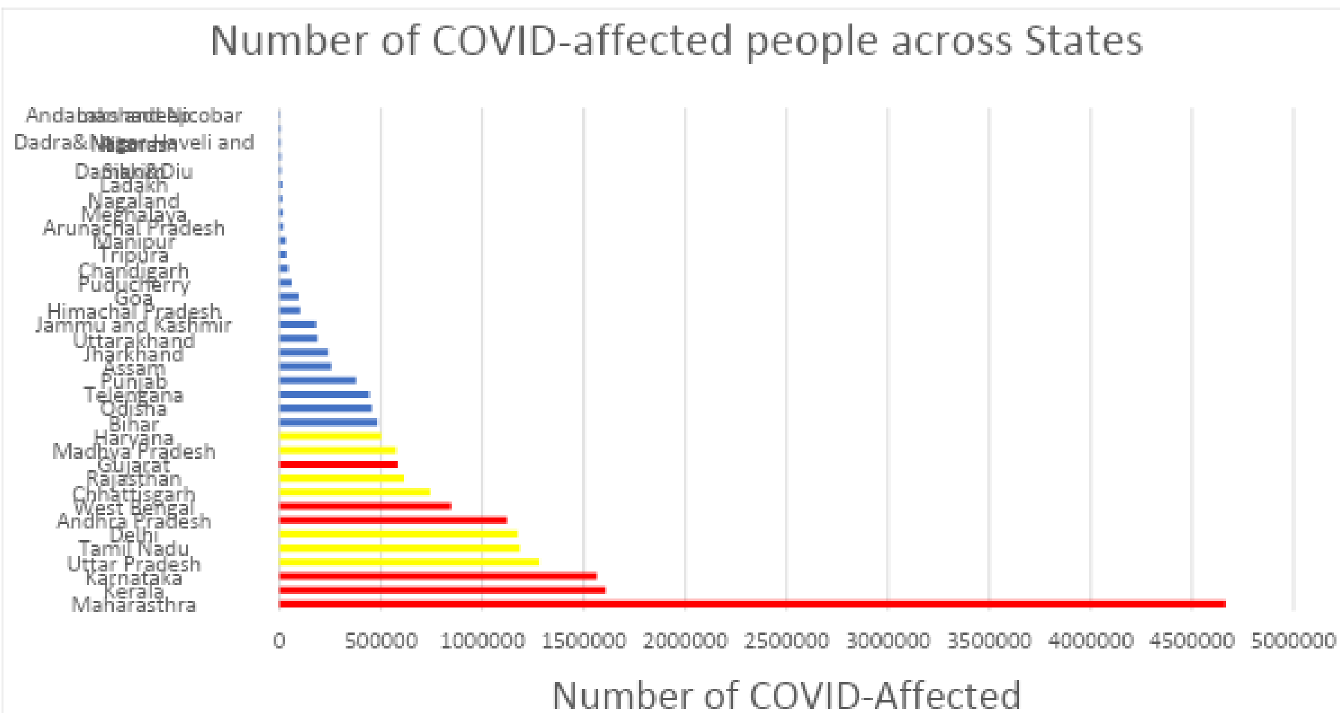
We divide the hypertension rates for the age group 15-49 by the population proportion of the same age group to obtain normalized rates.

The population proportion is assumed to be the same for both males and females.

It is assumed that average rates for the age group 50 and above in the country are the same for all the states.

3. <u>State Selection</u>:

For the present study we focus only on those states in Phase II which were heavily affected by COVID. To understand which states were most affected by COVID we extracted the data on COVID affected and deaths across the states and UT of India.



<u>Figure 2.1: Number of COVID-affected people across states as of 1st May 2021</u>

As of 1st May 2021, the total number of people affected by COVID in the states of India was 1,95,49,772. States with more than 5,00,000 (taking it as a threshold value) people affected by COVID which were studied in Phase-II of the 2019-21 NFHS report are Uttar Pradesh, Tamil Nadu, Delhi, Chhattisgarh, Rajasthan, Madhya Pradesh, and Haryana.

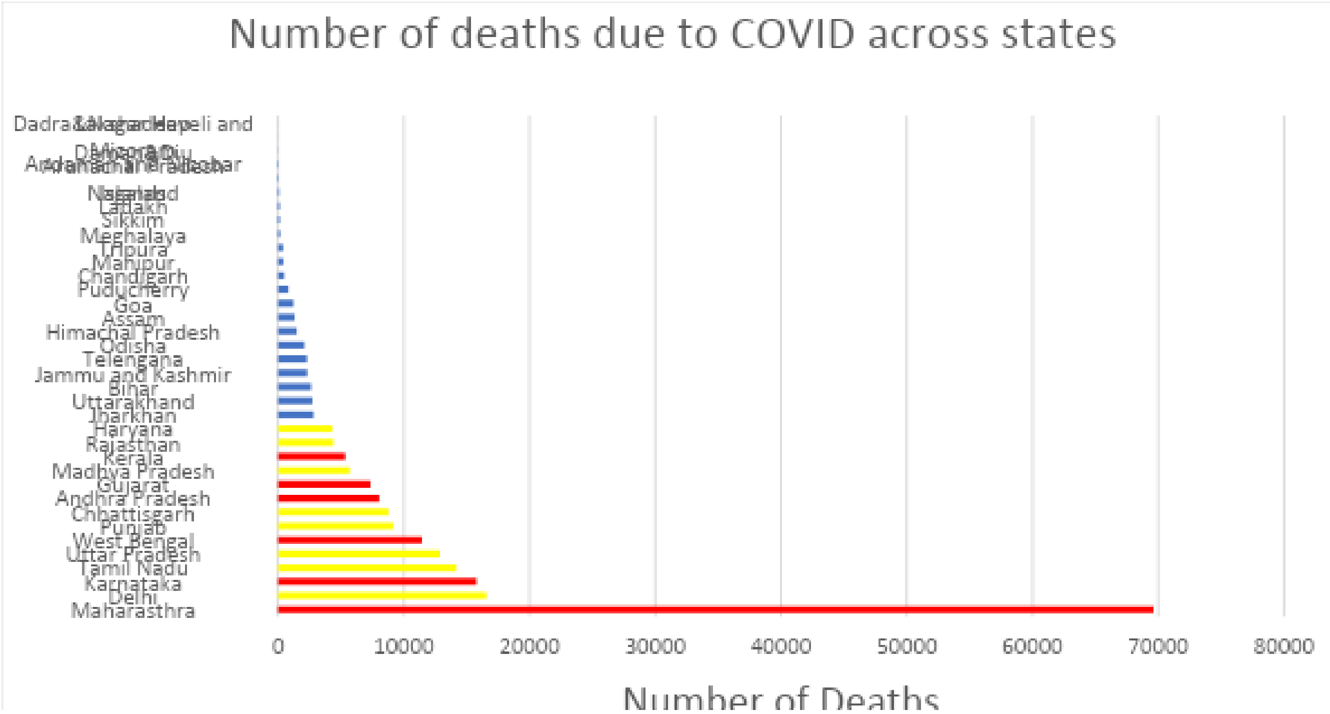


Figure 2.2: Number of deaths due to COVID across states as of 1st May 2021

As of 1st May 2021, the total number of deaths due to COVID in the states in India was 2,15,524. States with more than 4000 (taking it as a threshold value) deaths due to COVID studied in Phase-II of the 2019-21 NFHS report are Delhi, Tamil Nadu, Uttar Pradesh, Punjab, Chhattisgarh, Madhya Pradesh, Rajasthan and Haryana.

Combining the two sets of states we finally have **eight** states which are:

(i) Delhi

(ii) Haryana

(iii) Punjab

(iv) Rajasthan

(v) Chhattisgarh

(vi) Madhya Pradesh

(vii) Uttar Pradesh

(viii) Tamil Nadu

After removing the time factor using NFHS-5 Phase I data, a comparison between the adjusted rates from the NFHS-5 report and the rates from the NFHS-4 report is made between the eight selected states using the Wilcoxon-signed-rank test. A non-parametric test is performed due to the small sample size of eight.

Diagrammatic analysis:

We have drawn multiple bar diagrams to show the effect of COVID-19 on prevalence of various diseases. From the 2019-2021 Phase-2 NFHS report we deduct the time factor and then compare it with the 2015-2016 NFHS report.

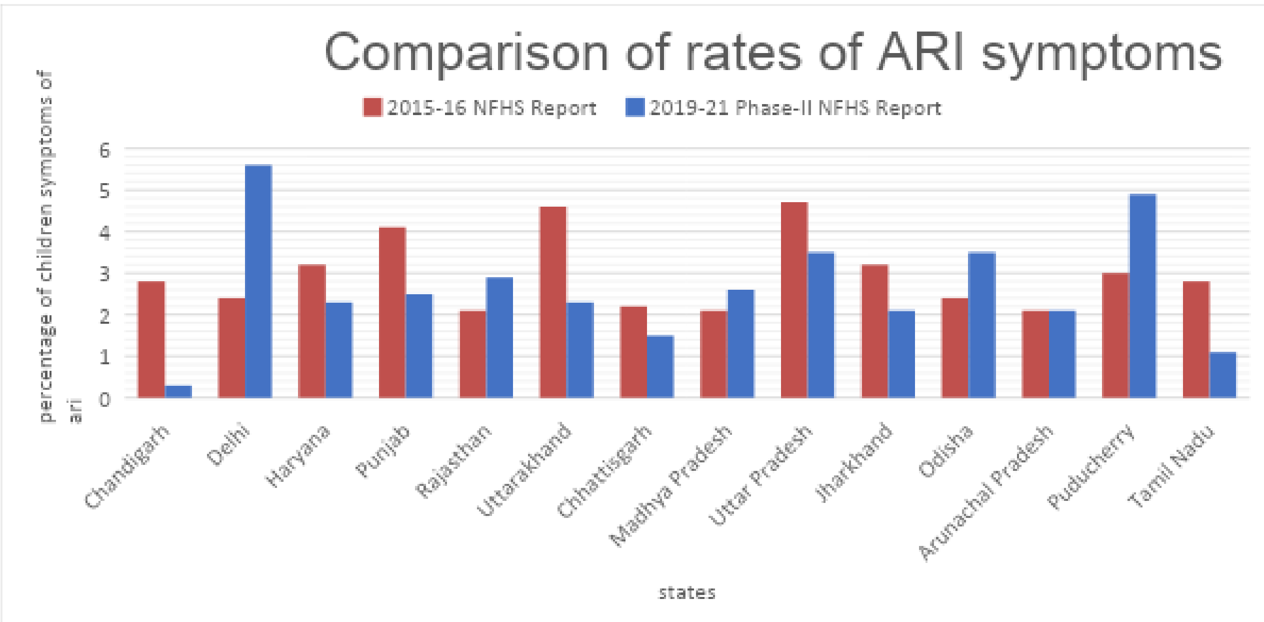


Figure 3.1: Comparison of rates of ARI symptoms

From figure 3.1, we can conclude that **in Delhi, Rajasthan, Madhya Pradesh, Odisha and Puducherry there are increments in rates during COVID-19**, i.e., during COVID-19, Rates of ARI symptoms seem to have increased than pre-COVID scenario, for these states.

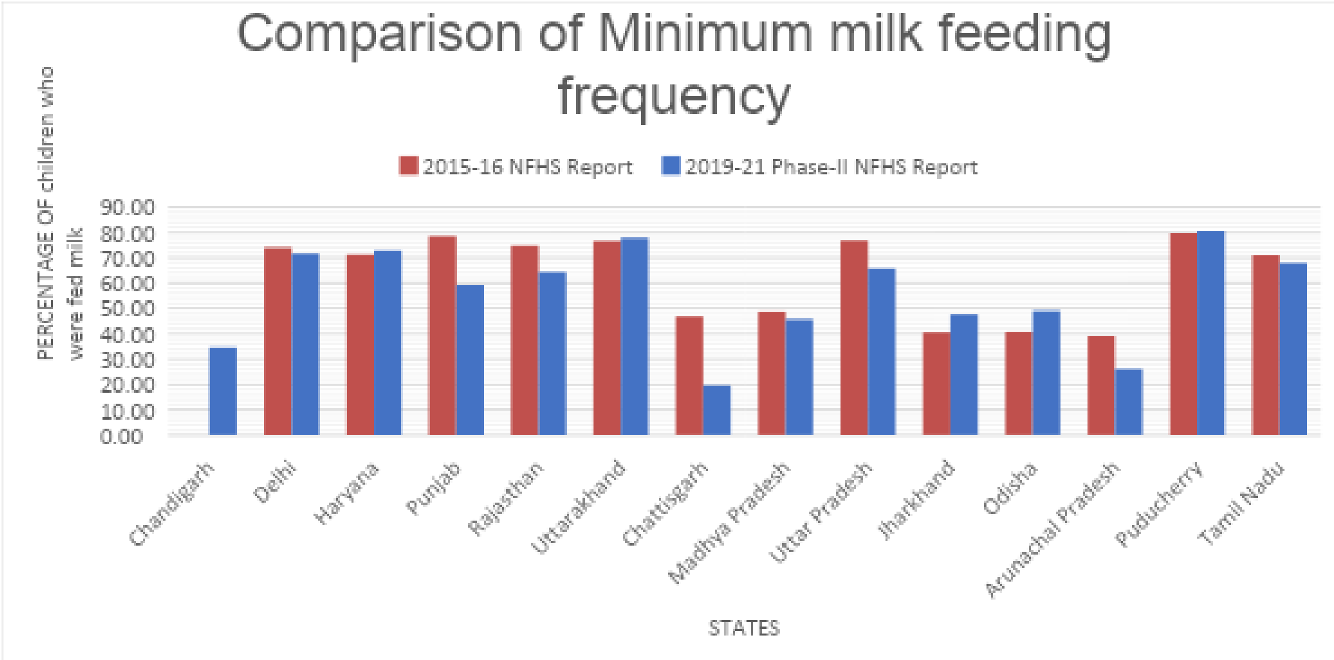


Figure 3.2: Comparison of minimum milk feeding frequency

From figure 3.2, we can conclude that **in Chandigarh, Haryana, Uttarakhand, Jharkhand, Odisha and Puducherry there are decrements in rates during COVID-19,** i.e., during COVID-19, minimum milk feeding frequency seem to have decreased than pre-COVID scenario, for these states.

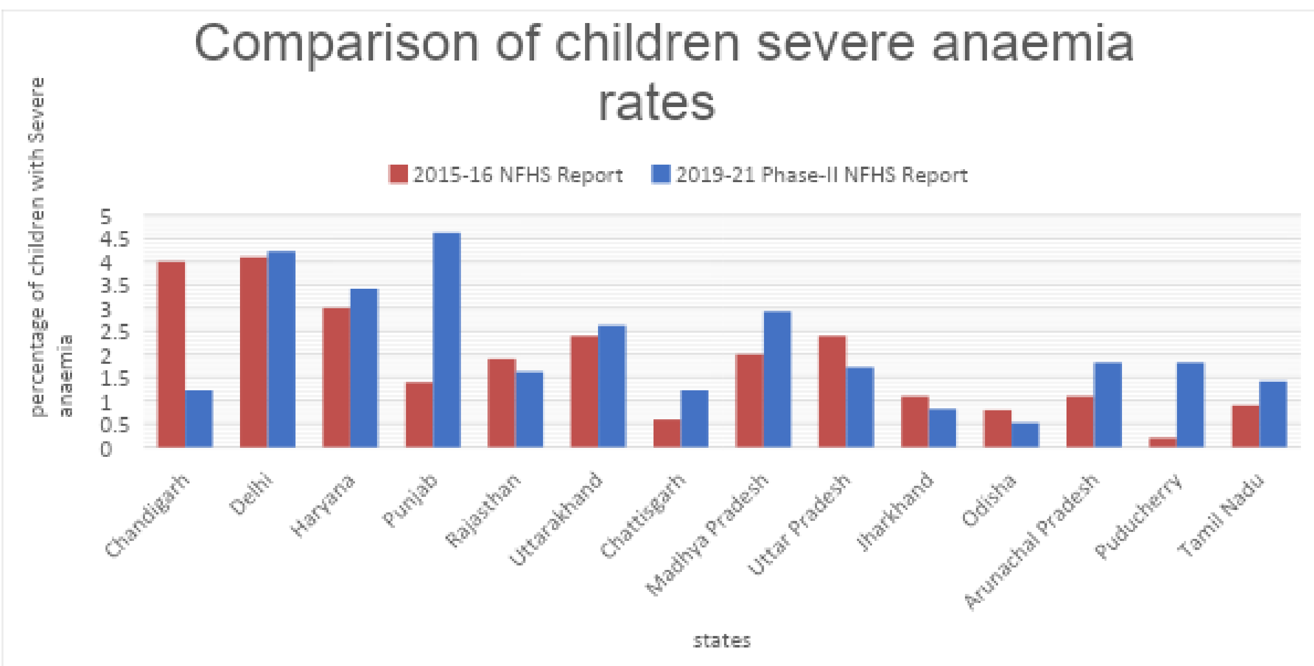


Figure 3.3: Comparison of children severe anaemia rates

From figure 3.3, we can conclude that **in Delhi, Haryana, Punjab, Uttarakhand, Chhattisgarh, and Madhya Pradesh there are increments in rates during COVID-19,** i.e., during COVID-19, children severe anaemia rates seem to have increased than pre-COVID scenario, for these states.

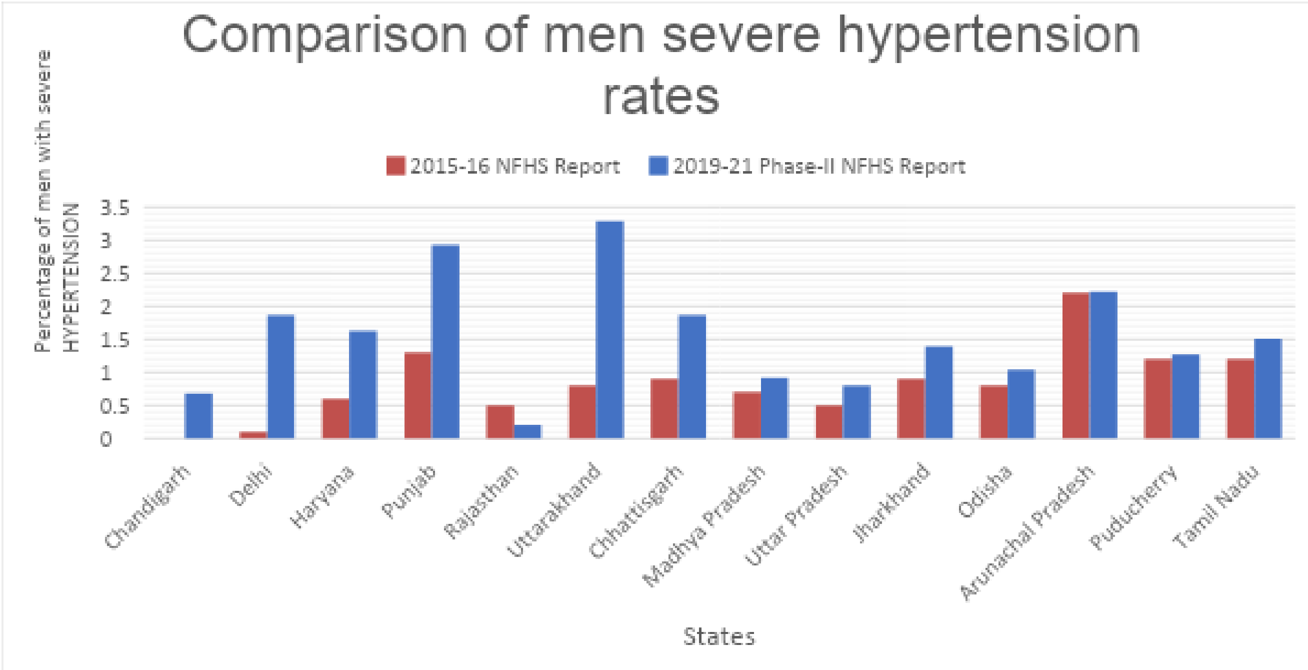


Figure 3.4: Comparison of men severe hypertension rates

From figure 3.4, we can conclude that **in all the states (under study) except Rajasthan, there are increments in rates during COVID-19**, i.e., during COVID-19, men severe hypertension rates seem to have increased than pre-COVID scenario, for these states.

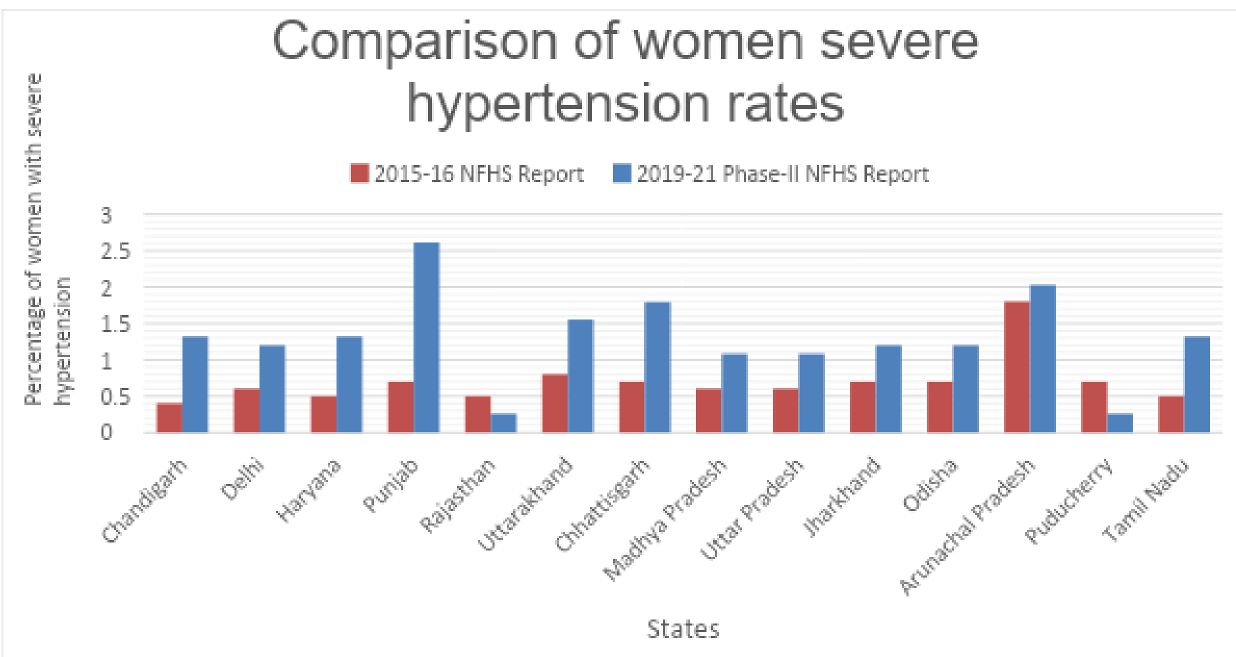


Figure 3.5: Comparison of women severe hypertension rates

From figure 3.5, we can conclude that **in all the states (under study) except Rajasthan, there are increments in rates during COVID-19,** i.e., during COVID-19, women severe hypertension rates seem to have increased than pre-COVID scenario, for these states.

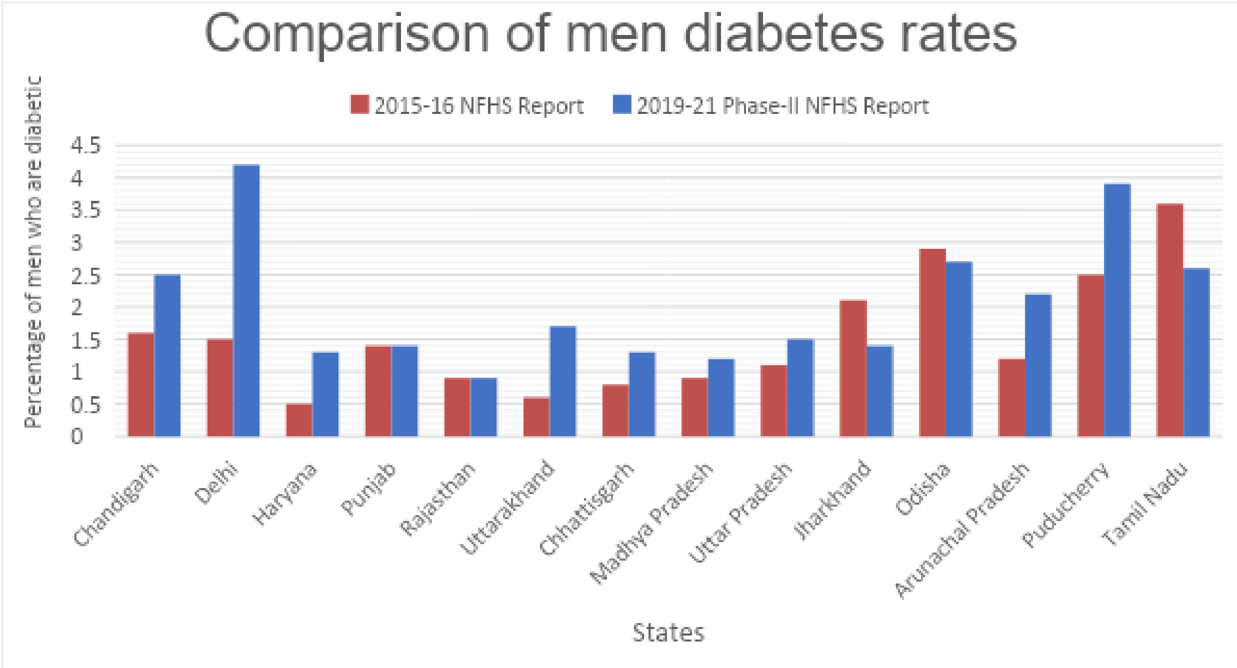


Figure 3.6: Comparison of men diabetes rates

From figure 3.6, we can conclude that **in Chandigarh, Delhi, Haryana, Uttarakhand, Chhattisgarh, Madhya Pradesh, Uttar Pradesh, Arunachal Pradesh and Puducherry there are increments in rates during COVID-19,** i.e., during COVID-19, men diabetes rates seem to have increased than pre-COVID scenario, for these states.

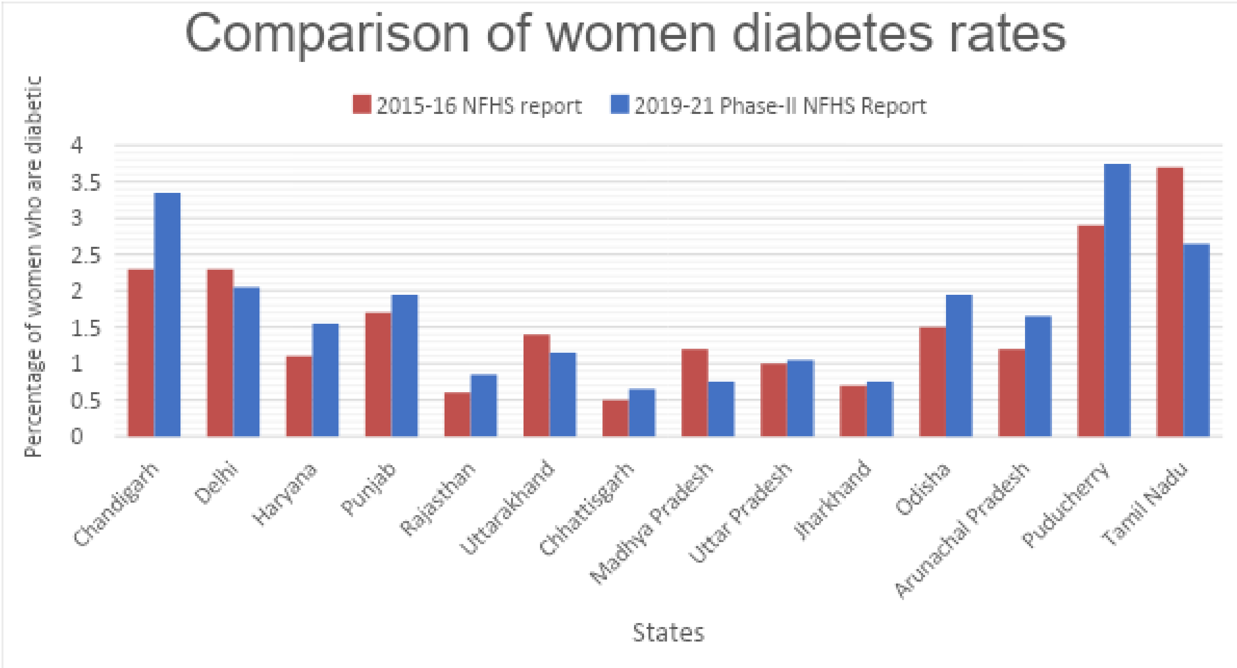


Figure 3.7: Comparison of women diabetes rates

From figure 3.7, we can conclude **that in Chandigarh, Haryana, Punjab, Rajasthan, Chhattisgarh, Odisha, Arunachal Pradesh and Puducherry there are increments in rates during COVID-19,** i.e., during COVID-19, women diabetes rates seem to have increased than pre-COVID scenario, for these states.

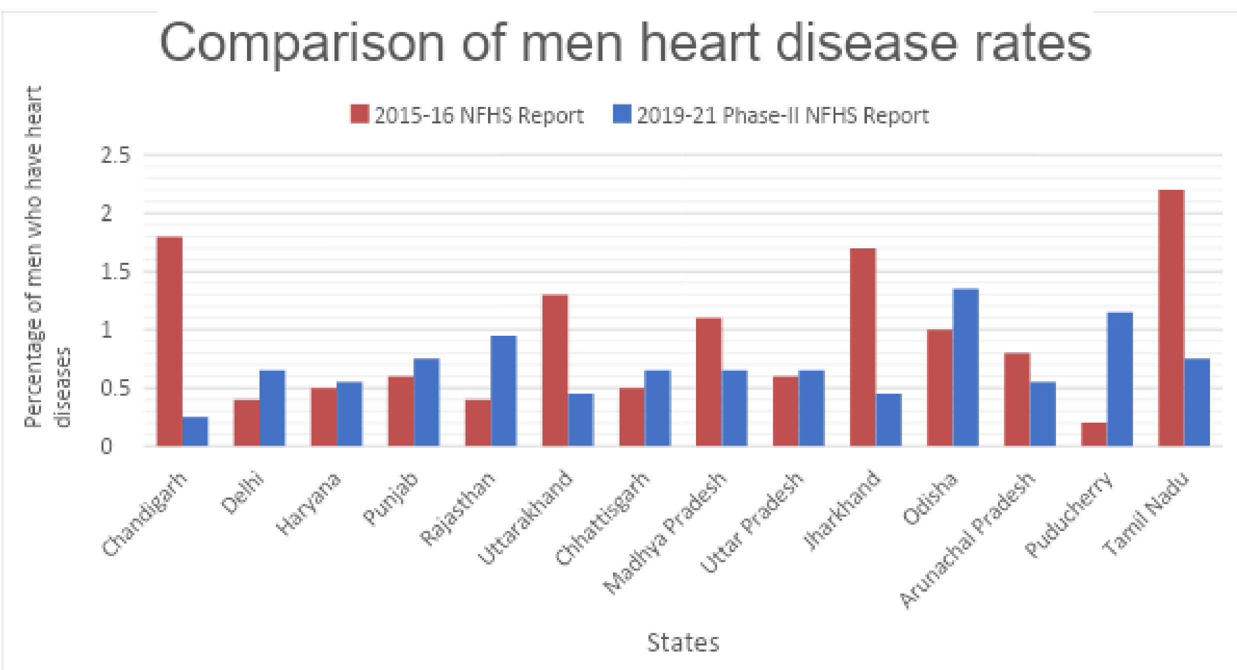


Figure 3.8: Comparison of men heart disease rates

From figure 3.8, we can conclude **that in Delhi, Punjab, Rajasthan, Chhattisgarh, Odisha and Puducherry there are increments in rates during COVID-19,** i.e., during COVID-19, men's heart disease rates seem to have increased than pre-COVID scenario, for these states.

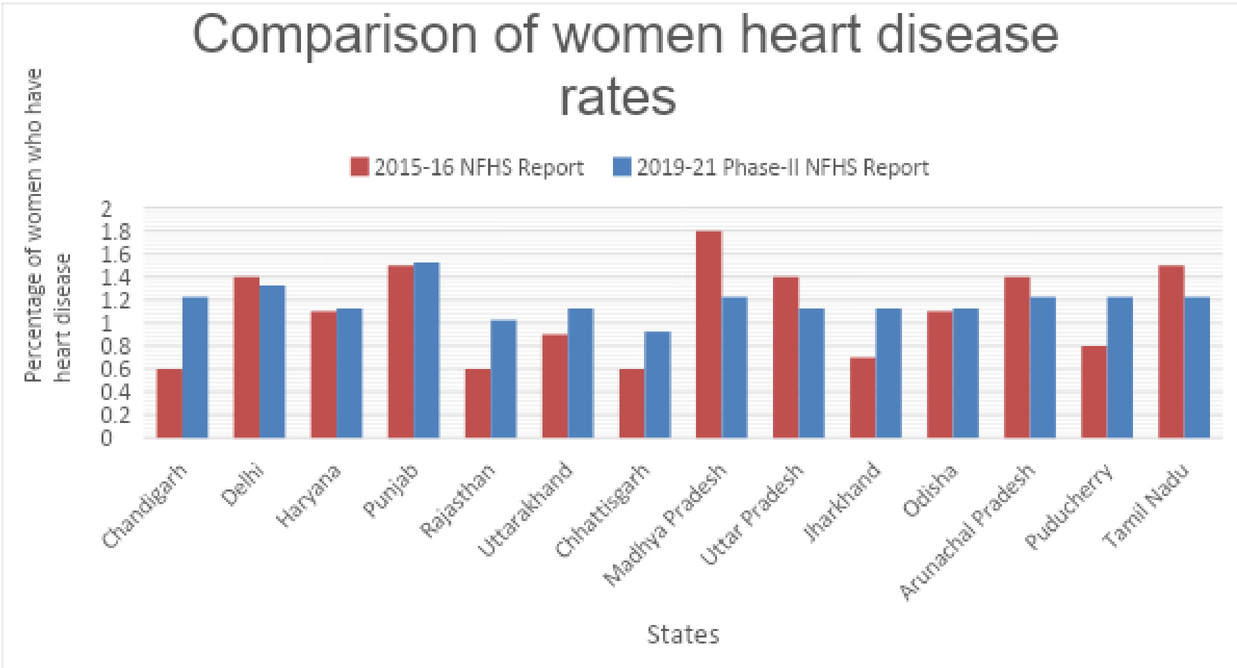


Figure 3.9: Comparison of women's heart disease rates

From figure 3.9, we can conclude **that in Chandigarh, Rajasthan, Uttarakhand, Chhattisgarh, Jharkhand and Puducherry there are increments in rates during COVID-19,** i.e., during COVID-19, women's heart disease rates seem to have increased than pre-COVID scenario, for these states.

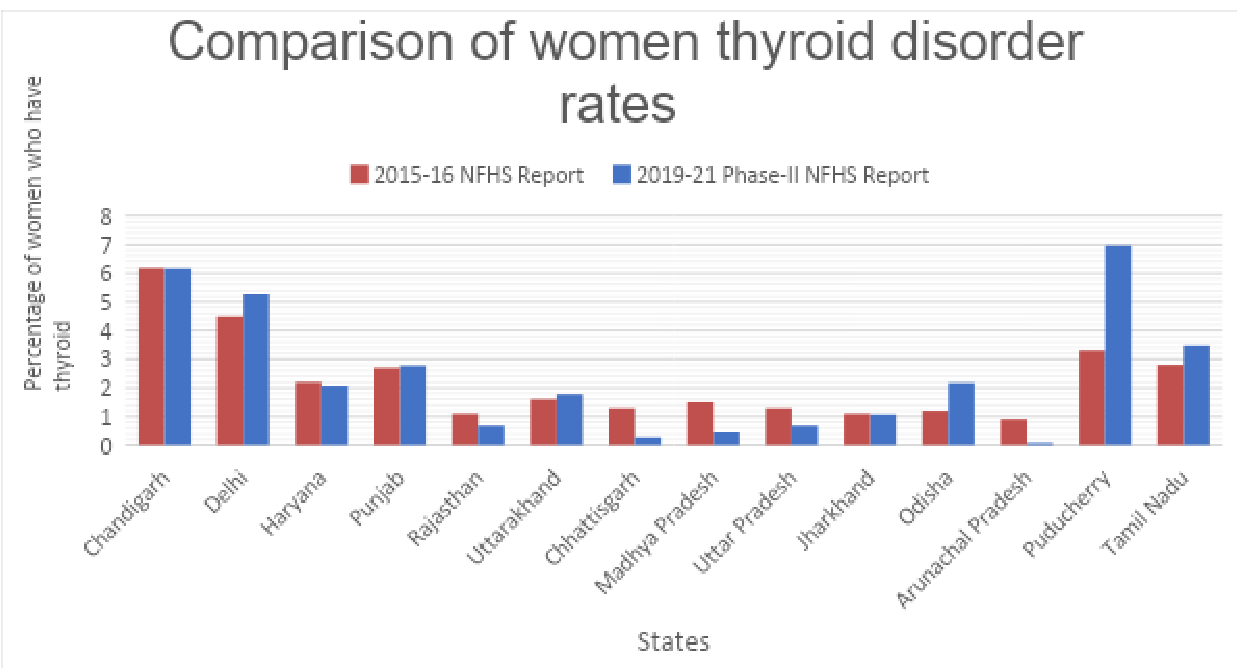


Figure 3.10: Comparison of women's thyroid disorder rates

From figure 3.10, we can conclude that **in Delhi, Uttarakhand, Odisha, Tamil Nadu and Puducherry there are increments in rates during COVID-19**, i.e., during COVID-19, women's thyroid disorder rates seem to have increased to pre-COVID scenario, for these states.

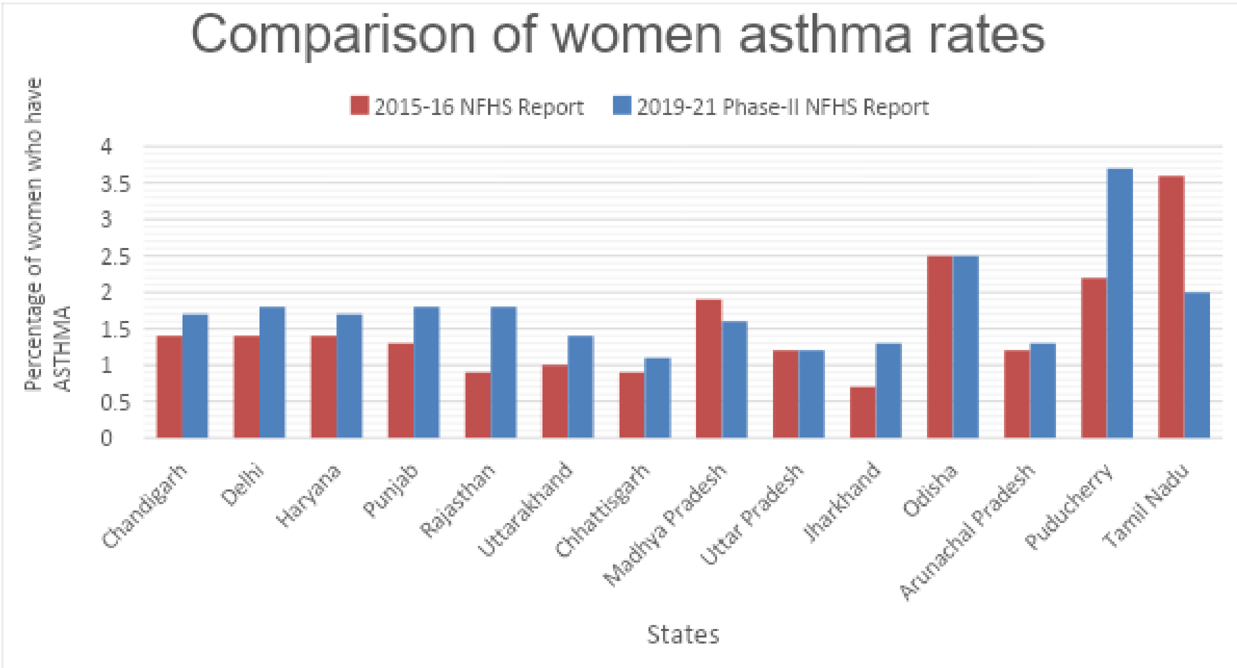


Figure 3.11: Comparison of women's asthma rates

From figure 3.11, we can conclude **that in Chandigarh, Delhi, Haryana, Punjab, Uttarakhand, Chhattisgarh, Jharkhand, Arunachal Pradesh and Puducherry there are increments in rates during COVID-19,** i.e., during COVID-19, men asthma rates seem to have increased than pre-COVID scenario, for these states.

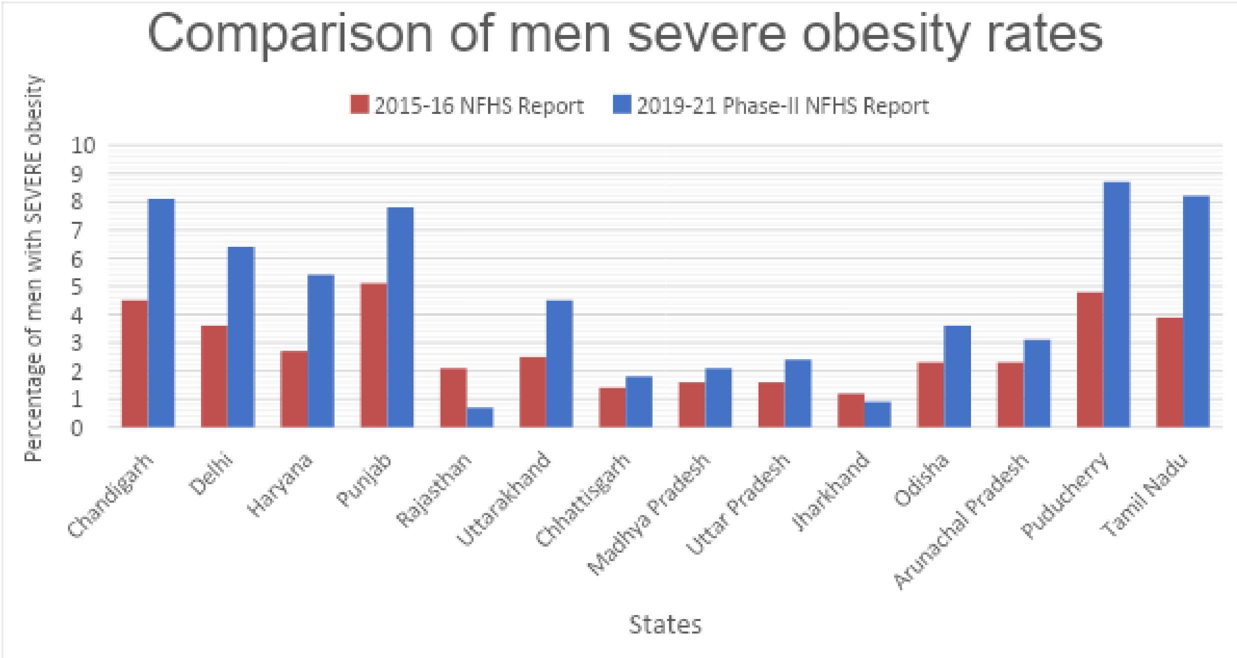


Figure 3.12: Comparison of men's severe obesity rates

From figure 3.12, we can conclude **that in Chandigarh, Delhi, Haryana, Punjab, Uttarakhand, Chhattisgarh, Madhya Pradesh, Uttar Pradesh, Arunachal Pradesh, Puducherry and Tamil Nadu there are increments in rates during COVID-19,** i.e., during COVID-19, men severe obesity rates seem to have increased than pre-COVID scenario, for these states.

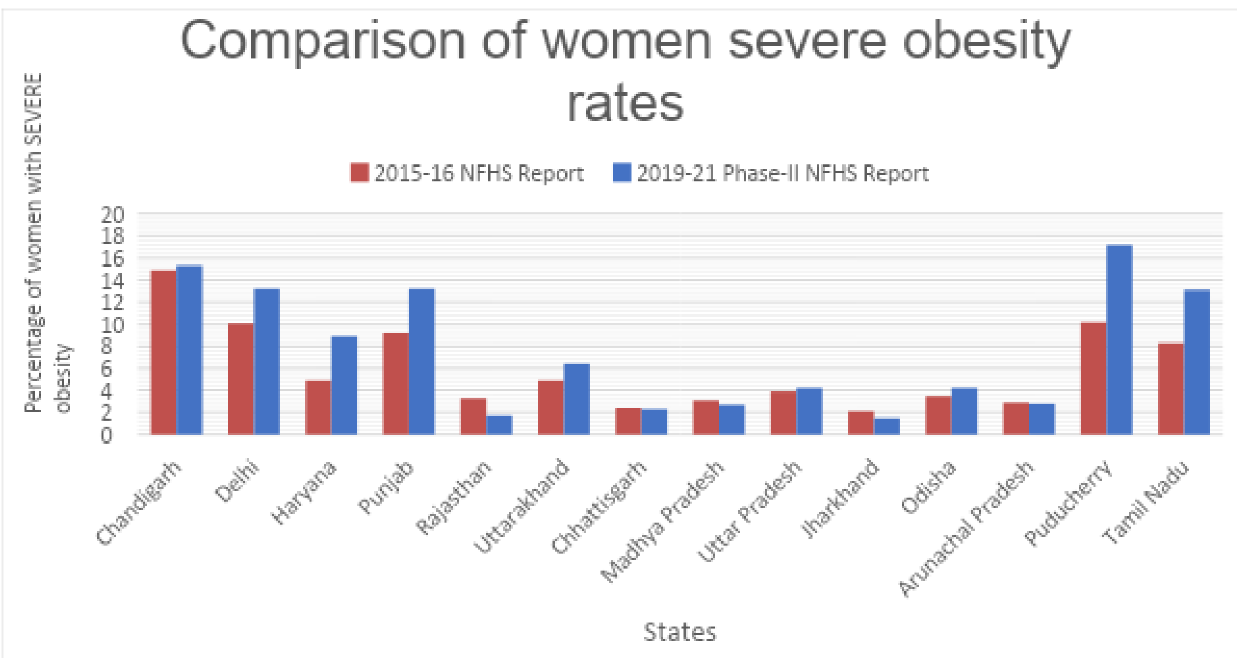


Figure 3.13: Comparison of women's severe obesity rates

From figure 3.13, we can conclude **that in Chandigarh, Delhi, Haryana, Punjab, Uttarakhand, Uttar Pradesh, Odisha, Puducherry and Tamil Nadu there are increments in rates during COVID-19,** i.e., during COVID-19, women severe obesity rates seem to have increased than pre-COVID scenario, for these states.

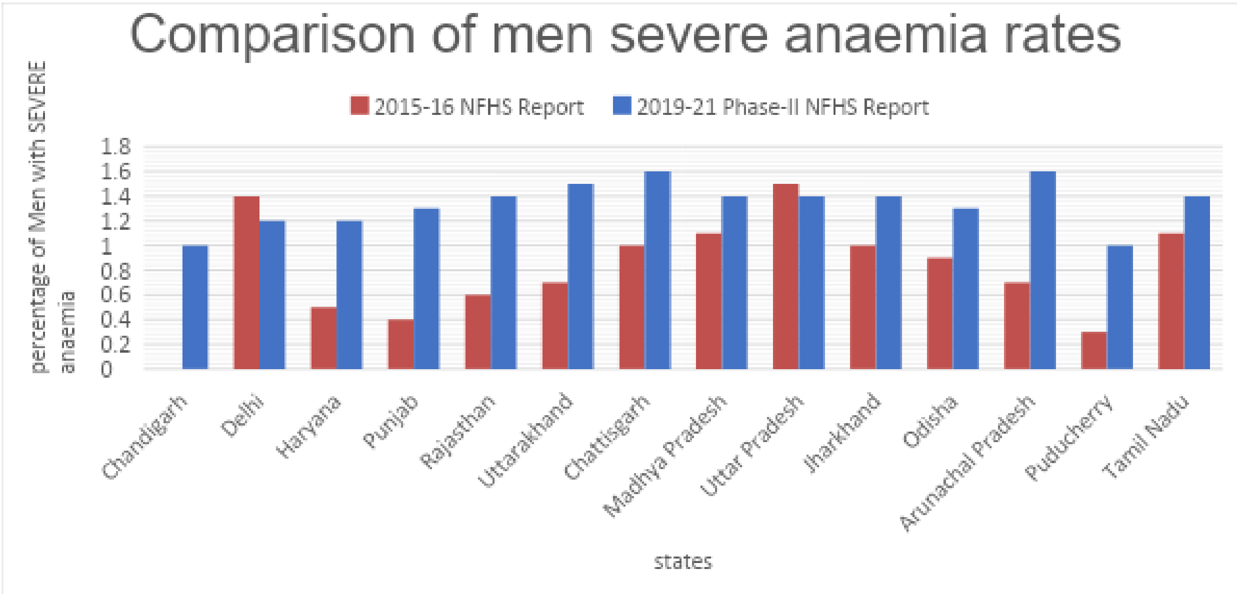


Figure 3.14: Comparison of men's severe anaemia rates

From figure 3.14, we can conclude **that in Chandigarh, Haryana, Punjab, Rajasthan, Uttarakhand, Chhattisgarh, Madhya Pradesh, Jharkhand, Odisha, Arunachal Pradesh, Puducherry and Tamil Nadu there are increments in rates during COVID-19,** i.e., during COVID-19, men severe anaemia rates seem to have increased than pre-COVID scenario, for these states.

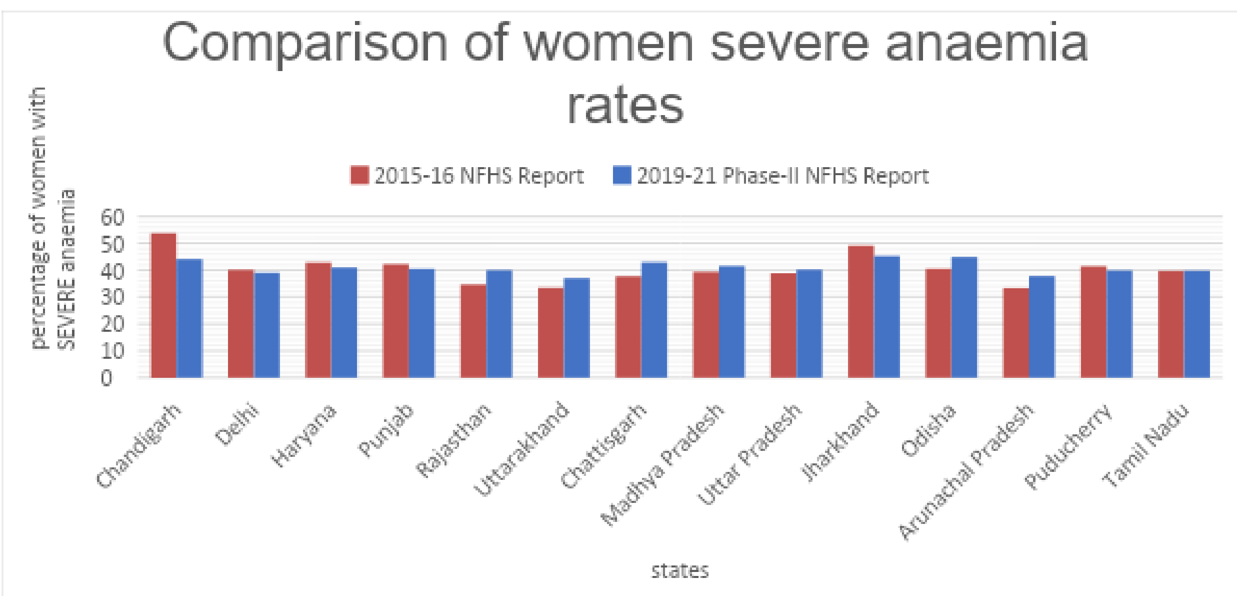


Figure 3.15: Comparison of women's severe anaemia rates

From figure 3.15, we can conclude **that in Haryana, Punjab, Chhattisgarh, Odisha, Arunachal Pradesh, Puducherry and Tamil Nadu there are increments in rates during COVID-19,** i.e., during

COVID-19, women with severe anaemia rates seem to have increased than pre-COVID scenario, for these states.

Results:

To examine whether the differences observed in the rates of the diseases under study from the bar diagrams are significant or not, we carry out the Wilcoxon signed-rank test (one-sided).

Population under study	Age under Study	Procedure of Test	Null Hypothesis	Alternative Hypothesis	P-Value	Test result	Conclusion
Children	Under 5 years	ARI rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on Acute Respiratory Infections rates during COVID-19	Acute Respiratory Infections rates increased during COVID-19	.7996	Fail to reject the Null Hypothesis at a 10% level of significance	No significant impact on Acute Respiratory Infections rates during COVID-19
	6-23 months	Milk feeding rates to non-breastfed children of 2015-16 were compared with 2019-21 Phase-II	No significant impact on children's immunity rates during COVID-19	Children's immunity rates decreased during COVID-19	**.0086**	**Reject the Null Hypothesis at a 10% level of significance**	**Children's immunity rates decreased during COVID-19**
	6-59 months	Severe anaemia rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on severe anaemia rates during COVID-19	Children severe anaemia rates increased during COVID-19	**.0807**	**Reject the Null Hypothesis at a 10% level of significance**	**Children severe anaemia rates increased during COVID-19**

Table 4.1: Table showing results for tests in Children

Population under study	Age under Study	Procedure of Test	Null Hypothesis	Alternative Hypothesis	P-Value	Test result	Conclusion
Women	15-49 years	Severe Anaemia rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on women's severe anaemia rates during COVID-19	Women's severe anaemia rates increased during COVID-19	.6136	Fail to reject the Null Hypothesis at a 10% level of significance	No significant impact on women's severe anaemia rates during COVID-19
	15-49 years	Diabetes rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on women's diabetes rates during COVID-19	Women's diabetes rates increased during COVID-19	.4712	Fail to reject the Null Hypothesis at a 10% level of significance	No significant impact on women's diabetes rates during COVID-19
	15-49 years	Severe Obesity rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on women's severe obesity rates during COVID-19	Women's severe obesity rates increased during COVID-19	**.0745**	**Reject the Null Hypothesis at a 10% level of significance**	**Women's severe obesity rates increased during COVID-19**
	15-49 years	Heart Disease rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on women's heart disease rates during COVID-19	Women's heart disease rates increased during COVID-19	.6172	Fail to reject the Null Hypothesis at a 10% level of significance	No significant impact on women's heart disease rates during COVID-19
	15-49 years	Severe Hypertension rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on women's severe hypertension rates during COVID-19	Women's severe Hypertension rates increased during COVID-19	**.0056**	**Reject the Null Hypothesis at a 10% level of significance**	**Women's severe Hypertension rates increased during COVID-19**
	15-49 years	Asthma rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on women's asthma rates during COVID-19	Women's asthma rates increased during COVID-19	.2136	Fail to reject the Null Hypothesis at a 10% level of significance	No significant impact on women's asthma rates during COVID-19
	15-49 years	Thyroid disorder rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on women's thyroid disorder rates during COVID-19	Women's severe thyroid disorder rates increased during COVID-19	.8068	Fail to reject the Null Hypothesis at a 10% level of significance	No significant impact on women's thyroid disorder rates during COVID-19

Table 4.2: Table showing results for tests in Women

Population under study	Age under Study	Procedure of Test	Null Hypothesis	Alternative Hypothesis	P-Value	Test result	Conclusion
Men	15-49 years	Severe Anaemia rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on men's severe anaemia rates during COVID-19	Men's severe anaemia rates increased during COVID-19	**.0152**	**Reject the Null Hypothesis at a 10% level of significance**	**Men's severe anaemia rates increased during COVID-19**
	15-49 years	Diabetes rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on men's diabetes rates during COVID-19	Men's diabetes rates increased during COVID-19	.1244	Fail to reject the Null Hypothesis at a 10% level of significance	No significant impact on men's diabetes rates during COVID-19
	15-49 years	Severe Obesity rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on men's severe obesity rates during COVID-19	Men's severe obesity rates increased during COVID-19	**.0250**	**Reject the Null Hypothesis at a 10% level of significance**	**Men's severe obesity rates increased during COVID-19**
	15-49 years	Heart Disease rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on men's heart disease rates during COVID-19	Men's heart disease rates increased during COVID-19	.2819	Fail to reject the Null Hypothesis at a 10% level of significance	No significant impact on men's heart disease rates during COVID-19
	15-49 years	Severe Hypertension rates of 2015-16 were compared with 2019-21 Phase-II	No significant impact on men's severe hypertension rates during COVID-19	Men's severe Hypertension rates increased during COVID-19	**.0125**	**Reject the Null Hypothesis at a 10% level of significance**	**Men's severe Hypertension rates increased during COVID-19**

Table 4.3: Table showing results for tests in Men

Bayesian Analysis

The central goal of the analysis is to identify whether there's an increase in the spread of some particular diseases during COVID-19.

One way to think about this is to identify the probability that is there an actual increase in the spread of a particular disease during the COVID-19 pandemic.

We compute estimate of the probability of an increase in the spread of other diseases during COVID-19. Hence, we use the bayesian method to compute this estimate.

For this purpose, we consider the average rates from the previous statistical analysis. The average rate for a particular disease is the average for those states which are considered for study.

Depending upon the scenario, that is, for pre-COVID, we consider the time-adjusted average rates from NFHS-4 report.

For during COVID-19, we consider average rates from the NFHS-5 report.

The average rate for a disease is nothing but the proportion of people who has that disease from the total number of people. The average rate for a disease is nothing but, the estimate of the probability that an individual will have that disease.

Hence, either the individual will be affected by a particular disease or will not be affected, which is nothing but a Bernoulli setup.

Now, for a population of 2000 people, we will have a binomial distribution. And the parameters of the binomial will follow a beta distribution in a Bayesian setup.

The form of the conjugate prior can generally be determined by inspection of the probability density or probability mass function of a distribution. For example, consider a random variable which consists of the number of successes s in n Bernoulli trials with an unknown probability of success p in [0,1]. This random variable will follow the binomial distribution, with a probability mass function of the form:

$$P(s) = (n\ s\ )p^{s}(1\ -\ p)^{n-s}$$

The usual conjugate prior is the beta distribution with parameters (α, β):

$$\pi(p) = \frac{p^{\alpha-1}(1-p)^{\beta-1}}{B(\alpha,\beta)}$$

where $\alpha\ and\ \beta$ are chosen to reflect any existing belief or information ($\alpha\ = 1$ and $\beta\ = 1$ would give a uniform distribution) and $B(\alpha, \beta)$ is the Beta function acting as a normalising constant.

In this context, α and β are called hyperparameters (parameters of the prior), to distinguish them from parameters of the underlying model (here p). It is a typical characteristic of conjugate priors that the dimensionality of the hyperparameters is one greater than that of the parameters of the original distribution. If all parameters are scalar values, then this means that there will be one more hyperparameter than parameter; but this also applies to vector-valued and matrix-valued parameters.

If we then sample this random variable and get s successes and f = n - s failures, we have,

$$P(p\ =\ \theta) = (n\ s\ )\theta^{s}(1\ -\ \theta)^{f},$$

$$\pi(p = \theta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{B(\alpha,\beta)},$$

$$\pi(s, f) = \frac{P(\theta)\pi(\theta)}{\int P(\theta)\pi(\theta)d\theta}$$

$$= \frac{\frac{(n\ s)\theta^{s+\alpha-1}(1-\theta)^{f+\beta-1}}{B(\alpha,\beta)}}{\int_{\theta=0}^{1} \frac{(n\ s)\theta^{s+\alpha-1}(1-\theta)^{f+\beta-1}}{B(\alpha,\beta)} d\theta}$$

$$= \frac{\theta^{s+\alpha-1}(1-\theta)^{f+\beta-1}}{B(s+\alpha, f+\beta)},$$

which is another Beta distribution with parameters $(\alpha + s, \beta + n - s)$. This posterior distribution could then be used as the prior for more samples, with the hyperparameters simply adding each extra piece of information as it comes. [8]

Here, in the Bayesian setup, we have considered a uniform prior distribution that is, a person under study being affected and not affected is equally likely. Thus, we have considered $\alpha = 1\ and\ \beta = 1$.

Note that, the posterior distribution is extremely data-dependent and gives us an idea of how likely a person is to be affected by a particular disease, even if we start with an assumption of equally likely in both the pre-COVID and during-COVID scenarios.

The posterior distribution in both scenarios that is, pre-COVID and during COVID-19 can be used to compare the likeliness of a particular disease pre-COVID and during COVID.

The differences in the posterior probabilities can be used to identify if there is an increase in the spread of a particular disease during the COVID-19.

Procedure:

1. For the beta-binomial model in a Bayesian setup, we divide the population of size 2000 into two groups:

   A. Those with a particular disease.

   B. Those who do not have the particular disease

The number of people who has the particular disease is calculated by:

Average rate for that disease * 2000

We do this calculation for both periods:

   A. Pre-COVID

   B. During COVID

2. Now we have a 2x2 table of people during COVID-19 and before COVID-19 who have a particular disease and who don't.

3. We make this 2x2 table for all those diseases which were considered in the frequentist approach in the form as mentioned below,

```
##         Period Affected Not_Affected
## 1    precovid     s1       n-s1
## 2 duringcovid     s2       n-s2
```

s_1 is the number of people who are affected by a particular disease before COVID-19

s_2 is the number of people who are affected by a particular disease during COVID-19

$n-s_1$ is the number of people who are not affected by a particular disease before COVID-19

$n-s_2$ is the number of people who are not affected by a particular disease during COVID-19

4. From this table, we construct two independent beta distributions. One for the pre-COVID scenario and the other for the during-COVID scenario.

The parameters for both beta distributions are as follows:

A. For the beta distribution of the pre-covid scenario, the first parameter is the number of people who have the particular and the second parameter is the number of people who don't have the specific disease before the COVID-19 period.

B. Similarly, for the beta distribution during the COVID-19 scenario, the first parameter is the number of people who have the particular and the second parameter is the number of people who don't have the particular disease during the COVID-19 period.

5. Now we generate a random sample of size 10,00,000 from both these beta distributions. The samples are nothing but the average rates of that particular disease for that particular period that is, before COVID-19 and during COVID-19.

6. We construct the difference between these sample rates that is the difference between the during COVID-19 rates and before COVID-19 rates and observe the number of scenarios in which these differences are positive that is, in how many of the 10,00,000 samples the rates during COVID-19 are more significant than that of before COVID-19 period.

7. We now find the proportion of times in which these differences are positive. This is nothing but the probability that there's an increase in the spread of a particular disease during the covid-19 period.

8. Now we construct a 95% interval (indicated by the blue line in the histograms) of the differences in the sample rates of pre-COVID and during the COVID-19 period. This construction is done to observe whether the differences for the particular disease during COVID-19 and the pre-COVID-19 period are significant or, not.

Bayesian analysis, results, and interpretations

Below we construct 2x2 tables, histograms, and also calculate the probability of increase in the spread of disease during the COVID-19 for all the diseases considered for analysis.

Children

Severe ARI Children

```
##         Period Affected Not_Affected
## 1     precovid       59         1941
## 2 duringcovid       55         1945
```

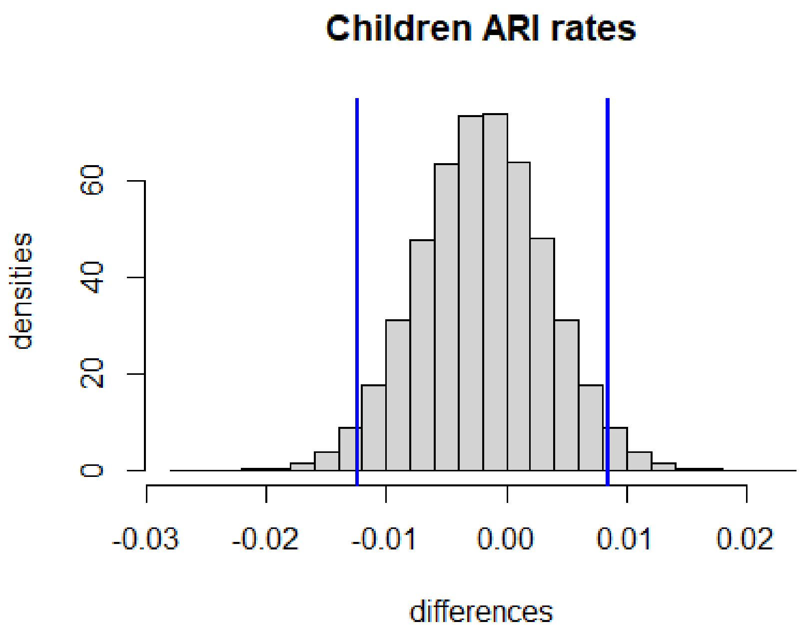


Figure 5.1

```
# Probability of positive differences of ARI rates

## [1] 0.352742
```

From the figure 5.1 we observe that the majority of the differences in the sample rates of Acute Respiratory Infection (ARI) of pre-COVID and during COVID-19 period are negative, and the probability that there's an increase in the spread of ARI is 0.3527, which indicates it's unlikely that there's an increase in the spread of ARI during the COVID-19.

Milk feeding rates in Children

```
##         Period Affected Not_Affected
## 1     precovid     1354          646
## 2 duringcovid     1167          833
```

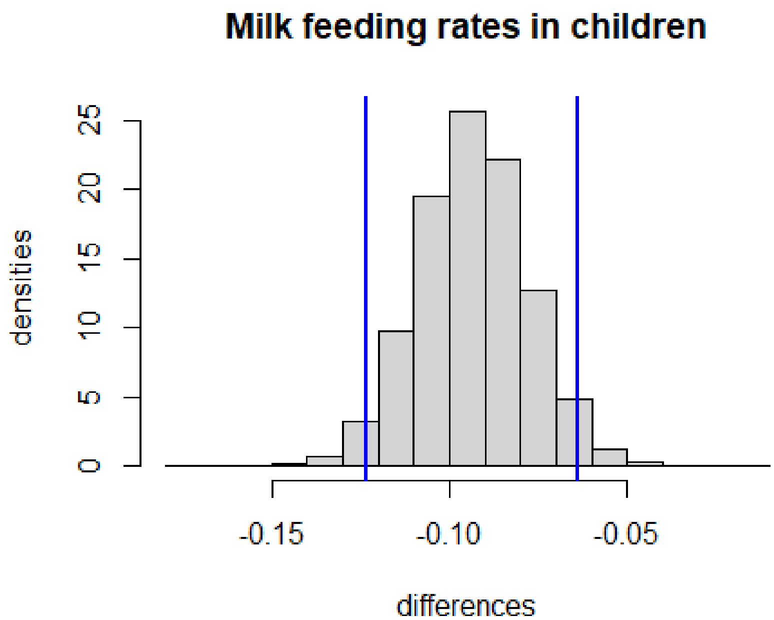


Figure 5.2

```
# Probability of negative differences of Milk feeding rates

## [1] 1
```

From the figure 5.2, we observe that the majority of the differences in the sample milk feeding rates of pre-COVID and during COVID-19 period are negative. And the probability that there's a decrease in the milk feeding rates is 1, which indicates it's certain that there's a decrease in the milk feeding rates during the COVID-19.

Severe anaemia in children

```
##        Period Affected Not_Affected
## 1    precovid       40         1960
## 2 duringcovid       53         1947
```

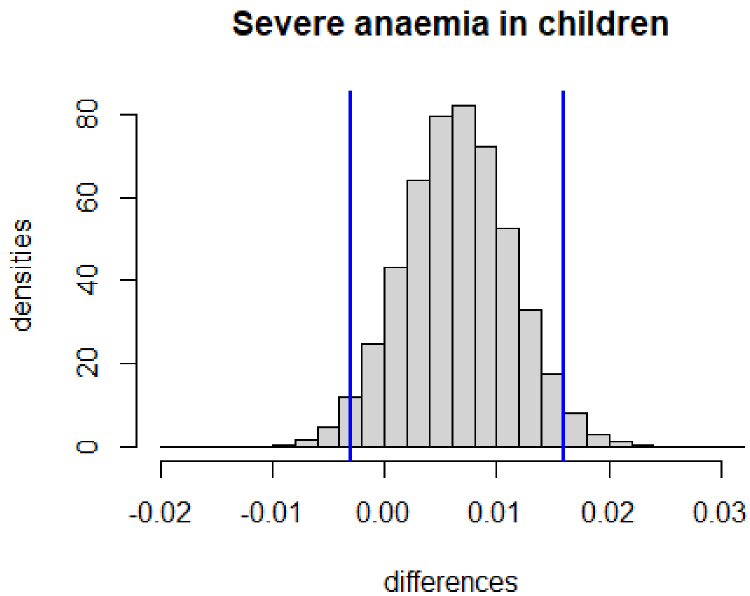


Figure 5.3

```
# Probability of positive differences of severe anaemia rates in
children
## [1] 0.912634
```

From the figure 5.3, we observe that the majority of the differences in the sample severe anaemia rates for children of pre-COVID and during COVID-19 period are positive. And the probability that there's an increase in the severe anaemia rates in children is 0.9126, which indicates it's very likely that there's an increase in the severe anaemia rates in children during the COVID-19 period.

Results for children:

Population under study	Age under Study	Procedure of ANALYSIS	2015-16 RATES	2019-21 PHASE II RATES	Pre-COVID DISTRIBUTION	DURING-COVID DISTRIBUTION	ESTIMATE OF THE PROBABILITY OF INCREMENT IN THE RATES OF THE DISEASE
Children	Under 5 years	ARI rates of 2015-16 were compared with 2019-21 Phase-II	2.95	2.75	$\beta(60, 1942)$	$\beta(56, 1946)$	*0.352742*
	6-23 months	Milk feeding rates to non-breastfed children of 2015-16 were compared with 2019-21 Phase-II	67.725	58.3875	$\beta(1355, 647)$	$\beta(1168, 834)$	***1***
	6-59 months	Severe anaemia rates of 2015-16 were compared with 2019-21 Phase-II	2.0375	2.65	$\beta(41, 1961)$	$\beta(54, 1948)$	***0.912634***

Table 5.1: Table showing results for analysis in Children

Women

Severe Anaemia Women

```
##          Period Affected Not_Affected
## 1     precovid       22         1978
## 2 duringcovid       21         1979
```

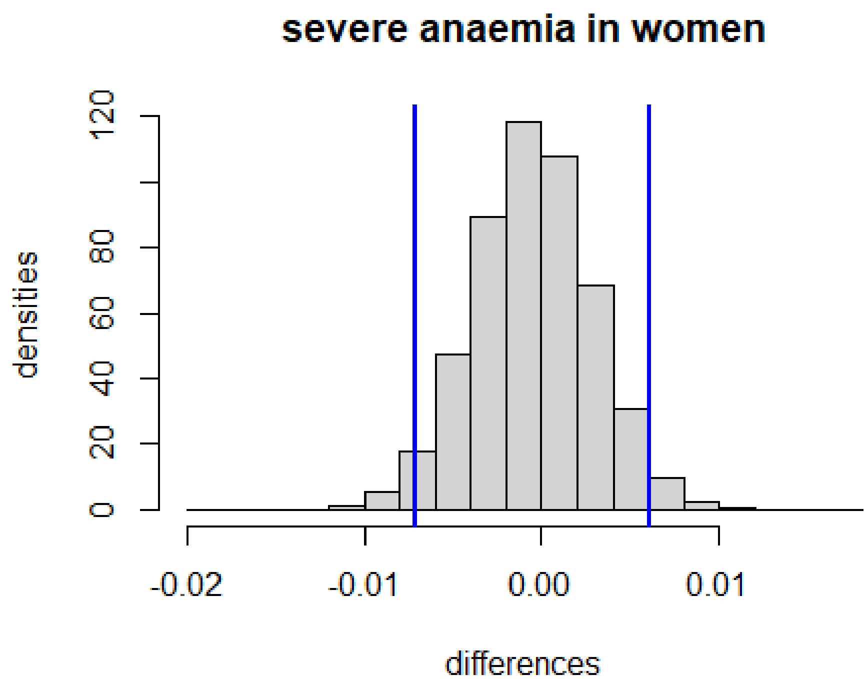


Figure 5.4

```
# Probability of positive differences of severe anaemia rates in women
## [1] 0.439881
```

From the figure 5.4, we observe that the majority of the differences in the sample severe anaemia rates for women of pre-COVID and during COVID-19 period are around zero. And the probability that there's an increase in the severe anaemia rates for women is 0.4398, which indicates it's unlikely that there's an increase in the severe anaemia rates for women during the COVID-19 period.

Diabetes in Women

```
##         Period Affected Not_Affected
## 1     precovid       30         1970
## 2 duringcovid       28         1972
```

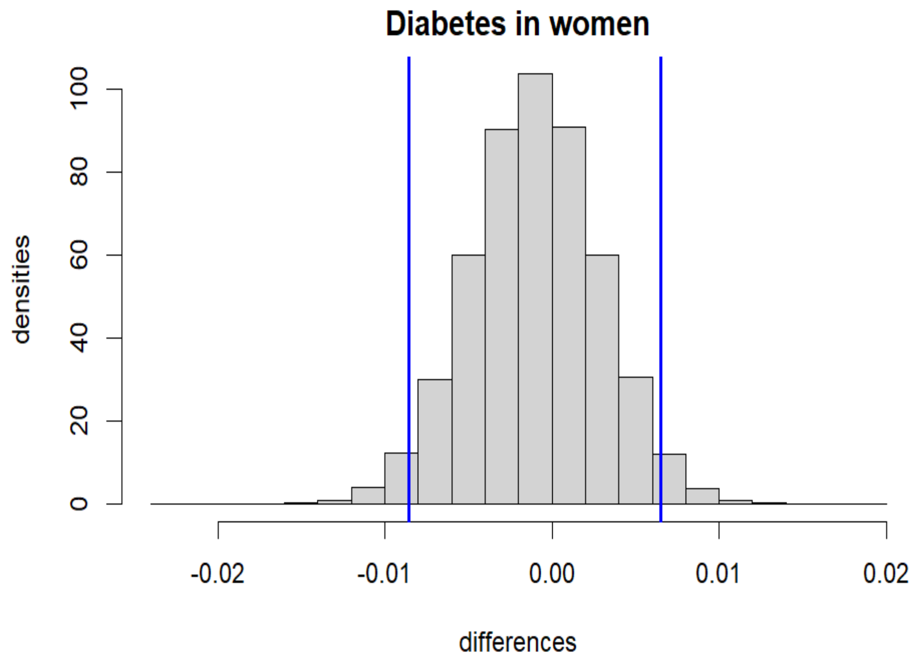


Figure 5.5

```
# Probability of positive differences of diabetes in women

## [1] 0.397501
```

From the figure 5.5, we observe that the majority of the differences in the sample diabetes rates for women of pre-COVID and during COVID-19 period are positive. And the probability that there's an increase in the rates of diabetes for women is 0.8983, which indicates it's very likely that there's an increase in the diabetes rates for women during the COVID-19 period.

Severe obesity Women

```
##         Period Affected Not_Affected
## 1    precovid      113         1887
## 2 duringcovid      148         1852
```

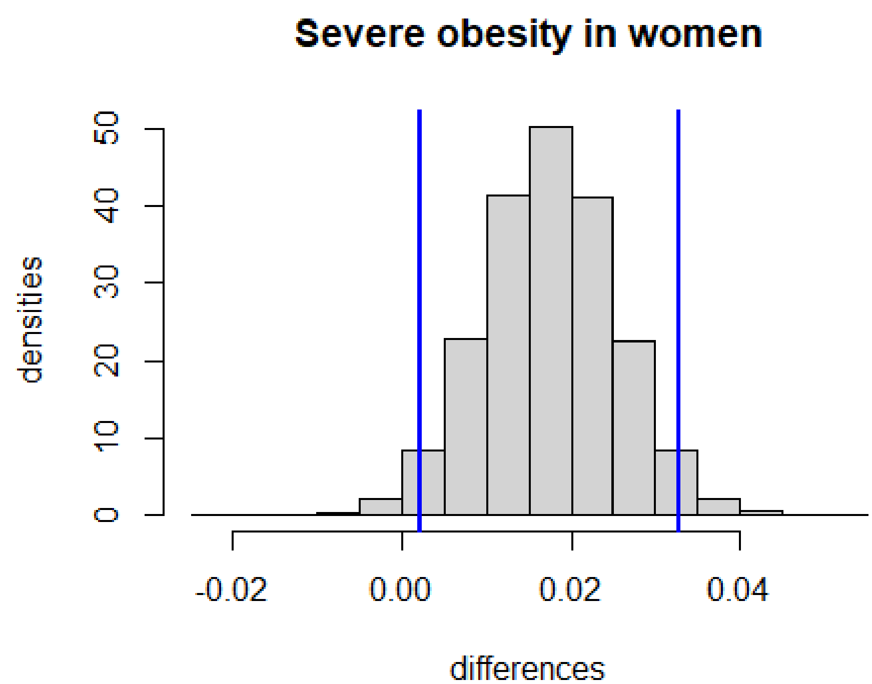


Figure 5.6

```
# Probability of positive differences of severe obesity rates in women
## [1] 0.987439
```

From the figure 5.6, we observe that the majority of the differences in the sample severe obesity rates for women of pre-COVID and during COVID-19 period are positive. And the probability that there's an increase in the rates of severe obesity for women is 0.9874, which indicates it's almost certain that there's an increase in the severe obesity rates for women during the COVID-19 period.

Heart Diseases in Women

```
##        Period Affected Not_Affected
## 1    precovid       24         1976
## 2 duringcovid       23         1977
```

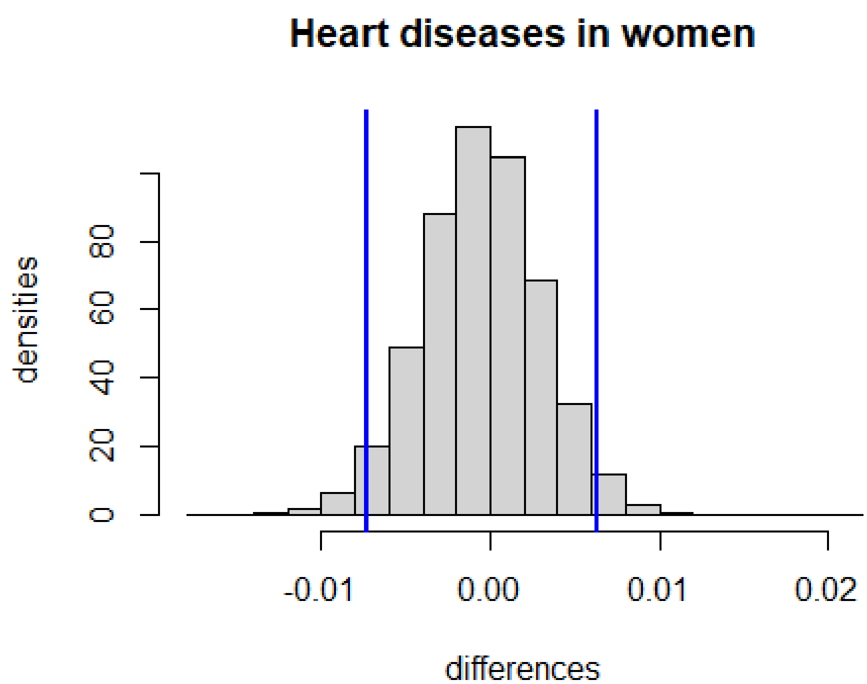


Figure 5.7

```
# Probability of positive differences of heart disease rates in women

## [1] 0.442843
```

From the figure 5.7, we observe that the majority of the differences in the sample heart disease rates for women of pre-COVID and during COVID-19 period are around zero. And the probability that there's an increase in the rates of heart disease for women is 0.4428, which indicates it's unlikely that there's an increase in the heart disease rate for women during the COVID-19 period.

Severe Hypertension in Women

```
##        Period Affected Not_Affected
## 1    precovid       11         1989
## 2 duringcovid       26         1974
```

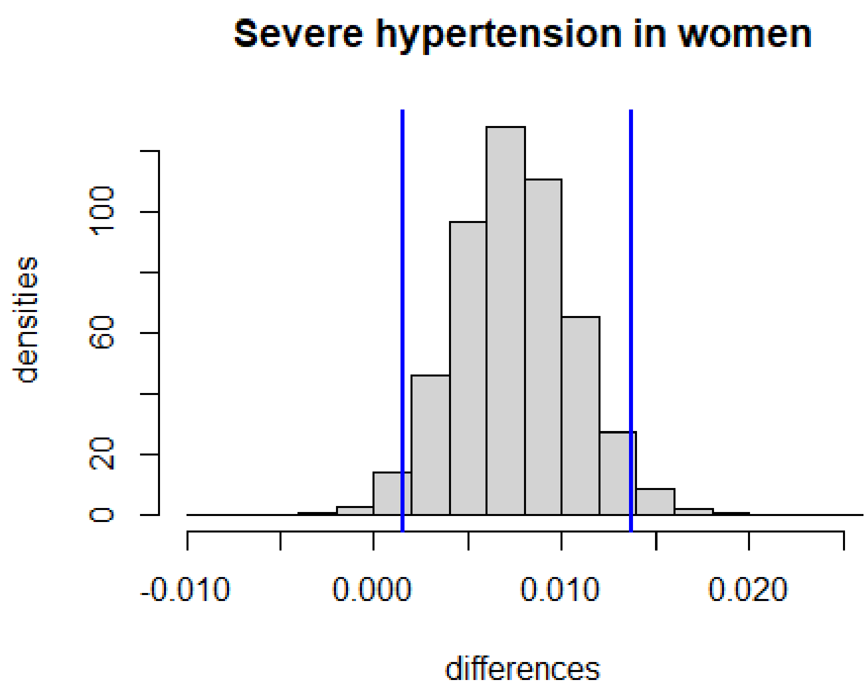


Figure 5.8

```
# Probability of positive differences of severe hypertension rates in women

## [1] 0.993249
```

From the figure 5.8, we observe that the majority of the differences in the sample severe hypertension rates for women of pre-COVID and during COVID-19 period are positive. And the probability that there's an increase in the rates of severe hypertension for women is 0.9932, which indicates it's almost certain that there's an increase in the severe hypertension rate for women during the COVID-19 period.

Asthma in Women

```
##        Period Affected Not_Affected
## 1    precovid       31         1969
## 2 duringcovid       32         1968
```

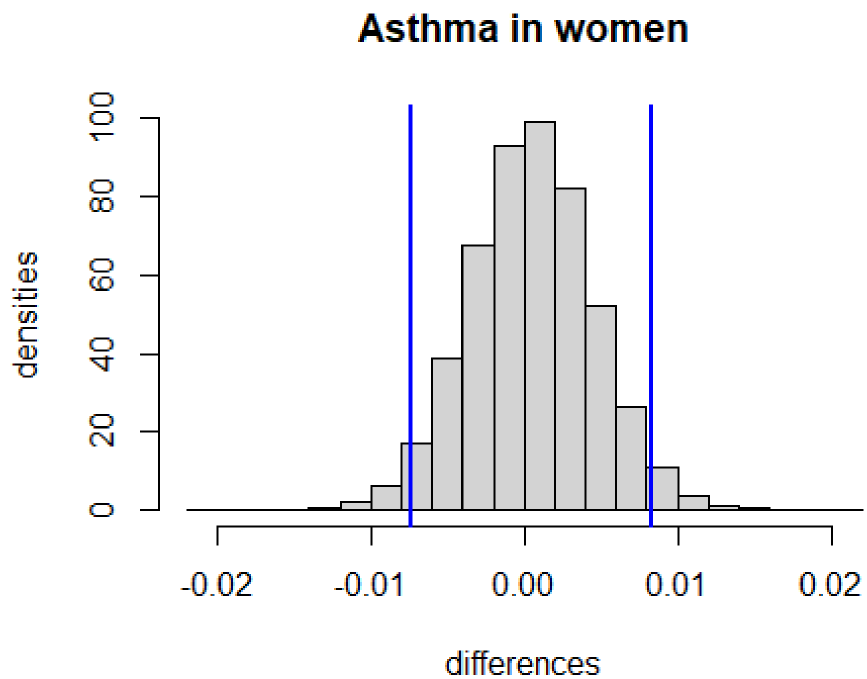


Figure 5.9

```
# Probability of positive differences of asthma rates in women

## [1] 0.550474
```

From the figure 5.9, we observe that the majority of the differences in the sample asthma rates for women of pre-COVID and during COVID-19 period are around zero. And the probability that there's an increase in the rates of asthma for women is 0.5504, which indicates it's somewhat likely that there's an increase in the asthma rate for women during the COVID-19 period.

Thyroid related disorders in Women

```
##         Period Affected Not_Affected
## 1    precovid       43         1957
## 2 duringcovid       39         1961
```

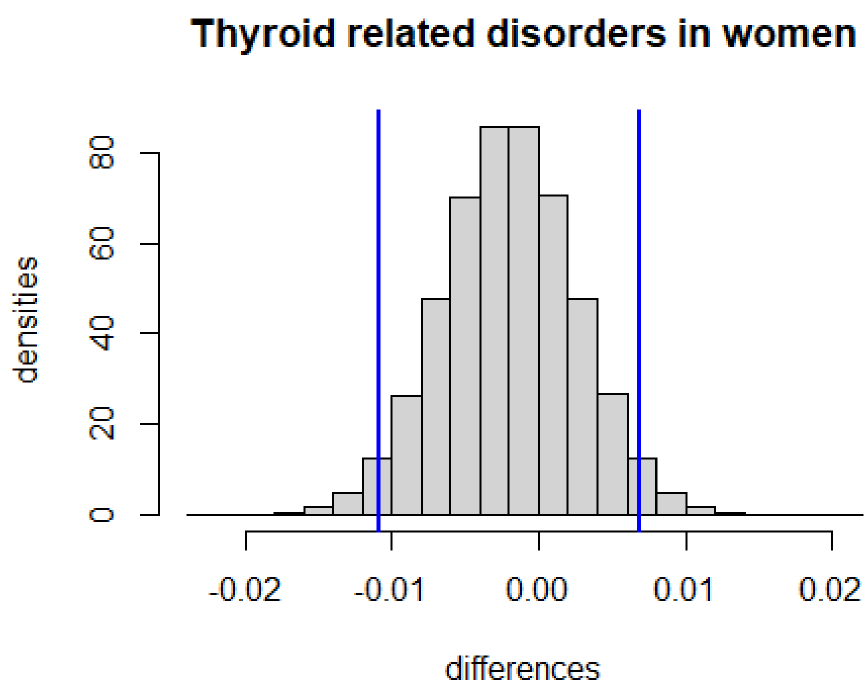


Figure 5.10

```
# Probability of positive differences of Thyroid related disorder
rates in women
## [1] 0.329227
```

From the figure 5.10, we observe that the majority of the differences in the sample thyroid related disorder rates for women of pre-COVID and during COVID-19 period are negative. And the probability that there's an increase in the rates of thyroid related disorder for women is 0.3292, which indicates it's unlikely that there's an increase in the thyroid related disorder rate for women during the COVID-19 period.

Results for women:

POPULATION UNDER STUDY	AGE UNDER STUDY	PROCEDURE OF ANALYSIS	2015-16 RATES	2019-21 PHASE II RATES	PRE-COVID DISTRIBUTION	DURING-COVID DISTRIBUTION	ESTIMATE OF THE PROBABILITY OF INCREMENT IN THE RATES OF THE DISEASE
WOMEN	15-49 years	Severe Anaemia rates of 2015-16 were compared with 2019-21 Phase-II	1.1125	1.075	$\beta(23, 1979)$	$\beta(22, 1980)$	*0.439881*
	15-49 years	Diabetes rates of 2015-16 were compared with 2019-21 Phase-II	1.5125	1.4375	$\beta(31, 1971)$	$\beta(29, 1973)$	*0.397501*
	15-49 years	Severe Obesity rates of 2015-16 were compared with 2019-21 Phase-II	5.65	7.4125	$\beta(114, 1888)$	$\beta(149, 1853)$	***0.987439***
	15-49 years	Heart Disease rates of 2015-16 were compared with 2019-21 Phase-II	1.2375	1.1875	$\beta(25, 1977)$	$\beta(24, 1978)$	*0.442843*
	15-49 years	Severe Hypertension rates of 2015-16 were compared with 2019-21 Phase-II	0.5875	1.3342	$\beta(12, 1990)$	$\beta(27, 1975)$	***0.993249***
	15-49 years	Asthma rates of 2015-16 were compared with 2019-21 Phase-II	1.575	1.625	$\beta(32, 1970)$	$\beta(33, 1969)$	*0.550474*
	15-49 years	Thyroid disorder rates of 2015-16 were compared with 2019-21 Phase-II	2.175	1.9625	$\beta(44, 1958)$	$\beta(40, 1962)$	*0.329227*

Table 5.2: Table showing results for analysis in Women

Men

Severe Anaemia in Men

```
##        Period Affected Not_Affected
## 1    precovid       19         1981
## 2 duringcovid       27         1973
```

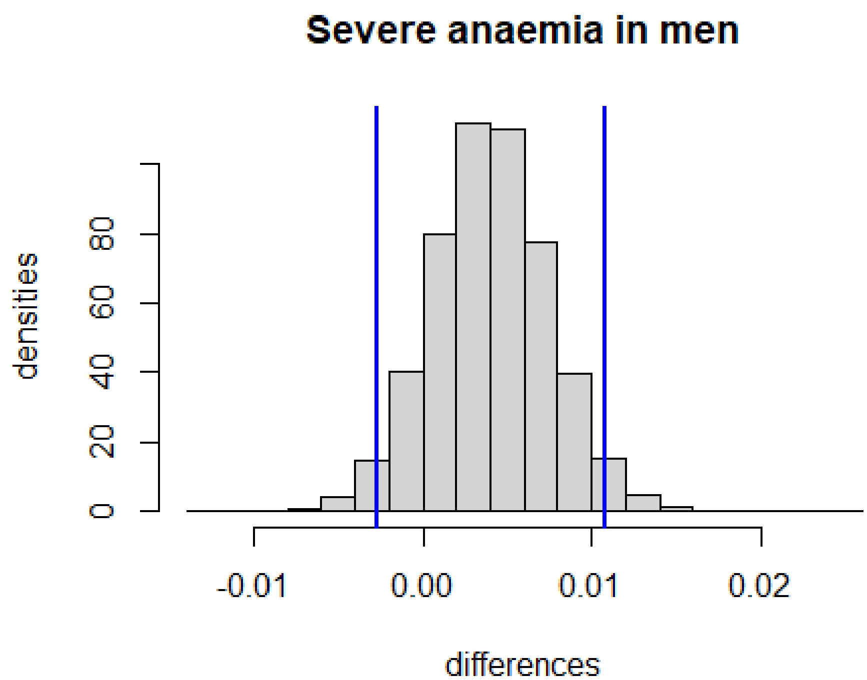


Figure 5.11

```
# Probability of positive differences of severe anaemia rates in men

## [1] 0.880353
```

From the figure 5.11, we observe that the majority of the differences in the sample severe anaemia rates for men of pre-COVID and during COVID-19 period are positive. And the probability that there's an increase in the rates of severe anaemia for men is 0.8803, which indicates it's very likely that there's an increase in the severe anaemia rate for men during the COVID-19 period.

Diabetes in men

```
##         Period Affected Not_Affected
## 1     precovid       26         1974
## 2 duringcovid       36         1964
```

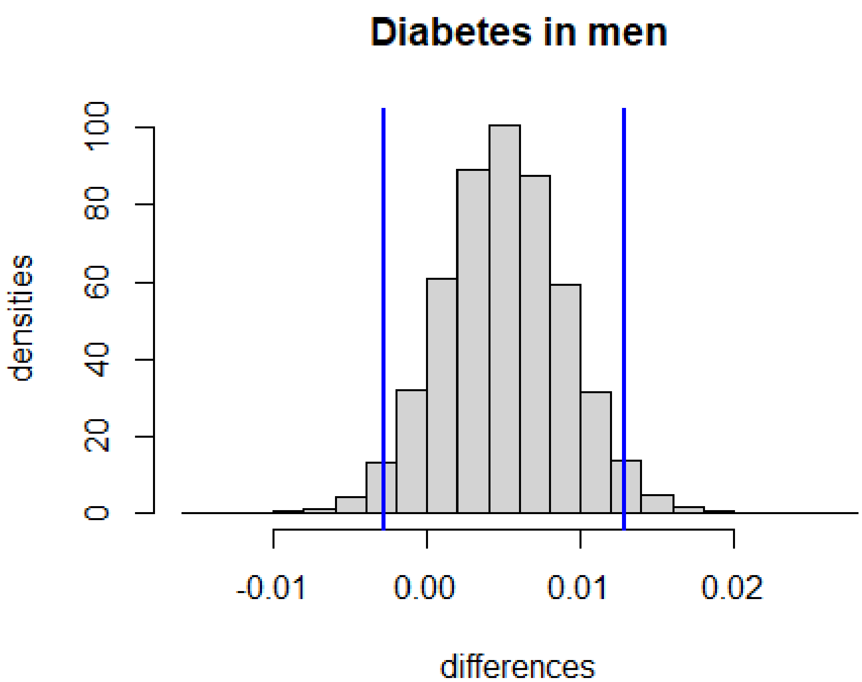


Figure 5.12

```
# Probability of positive differences of diabetes rates in men

## [1] 0.898397
```

From the figure 5.12, we observe that the majority of the differences in the sample diabetes rates for men of pre-COVID and during COVID-19 period are positive. And the probability that there's an increase in the rates of diabetes for men is 0.8983, which indicates it's very likely that there's an increase in the diabetes rate for men during the COVID-19 period.

Severe obesity in men

```
##          Period Affected Not_Affected
## 1      precovid       55         1945
## 2 duringcovid       87         1913
```

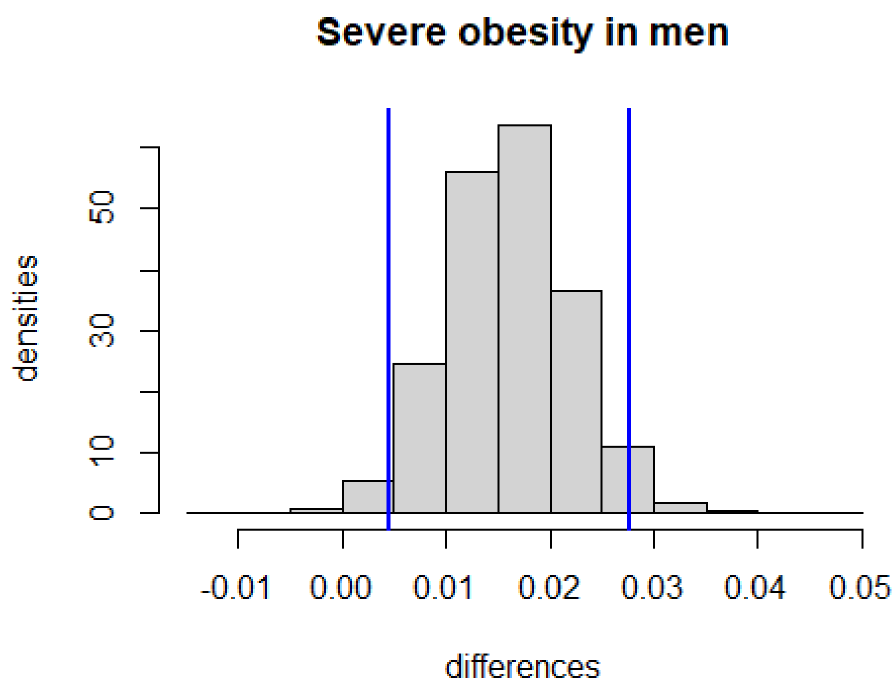


Figure 5.13

```
# Probability of positive differences of severe obesity rates in men

## [1] 0.99686
```

From the figure 5.13, we observe that the majority of the differences in the sample severe obesity rates for men of pre-COVID and during COVID-19 period are positive. And the probability that there's an increase in the rates of severe obesity for men is 0.9968, which indicates it's almost certain that there's an increase in the severe obesity rate for men during the COVID-19 period.

Heart Diseases in men

```
##        Period Affected Not_Affected
## 1    precovid       15         1985
## 2 duringcovid       13         1987
```

Figure 5.14

```
# Probability of positive differences of heart disease rates in men

## [1] 0.35507
```

From the figure 5.14, we observe that the majority of the differences in the sample heart disease rates for men of pre-COVID and during COVID-19 period are negative. And the probability that there's an increase in the rates of heart disease for men is 0.355, which indicates it's unlikely that there's an increase in the heart disease rate for men during the COVID-19 period.

Severe Hypertension in men

```
##        Period Affected Not_Affected
## 1    precovid       14         1986
## 2 duringcovid       29         1971
```

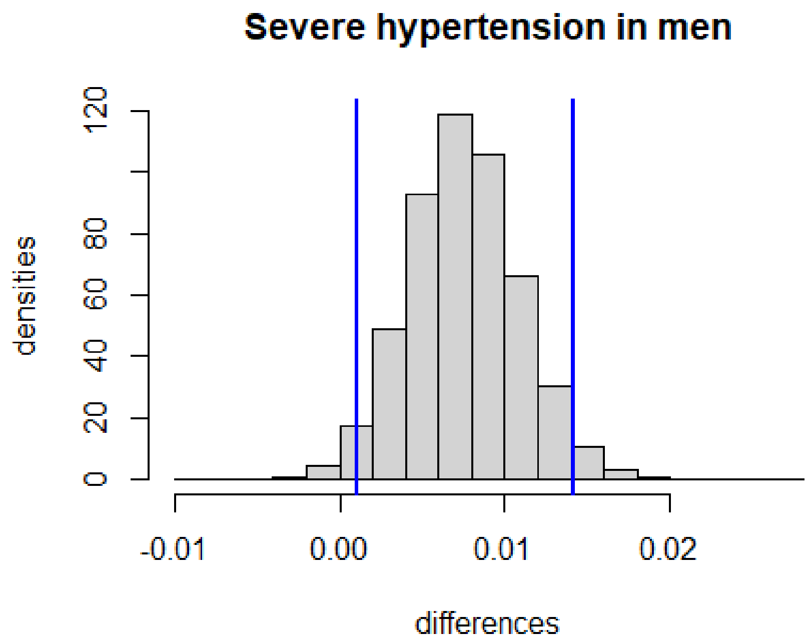


Figure 5.15

```
# Probability of positive differences of severe hypertension rates in men

## [1] 0.988894
```

From the figure 5.15, we observe that the majority of the differences in the sample severe hypertension rates for men of pre-COVID and during COVID-19 period are positive. And the probability that there's an increase in the rates of severe hypertension for men is 0.9888, which indicates it's almost certain that there's an increase in the severe hypertension rate for men during the COVID-19 period.

Results for men:

POPULATION UNDER STUDY	AGE UNDER STUDY	PROCEDURE OF ANALYSIS	2015-16 RATES	2019-21 PHASE II RATES	PRE-COVID DISTRIBUTION	DURING-COVID DISTRIBUTION	ESTIMATE OF THE PROBABILITY OF INCREMENT IN THE RATES OF THE DISEASE
MEN	15-49 years	Severe Anaemia rates of 2015-16 were compared with 2019-21 Phase-II	0.95	1.3625	$\beta(20, 1982)$	$\beta(28, 1974)$	*0.880353*
	15-49 years	Diabetes rates of 2015-16 were compared with 2019-21 Phase-II	1.3375	1.8	$\beta(27, 1975)$	$\beta(37, 1965)$	*0.898397*
	15-49 years	Severe Obesity rates of 2015-16 were compared with 2019-21 Phase-II	2.75	4.35	$\beta(56, 1946)$	$\beta(88, 1914)$	***0.99686***
	15-49 years	Heart Disease rates of 2015-16 were compared with 2019-21 Phase-II	0.7875	0.7	$\beta(16, 1986)$	$\beta(14, 1988)$	*0.35507*
	15-49 years	Severe Hypertension rates of 2015-16 were compared with 2019-21 Phase-II	0.725	1.4653	$\beta(15, 1987)$	$\beta(30, 1972)$	***0.988894***

Table 5.3: Table showing results for analysis in Men

Conclusion:

From the frequentist analysis we conclude the following:

After completing the comparison of rates for different diseases before COVID-19 and during COVID-19 for impacted states, we conclude the following:

During COVID-19, a significant increment is observed in the rates of anaemia in children, severe anaemia in men, severe hypertension, and severe obesity in adults. Similarly, a significant decrement is observed in the rates of immunity in children.

Thus, we can say that during COVID-19 there has been a negative impact on immunity and anaemia in children, severe anaemia in men, severe hypertension, and severe obesity in adults.

No significant impact is observed on the rates of diabetes, heart disease, thyroid disorders, and asthma in adults, Acute Respiratory Infections in children, and severe anaemia in women during COVID-19.

The above conclusion also points out the fact that adults are more prone to severe hypertension, severe obesity, and severe anaemia during COVID-19.

From the Bayesian analysis we conclude the following:

There is a significant probability of increase in the rates of diabetes, severe hypertension, and severe obesity for adults during COVID-19. There is a significant probability of increase in the rates of severe anaemia for men during COVID-19. For children, there is a significant probability of increase in the severe anaemia rates. Also, it's certain that there is a drop in the milk-feeding rates during the COVID-19 period.

One different conclusion of Bayesian from that of the frequentist approach from the analysis is that there is a significant probability of increase in the diabetes rates for adults. Whereas, in the frequentist approach we observed that there's no significant difference in the pre-COVID and during COVID-19 rates from Wilcoxon signed-rank test.

Acknowledgement:

We thank the Department of Statistics, Savitribai Phule Pune University.

Appendix:

The code for the computation in analysis by Bayesian approach:

Children

Severe ARI Children

```
set.seed(123)
s<-10^6
theta<-2.95/100
theta0<-2.75/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Children ARI rates",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Milk-feeding rates in Children

```
set.seed(123)
s<-10^6
theta<-67.725/100
theta0<-58.3875/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Milk feeding rates in children",
```

```
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u<0))/s
```

Severe anaemia in children

```
set.seed(123)
s<-10^6
theta<-2.0375/100
theta0<-2.65/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Severe anaemia in children",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Women

Severe Anaemia Women

```
set.seed(123)
s<-10^6
theta<-1.1125/100
theta0<-1.075/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
```

```r
hist(u, main = "severe anaemia in women",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Diabetes in Women

```r
set.seed(123)
s<-10^6
theta<-1.5125/100
theta0<-1.4375/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Diabetes in women",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Severe obesity Women

```r
set.seed(123)
s<-10^6
theta<-5.65/100
theta0<-7.4125/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Severe obesity in women",
```

```
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Heart Diseases in Women

```
set.seed(123)
s<-10^6
theta<-1.2375/100
theta0<-1.1875/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Heart diseases in women",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Severe Hypertension in Women

```
set.seed(123)
s<-10^6
theta<-0.5875/100
theta0<-1.334158855/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Severe hypertension in women",
```

```
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Asthma in Women

```
set.seed(123)
s<-10^6
theta<-1.575/100
theta0<-1.625/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Asthma in women",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Thyroid related disorders in Women

```
set.seed(123)
s<-10^6
theta<-2.175/100
theta0<-1.9625/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Thyroid related disorders in women",
```

```
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Men

Severe Anaemia in Men

```
set.seed(123)
s<-10^6
theta<-0.95/100
theta0<-1.3625/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Severe anaemia in men",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Diabetes in men

```
set.seed(123)
s<-10^6
theta<-1.3375/100
theta0<-1.8/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
```

```
hist(u, main = "Diabetes in men",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Severe obesity in men

```
set.seed(123)
s<-10^6
theta<-2.75/100
theta0<-4.35/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Severe obesity in men",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Heart Diseases in men

```
set.seed(123)
s<-10^6
theta<-0.7875/100
theta0<-0.7/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Heart diseases in men",
```

```
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

Severe Hypertension in men

```
set.seed(123)
s<-10^6
theta<-0.725/100
theta0<-1.465222135/100
n<-2000
precovidyes<-floor(n*theta);precovidno<-n-precovidyes
duringcovidyes<-floor(n*theta0);duringcovidno<-n-duringcovidyes
Period<-c("precovid","duringcovid")
Affected<-c(precovidyes,duringcovidyes)
Not_Affected<-c(precovidno,duringcovidno)
data.frame(Period,Affected,Not_Affected)

al1<-rbeta(s,precovidyes+1,precovidno+1)
al2<-rbeta(s,duringcovidyes+1,duringcovidno+1)
u<-al2-al1
q<-c(quantile(u,0.025),quantile(u,0.975))
hist(u, main = "Severe hypertension in men",
     xlab = "differences",ylab = "densities",prob = TRUE)
abline(v = q, col = "blue", lwd = 2)

length(which(u>0))/s
```

References:

[1] Pradeepa R, Mohan V. Epidemiology of type 2 diabetes in India. Indian J Ophthalmol. 2021 Nov;69(11):2932-2938. doi: 10.4103/ijo.IJO_1627_21. PMID: 34708726; PMCID: PMC8725109.

[2] Anchala R, Kannuri NK, Pant H, Khan H, Franco OH, Di Angelantonio E, Prabhakaran D. Hypertension in India: a systematic review and meta-analysis of prevalence, awareness, and control of hypertension. J Hypertens. 2014 Jun;32(6):1170-7. doi: 10.1097/HJH.0000000000000146. PMID: 24621804; PMCID: PMC4011565.

[3] Coronavirus disease (COVID-19)

[4] COVID Tracker

[5] Diabetes and Coronavirus (COVID-19). How COVID-19 Impacts People with Diabetes

[6] COVID impact: Indians are now more obese, hypertensive and prone to diabetes

[7] NFHS-5 report page-36

[8] https://en.wikipedia.org/wiki/Conjugate_prior

[9] Comparison of two proportions, Page No. 80, Jim Albert, Bayesian Computation with R, 3rd Printing 2008

[10] R version 4.2.1 (2022-06-23 ucrt) -- "Funny-Looking Kid"
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Platform: x86_64-w64-mingw32/x64 (64-bit)