Investigating the Correlation Between Unemployment Rates During COVID-19 and Healthcare Infrastructure Disparities Across Indian States

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1 Introduction

The COVID-19 pandemic has inflicted substantial economic repercussions on India, exacerbating unemployment rates across the nation. My research aims to analyse how variations in healthcare infrastructure and COVID-19 outbreaks relate to changes in unemployment rates across different states in India. This topic indeed holds significant relevance in the Indian context, as the severity of COVID-19 outbreaks varied widely across states due to differences in healthcare infrastructure. Understanding how these variations correlate with changes in unemployment rates can provide valuable insights for policymakers and governments in developing strategies to improve healthcare infrastructure and mitigate the economic impacts of future outbreaks.

India's healthcare capacity is significantly challenged in providing adequate services to its vast population.The healthcare system grapples with issues spanning five critical areas: awareness, accessibility, workforce availability, affordability, and accountability. Particularly notable are the disparities in access to healthcare facilities and the availability of medical professionals, with stark differences observed between states. On average, India has 28 public healthcare facilities, including primary health centers (PHCs), community health centers (CHCs), sub-divisional/district health hospitals (SDHs), and district hospitals (DHs), per million people. However, this figure masks the variations across the country: smaller states like Arunachal Pradesh, Himachal Pradesh, and others have over 70 such facilities per million, whereas larger states such as Uttar Pradesh, Bihar, and Jharkhand have fewer than 20 per million. These disparities in healthcare infrastructure and fiscal priorities have had significant implications during the Covid-19 pandemic and are expected to influence the economic outcomes of the states differentially including unemployment levels (Goswami et al., 2021).

The pandemic also highlighted the significant-quality discrepancies of healthcare facilities between the rural-urban areas and between public and private healthcare providers. rural healthcare in India, compared to its urban counterpart, is severely under-resourced in terms of public health facilities and workforce, leading to limited access to essential services. The challenges posed by the COVID-19 pandemic have been exacerbated in rural areas due to this underinvestment and the resulting reliance on the private sector, which is not sufficiently equipped to handle such crises (Sundararaman & Ranjan, 2020). Thus it makes it imperative for us to analyse the disparities between the urban and rural healthcare infrastructure to understand their impact on unemployment trends across different states.

Enhanced healthcare infrastructure and public health strategies are pivotal in mitigating the economic repercussions of the pandemic. Studies have indicated that states equipped with superior containment measures, more robust healthcare systems, and a higher proportion of employment in the primary sector have been relatively shielded from extensive economic downturns and rising unemployment levels (Goswami et al., 2021).

However, it is important to consider that other socioeconomic factors also play a role in influencing the level of unemployment during covid-19. For instance, the sectoral composition of each state meaning the number of people employees in each other three sectors(primary, secondary and tertiary) also need to be accounted for. India's manufacturing sector was strongly impacted by Covid-19 pandemic according to a study(Covid Strongly Impacted India's Manufacturing Sector, Study Shows," 2023). Urban areas often have a higher concentration of service-based industries such as tourism, hospitality, retail, and entertainment, which were disproportionately affected by lockdowns and social distancing measures during the pandemic. The reliance on face-to-face interactions in these sectors made them particularly vulnerable to COVID-19 restriction. Rural areas, on the other hand, tend to have a larger share of employment in agriculture, forestry, and other essential industries that were less impacted by pandemic-related restrictions. In fact, some experienced an increase in demand. For instance, the agriculture sector saw significant growth in the labor-intensive horticulture and livestock subsectors during covid (Chand, 2022).

The informal workers, making up a substantial portion of India's urban labor force, played a major role in the increase of the unemployment rate. The urban labour force in India which constitues of the informal workers significantly contributed to the rising unemployment rate. In India, the majority of migrant workers find employment in poorly paid, low-skill positions within the extensive informal sector. When COVID-19 emerged, India unexpectedly implemented a nationwide lockdown during the last week of March 2020, leading to the immediate loss of employment for many workers in the urban informal sector (Wijayaningtyas et al., 2022).

In my research, I analyze a broad set of data to dissect the dynamics of unemployment across all Indian states, making distinctions between rural and urban unemployment. I also examine different healthcare variables to specifically gauge the effectiveness of healthcare infrastructure and its disparities across states and how they impact unemployment. These variables are pivotal in estimating the state of healthcare infrastructure, directly tying into my main research question. Moreover, I investigate external socioeconomic influences, such as sectoral composition, by analyzing data on the concentration of service industry units within each state. This exploration is aimed at understanding how these factors might impact unemployment rates. Through this comprehensive dataset analysis, I seek to answer my broader research question about the influence of healthcare infrastructure and socio-economic variables on unemployment trends within India, narrating my findings from a first-person perspective.

My research significantly enhances the existing literature by offering a nuanced analysis of the relationship between healthcare infrastructure and unemployment within the diverse socioeconomic landscape of India during the COVID-19 pandemic. Prior studies have often considered healthcare infrastructure and economic outcomes in isolation or within limited regional scopes. In contrast, our comprehensive approach integrates a broad array of healthcare metrics, such as hospital beds and doctor availability per capita, with socioeconomic factors including sectoral GDP contributions and the unique dynamics of the informal labor market. This allows for a deeper understanding of how these variables interact across both urban and rural contexts, revealing complex patterns that previous studies may not have fully captured.

This paper not only extends the academic discourse on the economic impacts of healthcare infrastructure during pandemics but also provides empirical evidence to support targeted policy interventions. By dissecting the interplay between healthcare capacity and economic sector vulnerabilities, it offers policymakers data-driven insights to tailor strategies that bolster economic resilience and healthcare readiness in anticipation of future crises.

The following sections of this paper will delve deeper into the methodologies employed, the data analysis techniques used, and the specific findings from our study. Each aspect will be discussed in detail to elucidate how variations in healthcare infrastructure and economic conditions across Indian states have shaped their respective unemployment outcomes during the pandemic. This detailed exploration aims to provide a foundational understanding that supports robust policy formulation and implementation strategies tailored to the diverse Indian economic and healthcare landscapes.

2 Data

Unemployment Data The primary dataset for our research is sourced from the Centre for Monitoring Indian Economy (CMIE) and is accessible via `https://unemploymentinindia.cmie.com/`. This dataset provides a comprehensive view of unemployment rates across all Indian states from 2019 to 2020. It includes monthly data points for each state, segmented into rural and urban areas, thus enabling a detailed analysis of regional employment trends. Additionally, the dataset encompasses metrics such as the labor force participation rate and estimated number of employees, which are pivotal for evaluating the employment landscape across different geographies within the country.

Healthcare Variables To assess the impact of healthcare infrastructure on unemployment trends, we analyze a suite of healthcare-related data. State-wise daily COVID-19 case counts and recovery figures are sourced from the Indian Census data available on official government platforms. These daily observations are aggregated into monthly metrics for each state, allowing us to compute recovery rates, a critical indicator of the effectiveness of healthcare systems in managing the pandemic.

Additionally, data concerning the total number of hospital beds per state are obtained from the Ministry of AYUSH. This dataset not only provides a count of hospital beds but also distinguishes between public and private facilities and between urban and rural allocations. By leveraging population census data, we calculate the number of hospital beds per 1,000 people, providing a quantifiable measure of healthcare capacity in each state. State-wise public expenditure on healthcare for the fiscal year 2019-2020, gathered from the Reserve Bank of India Handbook, offers insights into budget allocations towards healthcare infrastructure. This expenditure data enriches our analysis by highlighting regional disparities in healthcare access and quality. Furthermore, the number of doctors per 1,000 population, also sourced from the Ministry of AYUSH, adds another dimension to our understanding of healthcare capacity. This metric, combined with hospital bed data, forms a robust framework for assessing the overall effectiveness of healthcare infrastructure across states.

Social Composition Data Our analysis is further complemented by data on the GDP contribution of each major economic sector (agriculture, manufacturing, and services) for each state for the years 2019-2020. This data, retrieved from the Reserve Bank of India's handbook of statistics on Indian states, documents the net contribution of each sector at constant prices for each state in 2019-2020. Understanding the sectoral economic structure is vital, as it allows us to discern how the economic composition influences unemployment dynamics, particularly in the context of the COVID-19 pandemic's impact on different sectors.

Together, these datasets provide a comprehensive empirical foundation for our investigation into the multifaceted relationship between healthcare infrastructure, economic sectors, and unemployment rates across Indian states during the COVID-19 pandemic. This rich data environment supports a nuanced analysis of the factors contributing to regional employment outcomes in a period marked by significant global disruption.

3 Summary Statistics and Visualization

Unemployment Dynamics This table summarises the overall data set. It gives us the mean, meadian, upper and lower quartiles for each of the variable. The standard deviation tells us how much these results vary from the true mean. Lastly, the maximum and minimum enables us to obtain the range of data for each variable. It gives an overview of the overall unemployment dynamic during the pandemic.

From the summary table, we can observe that the mean unemployment rate during this period is about 11.8%. This is significantly higher than the pre-pandemic average of around 5.3% (Forbes India, 2023). However, the average labour force participation still remained high during this period and did not experience a significant dip. On the contrary, it rose from a labour force participation rate of about 37% which is India's lowest recorded year. Despite that, the labour force participation is quite low compared to global average which range around 60% (Forbes India, 2023).
The standard deviation is quite high at around 10.72, indicating a large dispersion in unemployment rates among the observations. The range from 0% to 76.74% further highlights the vast differences in unemployment rates within the dataset, showing that some regions or periods had extremely low unemployment while others faced exceptionally high rates.

	Estimated Unemployment Rate (%)	Estimated Employed	Estimated Labour Participation Rate (%)
count	740.000000	7.400000e+02	740.000000
mean	11.787946	7.204460e+06	42.630122
std	10.721298	8.087988e+06	8.111094
min	0.000000	4.942000e+04	13.330000
25%	4.657500	1.190404e+06	38.062500
50%	8.350000	4.744178e+06	41.160000
75%	15.887500	1.127549e+07	45.505000
max	76.740000	4.577751e+07	72.570000

Figure 1: Employment Parameters

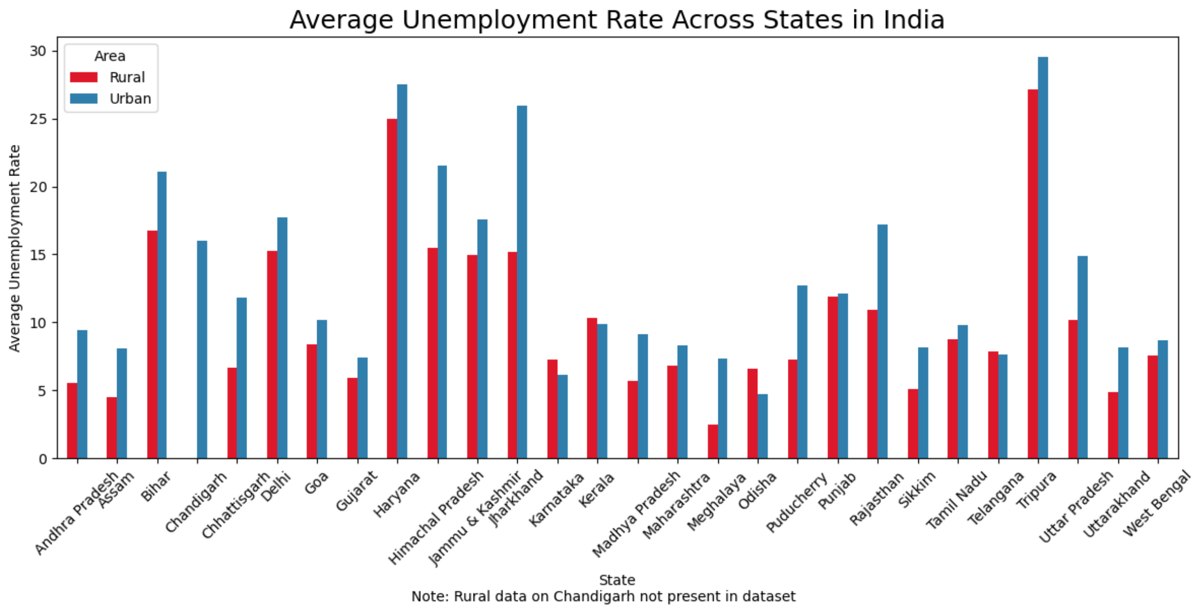
This table enables a comparative analysis of the summary statistics for the estimated unemployment rate in rural and urban regions, presenting aggregated results based on respective groupings. The analysis reveals that, on average, urban areas exhibit a higher overall unemployment rate compared to rural areas, as evidenced by the summary statistics. This comparison highlights distinct patterns in unemployment dynamics between rural and urban regions, offering valuable insights into labor market disparities and potential socio-economic implications.
This may be explained by the difference between urban and rural sectoral composition of employment. Urban areas often have a higher concentration of service-based industries such as tourism, hospitality, retail, and entertainment, which were disproportionately affected by lockdowns and social distancing measures during the pandemic. The reliance on face-to-face interactions in these sectors made them particularly vulnerable to COVID-19 restriction. Rural areas, on the other hand, tend to have a larger share of employment in agriculture, forestry, and other essential industries that were less impacted by pandemic-related restrictions. In fact, some experienced an increase in demand. For instance, the agri-

culture sector saw significant growth in the labor-intensive horticulture and livestock subsectors during covid (Chand, 2022).

	Area	Mean	Median	Q1	Q3	Std	Max	Min
0	Rural	10.324791	6.76	3.79	13.755	10.038895	74.51	0.0
1	Urban	13.166614	9.97	5.82	18.040	11.165444	76.74	0.0

Figure 2: Estimated Unemployment

The barplot illustrating the share of the overall average unemployment rate between rural and urban regions for each state is crucial in the overall research context as it provides insights into the rural-urban disparities in unemployment rates across Indian states. The observed trend highlights that urban unemployment rates are generally higher in most states except for Karnataka, Kerala, Telangana, and Odisha. While urban areas generally tend to have more access to helathcare, they also tend to have higher population density leading to more severe COVID outbreaks. This prompts further investigation to see if these urban areas experience higher numbers of COVID cases and whether their healthcare infratructure was capable enough to deal with the outbreak. This would inform us if the unemployment rate has any correlation with healthcare infrastructure.

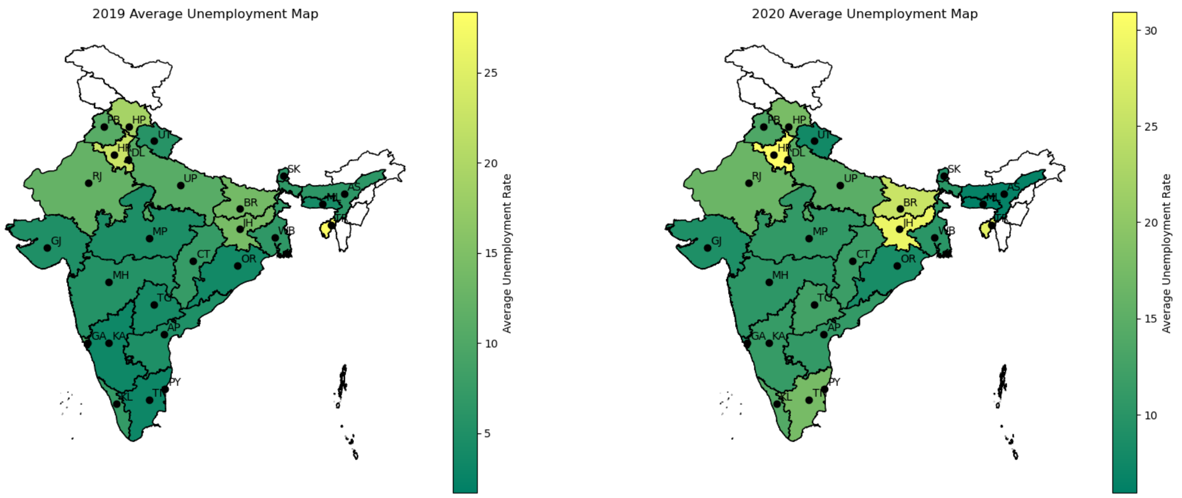


The maps presented illustrate the average unemployment rates across Indian states for the years 2019 and 2020. Each state is color-coded to represent its unemployment rate, with the color gradient ranging from blue (lower unemployment) to red (higher unemployment).

From the 2019 to the 2020 map, there is a noticeable shift towards warmer colors in several states, indicating an increase in unemployment rates. This change is particularly stark in states like Bihar, Jharkhand and Haryana, where the color deepens significantly, suggesting a sharp rise in unemployment. The maps visually capture the economic impact of the COVID-19 pandemic, as the increase in unemployment rates corresponds with the timeline of the health crisis.

Notably, the southern states like Tamil Nadu and Karnataka, which are generally known for their robust economies, also display a shift towards higher unemployment rates, pointing towards the widespread impact of the pandemic irrespective of the pre-existing economic strength of the states.

These maps serve as a stark visual representation of the economic disruption caused by the COVID-19 pandemic, with the color shifts highlighting the states that faced particularly significant challenges in maintaining employment levels during this period.



Healthcare The summary statistics show that the mean recover rate across India in 2020 was approximately 0.7% with a standard deviation of 0.4% which is quite high.The maximum value shows that the range is very wide and the thus there is a large dispersion in the data.

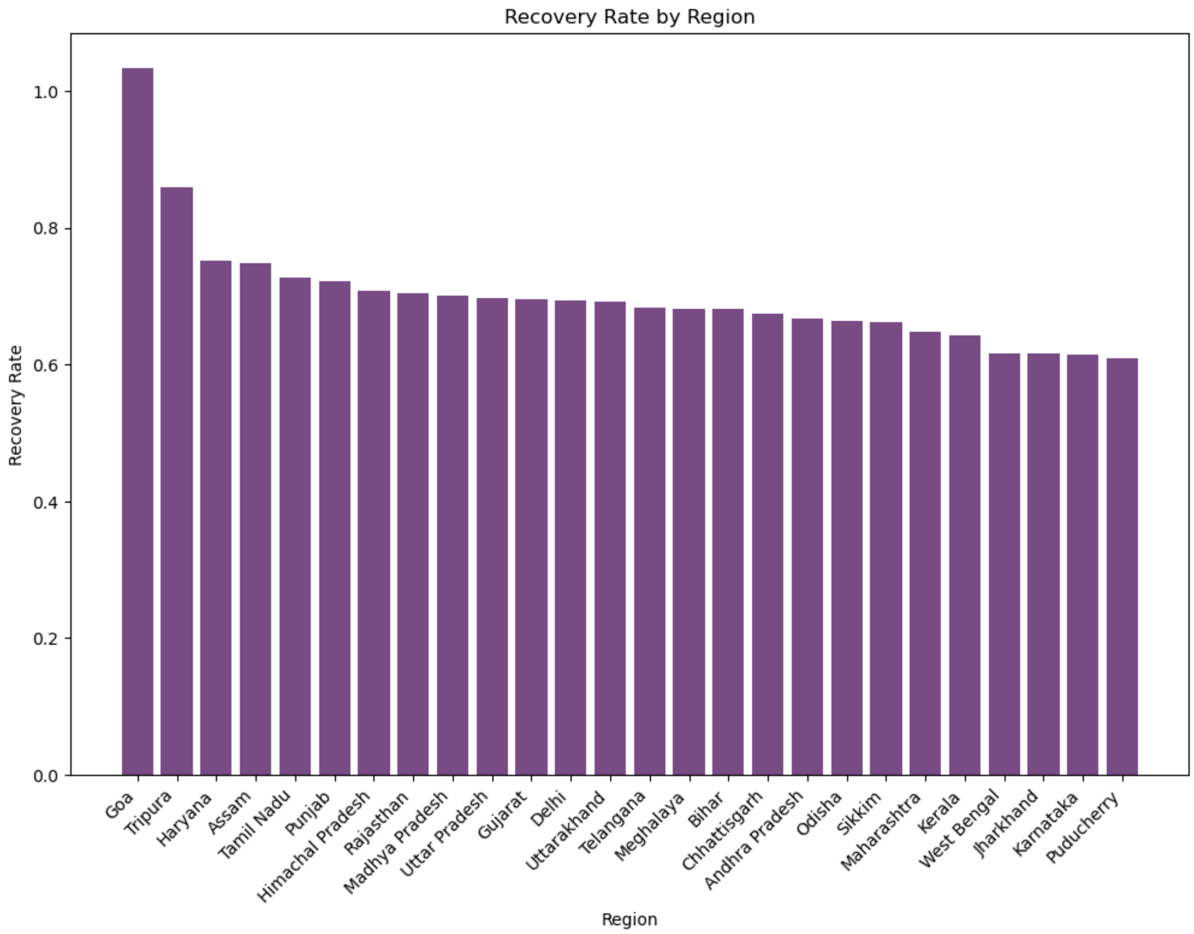
	Recovery Rate
count	220.000000
mean	0.696562
std	0.424663
min	0.000000
25%	0.427624
50%	0.732516
75%	0.927670
max	3.500000

Figure 3: Recovery Rate

The bar chart shows the recovery rate across the different states. The COVID-19 recovery rate refers to the proportion of individuals who have recovered from the virus out of the total number of confirmed cases. It is calculated using the formula by diving the total number of people recovered by the total number of confirmed cases and we express it as a percentage.

A good COVID-19 recovery rate signifies several positive aspects of a healthcare system and its pandemic response. It suggests adequate medical facilities and resources, accessible and high-quality healthcare, effective public health measures, a robust healthcare workforce, high public compliance with health guidelines, swift adaptation to new medical knowledge, and potentially high vaccination rates. Essentially, a high recovery rate reflects not just the strength of the physical healthcare infrastructure but also the effectiveness of public health strategies, professional healthcare response, and community engagement in mitigating the virus's impact.

We observe that Tripura and Goa have the highest recovery rate which may explain its very small change in unemployment rate as it is indicative of a good healthcare infrastructure. Jharkhand, Puducherry and Karnataka experienced a steep rise in unemployment and the relatively lower recovery rate may explain the trend as COVID had a more damaging effect on the health and well being of workers preventing them from being part of the workforce.



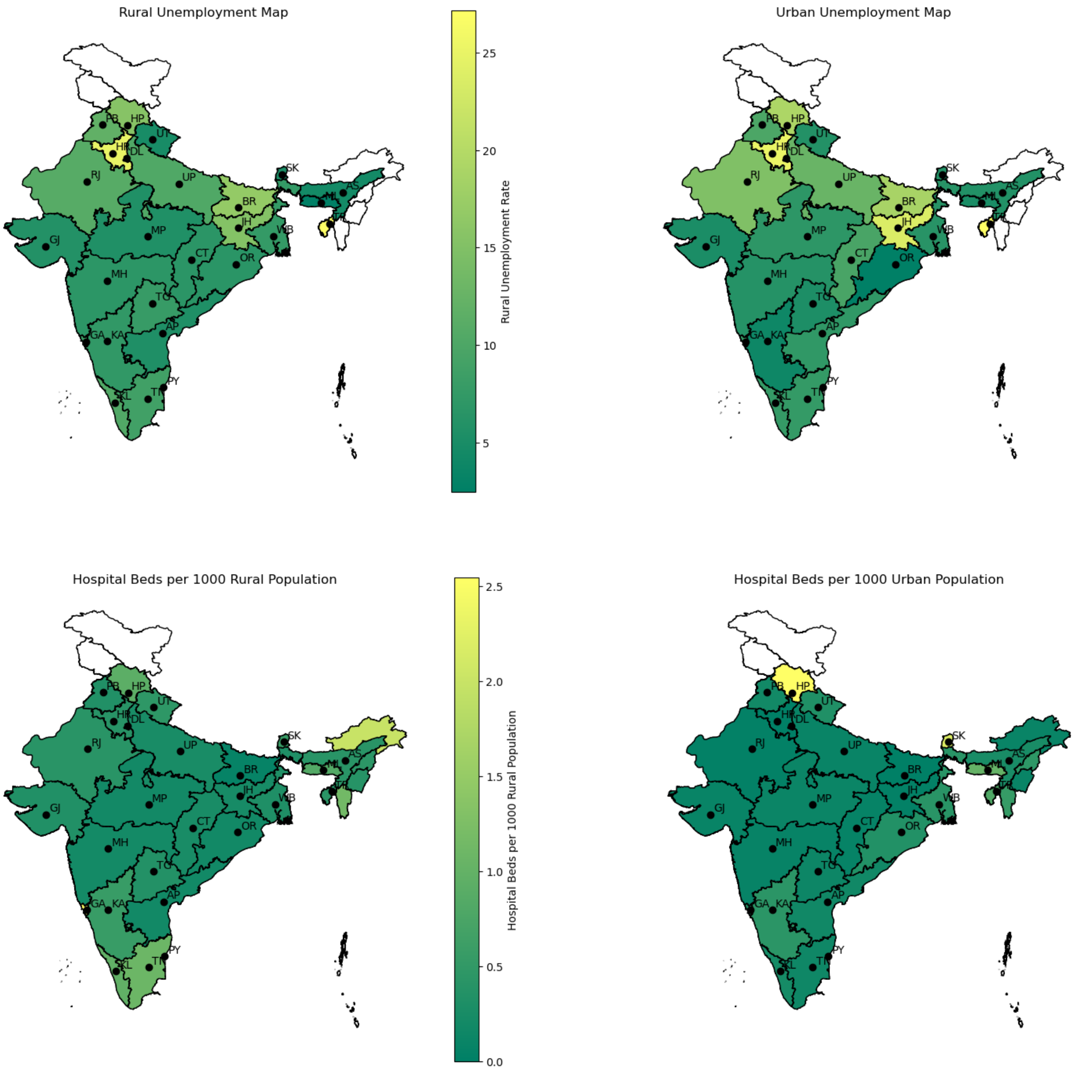
The summary statistics very clearly depict the disparity in the urban and rural healthcare infrastructure with the mean urban hospital beds per 1000 being significantly higher than the rural mean. However, the standard deviation is larger for urban beds showing greater variability.
A large standard deviation in urban hospital beds per 1,000 people within a dataset indicates significant disparities in healthcare infrastructure across different urban areas. This variability suggests that while some urban regions may have adequate or even surplus healthcare resources, others could be experiencing severe shortages, leading to uneven access to medical care for urban populations. In essence, it highlights the inequality in healthcare provision within urban settings, affecting the overall effectiveness of healthcare delivery and potentially exacerbating health disparities among urban populations.

	Urban Hospital Beds per 1000	Rural Hospital Beds per 1000
count	31.000000	31.000000
mean	1.992921	0.539255
std	2.150911	0.551878
min	0.506070	0.000000
25%	0.817658	0.238390
50%	1.167564	0.384287
75%	2.051604	0.565678
max	9.777786	2.547995

Figure 4: Hospital Beds per 1000

Overall, the healthcare infrastructure may be slightly better in the urban areas comapred to the rural areas for most states as shown by the darker hue of colours on the urban map for beds per 1000. This is because the healthcare infrastructure tends to be more developed in urban areas compared to rural areas. On the other hand, unemployment rate show the opposite trend. For most states urban areas tend to have slightly higher unemployment rate compared to rural areas. Although economic intuition suggests that states with better healthcare infrastructure, particularly in urban areas where the pandemic's impact on employment was severe, could mitigate some of the negative economic effects. This could be due to the ability of these states to manage health crises more efficiently, leading to shorter durations of lockdowns, quicker medical responses to COVID-19 cases, and a faster return of the workforce to the job market. Some southern states like Tamil Nadu, Kerala, Karnataka and other states like Odisha reinforce this intuition as they have lower urban unemployment. However, the other states underscore the importance of other socioeconomic factors lie sectoral composition while determining the impact on unemployment levels. Urban areas, often reliant on industrial and service sectors, may have been more vulnerable to the economic disruptions caused by COVID-19, such as lockdowns and the reduction in demand for services.

Overall, the economic rationale points to healthcare infrastructure as a critical factor in determining a state's resilience to economic shocks like a pandemic. However, it is also evident that healthcare is just one of many factors, including economic diversification, sectoral employment distribution, and regional economic policies, that influence unemployment rates during a crisis.



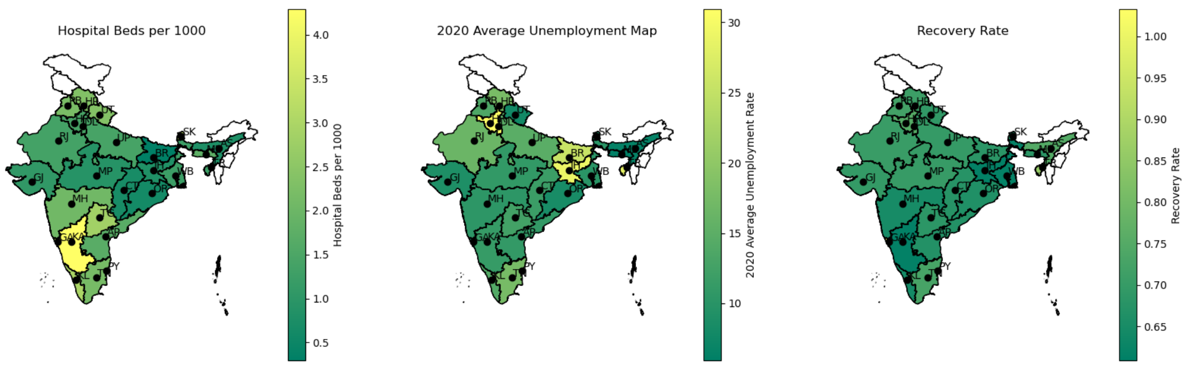
The maps provided compare three distinct yet interrelated metrics across Indian states: hospital beds per 1,000 people, average unemployment rate in 2020, and the COVID-19 recovery rate. The hospital beds per 1,000 people map indicates the healthcare infrastructure's capacity, while the recovery rate reflects the effectiveness of the healthcare system in managing the pandemic. Both are crucial in understanding the economic outcomes, such as the unemployment rate during the pandemic.

Upon examining the first map displaying hospital beds per 1,000 people, we can infer that states with a higher number of hospital beds, such as Kerala and Kernataka, have more robust healthcare infrastructures. These are typically states that have invested in health services over time, leading to better preparedness for healthcare crises.

Moving to the recovery rate map, there seems to be a correlation where states with worse healthcare infrastructure, signified by less hospital beds per 1,000 people, also have relatively lower recovery rates. This could be due to less accessible healthcare services and the lack of adequate treatment, leading to slower recovery of patients. For example, states like Bihar and Jharkhand with smaller number of beds per 1000 also have a very low recovery rate and consequently higher unemployment rate during COVID. However for Karnataka, we see a very low recovery rate despite having a very good healthcare infrastructure. This may be due to the huge spike in cases that may have overwhelmed the healthcare system. The average unemployment map for 2020, when juxtaposed with the other two maps, suggests that states with higher recovery rates, and presumably better healthcare infrastructure, may have been able to mitigate the worst of the economic impact caused by the pandemic. This could be because a higher recovery rate implies a shorter duration of illness and quicker return to work, which helps maintain economic stability and workforce productivity.

However, the relationship is not perfectly linear, as seen in the deviations noted. Some states with robust healthcare infrastructure faced significant unemployment rates. This could be due to the nature of their economies. For example, states with economies heavily reliant on sectors like tourism, hospitality, and services, which were disproportionately affected by lockdowns and social distancing measures, might still experience higher unemployment despite having strong healthcare systems.

The overall research question probes into how disparities in healthcare infrastructure impact unemployment rates across states during the COVID-19 pandemic. These maps collectively suggest that while a strong healthcare infrastructure, as indicated by a higher number of hospital beds, generally leads to better health outcomes and could contribute to lower unemployment through quicker recovery rates, the actual impact on unemployment is also contingent upon the economic structure of the state and the sectoral composition of employment. Economic intuition suggests that healthcare is one piece of the puzzle, providing a cushion against health crises, but the broader economic context also determines the pandemic's employment impact.

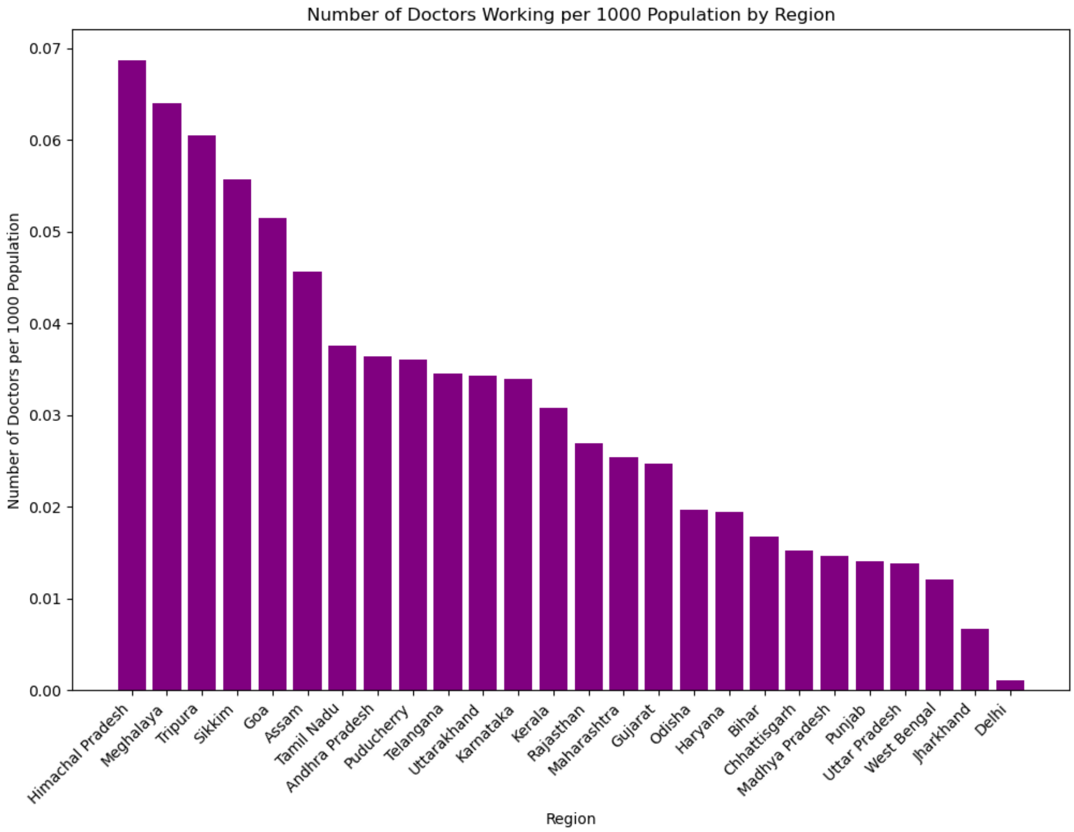


The summary statistics for healthcare expenditure and the ratio of doctors per population exhibit a high standard deviation, indicating a large dispersion. This variability suggests that there's considerable heterogeneity in the healthcare infrastructure across different states, which could reduce the reliability of our assessments regarding the relationship between healthcare infrastructure and unemployment rates.

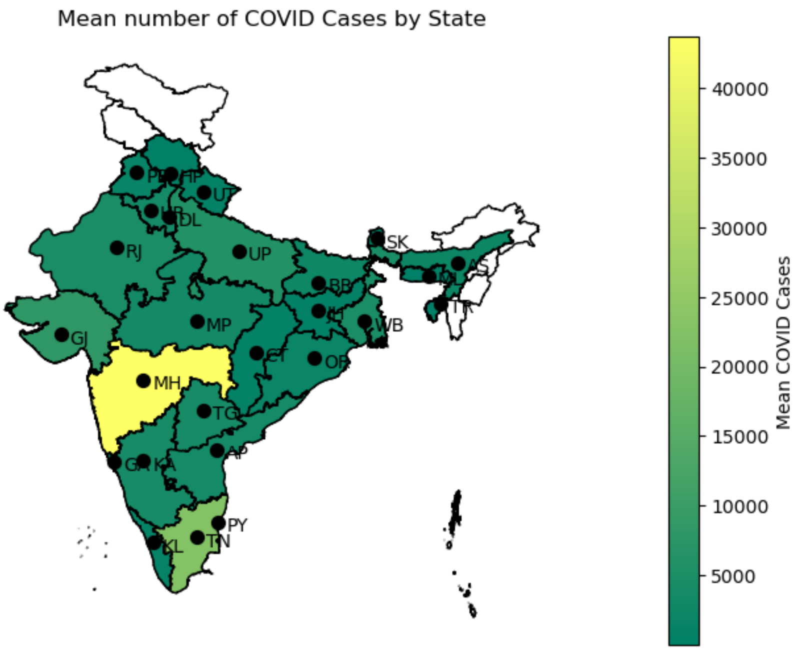
	Healthcare Expenditure	Doctors Working
count	26.000000	26.000000
mean	6737.503846	1031.230769
std	4954.420146	899.058010
min	427.100000	18.000000
25%	2633.625000	253.000000
50%	6111.700000	927.500000
75%	9623.050000	1681.250000
max	20250.200000	2848.000000

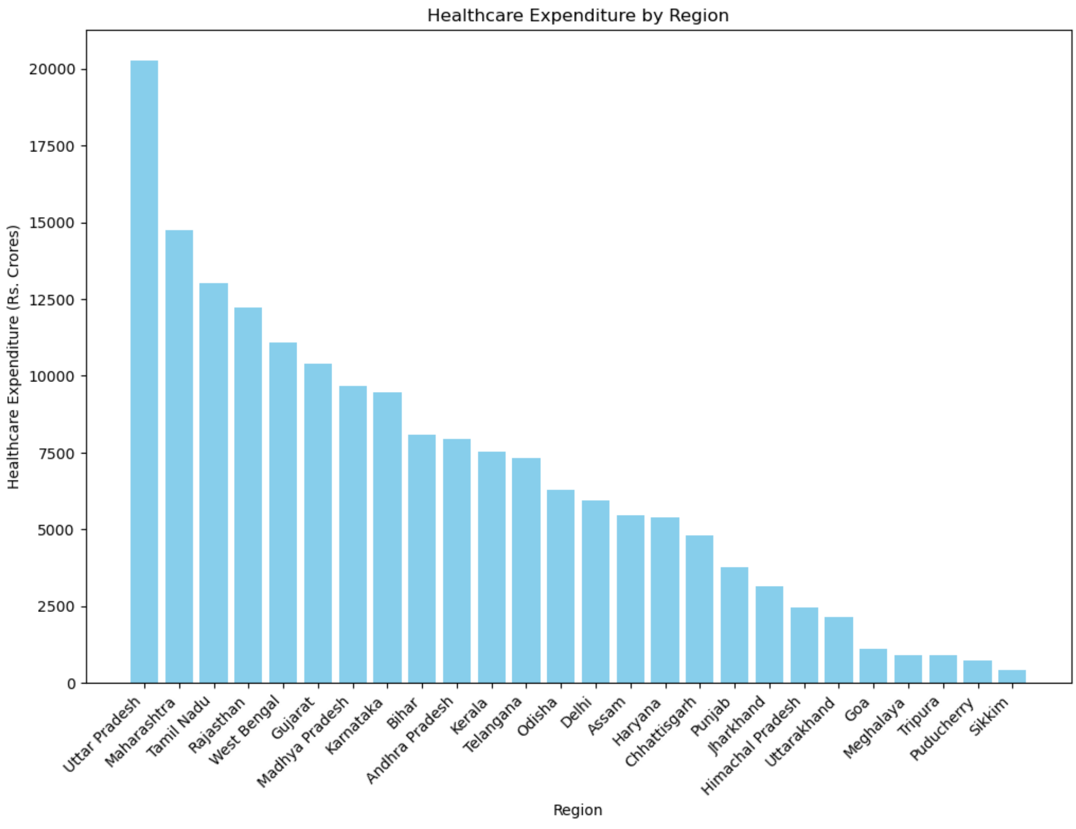
Figure 5: Healthcare Expenditure & No. of Doctors

The disparity in the number of working doctors per 1000 of the population across states like Himachal Pradesh and Tripura versus Jharkhand and West Bengal highlights the variation in healthcare infrastructure. This variation may partly explain the differences in unemployment levels during COVID-19, with states having better healthcare infrastructure, such as Himachal Pradesh, potentially experiencing lower unemployment rates while Jharkand was one of teh most impacted due to the pandemic. This suggests an economic intuition that robust healthcare systems can contribute to economic resilience during health crises.



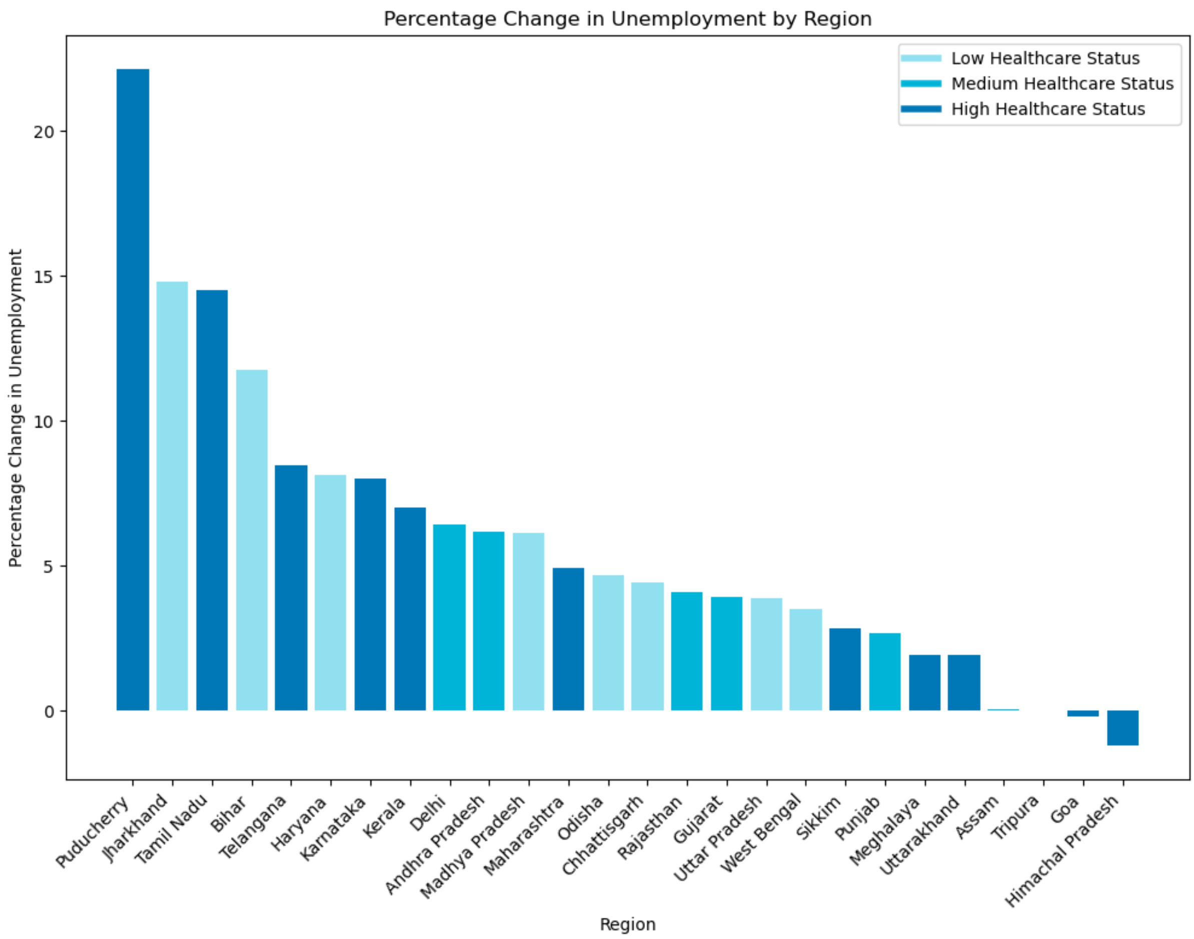
The observation that Maharashtra, despite its high healthcare expenditure, experienced the highest number of COVID-19 cases, underscores potential inefficiencies in fund management and allocation within the healthcare sector. This scenario suggests a mismanagement of resources allocated for critical needs such as testing and PPE kits, highlighting systemic inadequacies and potential corruption. Conversely, states like Uttarakhand and Goa, with lesser healthcare budgets, managed COVID-19 more effectively, illustrating that efficient allocation and management of funds are crucial. These insights are vital for policymakers to understand the importance of not just the quantity but the quality of budget allocation towards healthcare, which directly ties into broader issues of healthcare disparities and their impact on unemployment rates. This is important in our assessmenet to understand how we can optimize helath-care infrastructure with the given budget that will help to create more resilient economies and workforce.





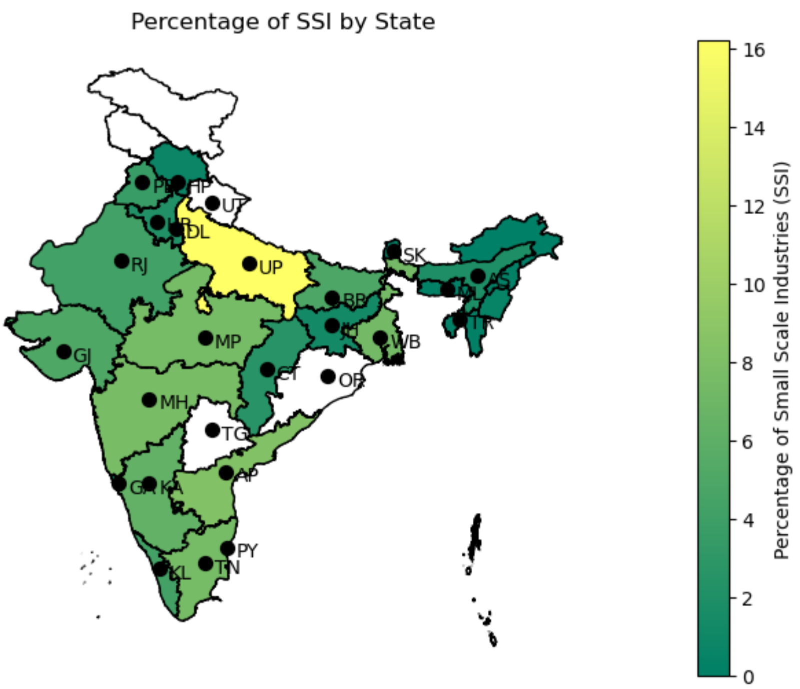
By integrating the number of working doctors per 1000 population as a control variable alongside hospital beds per 1000, we have refined our method of classifying healthcare system quality. This dual-variable approach enhances the reliability and accuracy of our healthcare quality assessments, categorizing states into high, medium, or low healthcare status based on these combined metrics. The classification system for healthcare quality combines hospital beds and doctors per 1000 population metrics. States are categorized as high, medium, or low based on these factors. A high status requires high metrics in both categories, while a low status reflects low metrics in both. States with mixed ratings (high in one, medium or low in the other) receive a composite rating that balances these factors, ensuring a nuanced assessment of healthcare infrastructure.

Observations reveal that states with low healthcare infrastructure, like Jharkhand and Bihar, saw significant increases in unemployment during COVID-19, contrasting with states like Himachal Pradesh, Goa, and Tripura, which were less impacted, likely due to their robust healthcare infrastructure. Interestingly, southern states such as Tamil Nadu, Telangana, and Karnataka, despite strong healthcare systems, experienced high unemployment impacts, attributable to their sectoral composition, with heavy reliance on the severely hit service and manufacturing industries. In the earlier parts we examined how Tamil Nadu has a very large concetration of the service sector which is a client facing industry and as discussed above was severly impacted by covid-19 imposed social distancing and lockdown restrictions.

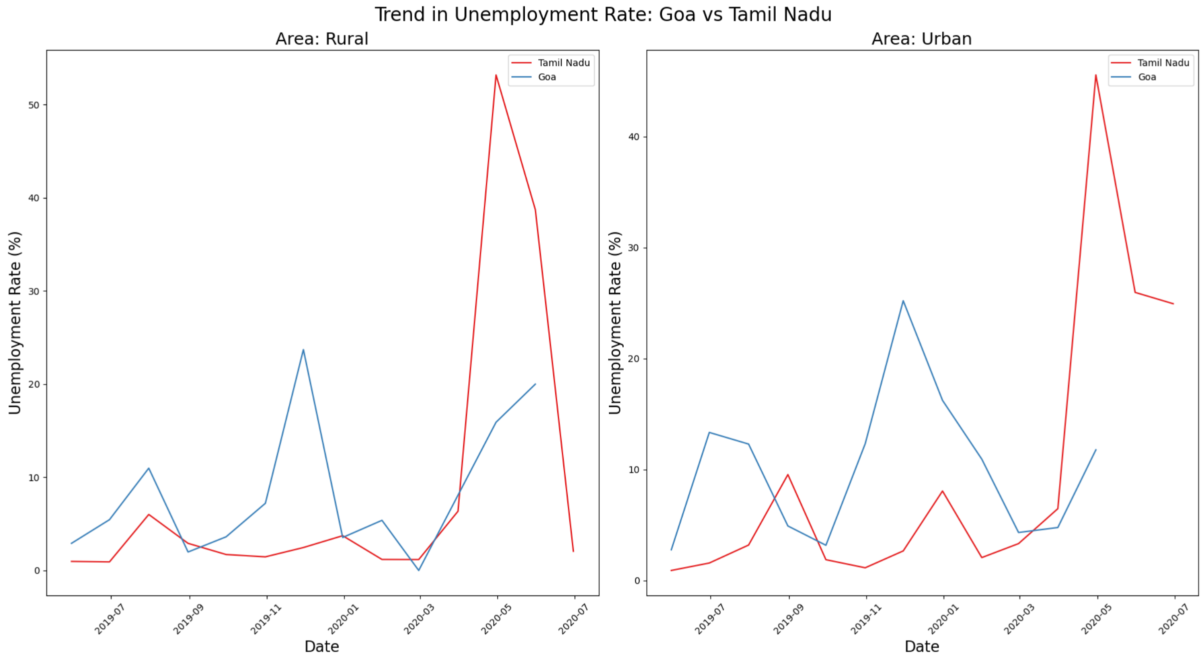


Sector Composition The provided map illustrates the prevalence of the small-scale service industry across the various states of India. We also use a bar plot along with it to clearly identify the states with highest concentration of service sector and thus the bar plot aids us in undersatnding and reading the map more clearly.It becomes apparent that regions in the north such as Uttar Pradesh, as well as southern territories including Tamil Nadu and Andhra Pradesh, not to mention Maharashtra and Madhya Pradesh in other parts of the country, exhibit a significant presence of the service industry. These states are notably dependent on the service sector, which has exposed their economies to the brunt of the COVID-19 pandemic. The compulsory lockdowns and social distancing protocols have severely disrupted service operations, culminating in extensive job losses.

By juxtaposing this map with one that portrays unemployment rates, we could potentially discern a correlation between a state's industrial composition and its employment patterns. Such an analysis would be instrumental in understanding how sectoral dynamics influence economic resilience in the face of global health crises and to overall determine factors other than helathcare that can affect the unemployment levels during covid. Overall this may explain why states like Tamil Nadu which has a robust healthcare system experienced a steep rise in unemployment levels during the pandemic.



In our comparative analysis of Goa and Tamil Nadu, despite both having strong healthcare systems, Tamil Nadu, with its higher concentration in the service sector, experienced a sharper rise in unemployment during the pandemic across both rural and urban areas. This disparity can be attributed to Tamil Nadu's economy being more heavily reliant on service-oriented industries, which were more directly impacted by lockdowns and social distancing measures. In contrast, Goa's less prominent service sector meant its employment levels were not as severely affected, highlighting how sectoral composition influences economic resilience in crisis situations and undersores the importance of considering other factors other than healthcare to assess the impact of pandemic on unemployment levels.



4 Results

OLS Regression

Table 1: Healthcare and Sectoral Variables

For the first table of our analysis, conducting a two-way fixed effects analysis offers a robust framework for investigating the relationship between various healthcare variables and the unemployment rate. This approach allows for the examination of how different aspects of healthcare infrastructure—such as COVID-19 recovery rates, healthcare expenditure, availability of doctors, and hospital bed capacity—impact unemployment, while also assessing the statistical significance of these effects.

Time Fixed Effects: These control for unobserved variables that change over time but are constant across regions. This includes macroeconomic trends, nationwide policies, or seasonal effects that might influence unemployment rates independently of the healthcare variables under study. This is shown by the alpha parameter.

Region Fixed Effects: These account for unobserved characteristics specific to each region that do not change over time. This could encompass factors like the inherent economic structure of a region, cultural aspects affecting labor market participation, or long-standing differences in healthcare infrastructure quality. This is shown by the gamma parameter.

Model 1

$$\text{Unemp\_Rate}_{it} = \beta_0 + \beta_2(\text{Recovery\_Rate}_{it}) + \epsilon_{it}$$

This is the baseline model where we are measuring the effect of recovery rate against unemployment rate. This is to see the relationship between the X and Y variables. We have not controlled for time or region effects.

Model 2

$$\text{Unemp\_Rate}_{it} = \beta_0+\beta_1(\text{Cases\_1000}_{it})+\beta_2(\text{Recovery\_Rate}_{it})+\beta_3(\text{Health\_Exp}_{it})+\beta_4(\text{Doctors\_1000}_{it})+\epsilon_{it}$$

For this we carry out a multivariable regression without fixed effects to see how they impact unemployment if we do not account for time and region fixed effects. This makes it eaiser for us to compare the difference when we add fixed effects.

Model 3

$$\text{Unemp\_Rate}_{it} = \beta_0+\beta_1(\text{Cases\_1000}_{it})+\beta_2(\text{Recovery\_Rate}_{it})+\beta_3(\text{Health\_Exp}_{it})+\beta_4(\text{Doctors\_1000}_{it})+\alpha_i+\epsilon_{it}$$

For this model, we only check for time fixed effects but do not control region fixed effects to comapre teh differences and observe how accounting for different fixed effects changes our results.

Model 4

$$\text{Unemp\_Rate}_{it} = \beta_0+\beta_1(\text{Cases\_1000}_{it})+\beta_2(\text{Recovery\_Rate}_{it})+\beta_3(\text{Health\_Exp}_{it})+\beta_4(\text{Doctors\_1000}_{it})+\gamma_t+\epsilon_{it}$$

For this model, we only check for region fixed effects but do not control time fixed effects to comapre the differences and observe how accounting for different fixed effects changes our results.

Model 5

$$\text{Unemp\_Rate}_{it} = \beta_0+\beta_1(\text{Cases\_1000}_{it})+\beta_2(\text{Recovery\_Rate}_{it})+\beta_3(\text{Health\_Exp}_{it})+\beta_4(\text{Doctors\_1000}_{it})+\alpha_i+\gamma_t+\epsilon_{it}$$

For this model we are carrying out two-way fixed effect on to see hour healthcare variables predict unemployment. It isolates the variables' effects from time-specific trends and regional disparities to give a more clear, reliable amd comprehensive understanding.

Model 6

$$\text{Unemp\_Rate}_{it} = \beta_0+\beta_1(\text{Cases\_1000}_{it})+\beta_2(\text{Recovery\_Rate}_{it})+\beta_3(\text{Health\_Exp}_{it})+\beta_4(\text{Beds\_1000}_{it})+\beta_5(\text{Agri\_GDP}_{it})$$

$$+\beta_6(\text{Man\_GDP}_{it}) + \beta_7(\text{Service\_GDP}_{it}) + \alpha_i + \gamma_t + \epsilon_{it}$$

This model integrates health-related variables with economic variables (sectoral GDP contributions from agriculture, manufacturing, and services) to provide a holistic view of the factors influencing unemployment rates during the pandemic.

Out[170]:

						Dependent variable: Unemp_Rate
	(1)	(2)	(3)	(4)	(5)	(6)
const	11.277***	17.178***	7.635***	4.769***	3.839***	4.843***
	(0.441)	(1.261)	(0.868)	(0.585)	(0.665)	(0.714)
Recovery_Rate	7.770***	7.400***	-1.557	7.299***	-2.303*	-2.303*
	(1.231)	(1.241)	(1.677)	(0.997)	(1.265)	(1.265)
Cases_1000		1.318	1.641	0.844	1.244	1.244
		(1.616)	(1.585)	(1.344)	(1.219)	(1.219)
Doctors_1000		-76.293***	-72.735***	-0.935***	-0.994***	
		(23.808)	(21.750)	(0.277)	(0.234)	
Health_Exp		-0.489***	-0.506***	-0.360***	-0.400***	-0.418***
		(0.091)	(0.083)	(0.078)	(0.066)	(0.065)
Beds_1000						-1.131***
						(0.262)
Time Fixed Effects	No	No	Yes	No	Yes	Yes
Region Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	598	598	598	598	598	598
R^2	0.063	0.109	0.273	0.459	0.627	0.627
Adjusted R^2	0.061	0.103	0.252	0.437	0.603	0.603
Residual Std. Error	9.977 (df=596)	9.752 (df=593)	8.906 (df=580)	7.722 (df=574)	6.488 (df=561)	6.488 (df=561)
F Statistic	39.826*** (df=1; 596)	18.123*** (df=4; 593)	12.811*** (df=17; 580)	21.183*** (df=23; 574)	26.181*** (df=36; 561)	26.181*** (df=36; 561)
Note:						*p<0.1; **p<0.05; ***p<0.01

When evaluating our regression models, the F-statistic serves as an initial gauge of the models' collective explanatory power. While lower F-statistics in some models might suggest a weaker overall fit to our data—potentially a limitation—it is noteworthy that all models, except the third, yield an F-statistic above 15, indicating statistical significance. This suggests that, contrary to the null hypothesis, there is at least one coefficient not equal to zero, affirming the relevance of the independent variables in explaining unemployment rates.

The R-squared values reflect the proportion of the variance in the dependent variable that's explained by the independent variables in the model. A higher $\mathbf{R^2}$ indicates that the model explains a greater portion of the variability in the outcomeThe R-squared values, particularly for models 5 and 6, which incorporate both time and region fixed effects, are the highest, suggesting these models account for a greater variance in unemployment rates. This enhancement in R-squared upon the inclusion of fixed effects underscores their importance in our analysis. The adjusted R-squared values for these models are also substantial, suggesting a robust fit that acknowledges the complexity of the models without succumbing to overfitting.

The residual standard error is smallest for the final two models, further corroborating the strength of their fit. This implies that the predicted unemployment rates from these models are, on average, closer to the actual values, offering more precise estimates.

In our baseline model, we observe an unexpected positive relationship between the unemployment rate and the COVID recovery rate. However, this model does not account for fixed time effects, which could potentially elucidate this counterintuitive result. When time and region fixed effects are considered in the latter models, the relationship between unemployment and recovery rate becomes negative, suggesting that a one-unit increase in the recovery rate is associated with a decrease in the unemployment rate by approximately 2.3 units, significant at the 10% level.

Healthcare expenditure, doctors, and hospital beds per 1000 each exhibit a negative association with the unemployment rate, with significance at the 1% level, indicating a strong inverse relationship between these healthcare variables and unemployment. The impact of hospital beds per 1000 is slightly more pronounced than that of doctors per 1000, implying that increasing hospital bed availability by one unit is associated with a reduction in the unemployment rate by about 2 units, compared to a one-unit reduction for doctors per 1000. We observe that higher GDP contribution from teh agricultural sector which means a more prominent agricultural structure si associated with lwoer unemployment as can be seen with the negative coefficient which is significant at 1% signicance level.

These results collectively reinforce the underlying economic theory positing that robust healthcare infrastructure can serve as a mitigating factor against unemployment in times of health crises, such as the COVID-19 pandemic. Consequently, they provide crucial insights for policymakers on the importance of investing in healthcare to cushion the economy against the shocks of future pandemics.

Table 2: Interaction with Dummy Variables

In this table, we created dummy variables for healthcare status, rural and urban, and the sector composition. We acrry two-way fixed effect for all of these.

Model 1

$$\text{Unemp\_Rate}_{it} = \beta_0 + \beta_1(\text{Urban\_Beds\_1000}_{it}) + \beta_2(\text{Recovery\_Rate}_{it}) + \beta_3(\text{Area\_Urban}_{it}) + \alpha_i + \gamma_t + \epsilon_{it}$$

This regression investigates how urban healthcare infrastructure (Urban_Beds_1000) and the extent of urban areas (Area_Urban) relate to unemployment rates, alongside recovery rates. It can reveal if urban centers with better healthcare facilities experience lower unemployment post-COVID, contributing to our understanding of how urbanization impacts economic resilience.

Model 2

$$\text{Unemp\_Rate}_{it} = \beta_0+\beta_1(\text{Recovery\_Rate}_{it})+\beta_2(\text{Healthcare\_Status\_High}_{it})+\beta_3(\text{Healthcare\_Status\_Low}_{it})+\alpha_i+\gamma_t+\epsilon_{it}$$

By examining the direct effects of healthcare status categorized as high or low without interaction terms, this model assesses the differential impacts of healthcare infrastructure quality on unemployment rates across regions, helping to understand the role of healthcare quality in economic recovery.

Model 3

$$\text{Unemp\_Rate}_{it} = \beta_0 + \beta_1(\text{Urban\_Beds\_1000}_{it}) + \beta_2(\text{Area\_Urban}_{it} \times \text{Recovery\_Rate}_{it}) + \alpha_i + \gamma_t + \epsilon_{it}$$

This model introduces an interaction between the recovery rate and the area's urban status to understand if urbanization modifies the effect of recovery rate on unemployment, potentially indicating that urban areas recover differently from COVID impacts on employment.

Model 4

$$\text{Unemp\_Rate}_{it} = \beta_0+\beta_1(\text{Healthcare\_Status\_Low}_{it}\times\text{Recovery\_Rate}_{it})+\beta_2(\text{Healthcare\_Status\_High}_{it}\times\text{Recovery\_Rate}_{it})$$

$$+\alpha_i + \gamma_t + \epsilon_{it}$$

By focusing on the interaction between healthcare status and recovery rates, this regression assesses whether the effect of recovery rate on unemployment is influenced by the quality of healthcare infrastructure, providing nuanced insights into healthcare's role in economic recovery post-COVID.

Model 5

$$\text{Unemp\_Rate}_{it} = \beta_0 + \beta_1(\text{GDP\_Type\_Service}_{it} \times \text{Cases\_1000}_{it}) + \alpha_i + \gamma_t + \epsilon_{it}$$

This model tests the interaction between the service sector's GDP and covid cases to investigate if a robust service sector alters the relationship between health outcomes and unemployment, offering insights into sectoral composition may affect the number of covid cases and unemployment rates.

	Dependent variable: Unemp_Rate				
	(1)	(2)	(3)	(4)	(5)
Intercept	2.035	4.435***	2.009	4.828***	3.875***
	(1.669)	(1.554)	(1.673)	(1.548)	(0.948)
Urban_Beds_1000	0.693***		0.692***		
	(0.190)		(0.190)		
Recovery_Rate	-2.334*	-2.342*	-2.136	-4.383*	
	(1.224)	(1.264)	(1.447)	(2.428)	
Area_Urban[T.True]	3.181***		3.235***		
	(0.515)		(0.557)		
Healthcare_Status_High[T.True]		3.528***		3.385***	
		(1.170)		(1.182)	
Healthcare_Status_Low[T.True]		6.391***		5.491***	
		(1.147)		(1.167)	
GDP_Type_Service[T.True]					0.640
					(1.097)
Area_Urban[T.True]:Recovery_Rate			-0.399		
			(1.554)		
Healthcare_Status_Low[T.True]:Recovery_Rate				8.014***	
				(2.508)	
Healthcare_Status_High[T.True]:Recovery_Rate				1.506	
				(2.326)	
GDP_Type_Service[T.True]:Cases_1000					22.126
					(34.434)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	598	598	598	598	598
R^2	0.650	0.626	0.650	0.635	0.625
Adjusted R^2	0.627	0.603	0.627	0.611	0.601
Residual Std. Error	6.284 (df=561)	6.488 (df=562)	6.289 (df=560)	6.426 (df=560)	6.505 (df=561)
F Statistic	28.935*** (df=36; 561)	26.897*** (df=35; 562)	28.107*** (df=37; 560)	26.291*** (df=37; 560)	25.966*** (df=36; 561)
Note:					*p<0.1; **p<0.05; ***p<0.01

For this table, all models have similar F-statistic and high R-squared values.These values indeed underscore the significance of the models and their goodness of fit. From Model 1, we can conclude that the unemployment rate is approximately 3.18 times higher in urban areas compared to rural areas. From Model 2, we observe that the unemployment rates in areas with high healthcare status are about 3.5 times higher compared to areas with medium healthcare status, and approximately 6.3 times higher for areas with low healthcare status when compared to the medium status. While these findings might suggest that better healthcare systems are associated with higher unemployment rates the unemployment in high sttus meding higher tahn medium status suggests that relationship between healthcare infrastructure and unemployment rates is more complex and may involve additional factors not captured by the model. For isnatnce, This could reflect a range of economic dynamics, such as a potential trade-off between public health and short-term employment levels during a health crisis like COVID-19, where more robust healthcare systems might be associated with more aggressive public health measures that temporarily impact jobs.

The coefficient 8.014 for the interaction term Healthcare_Status_Low and Recovery_Rate,indicating a high level of statistical significance at 1%, suggests a significant interaction between low healthcare status and the COVID recovery rate on the unemployment rate.

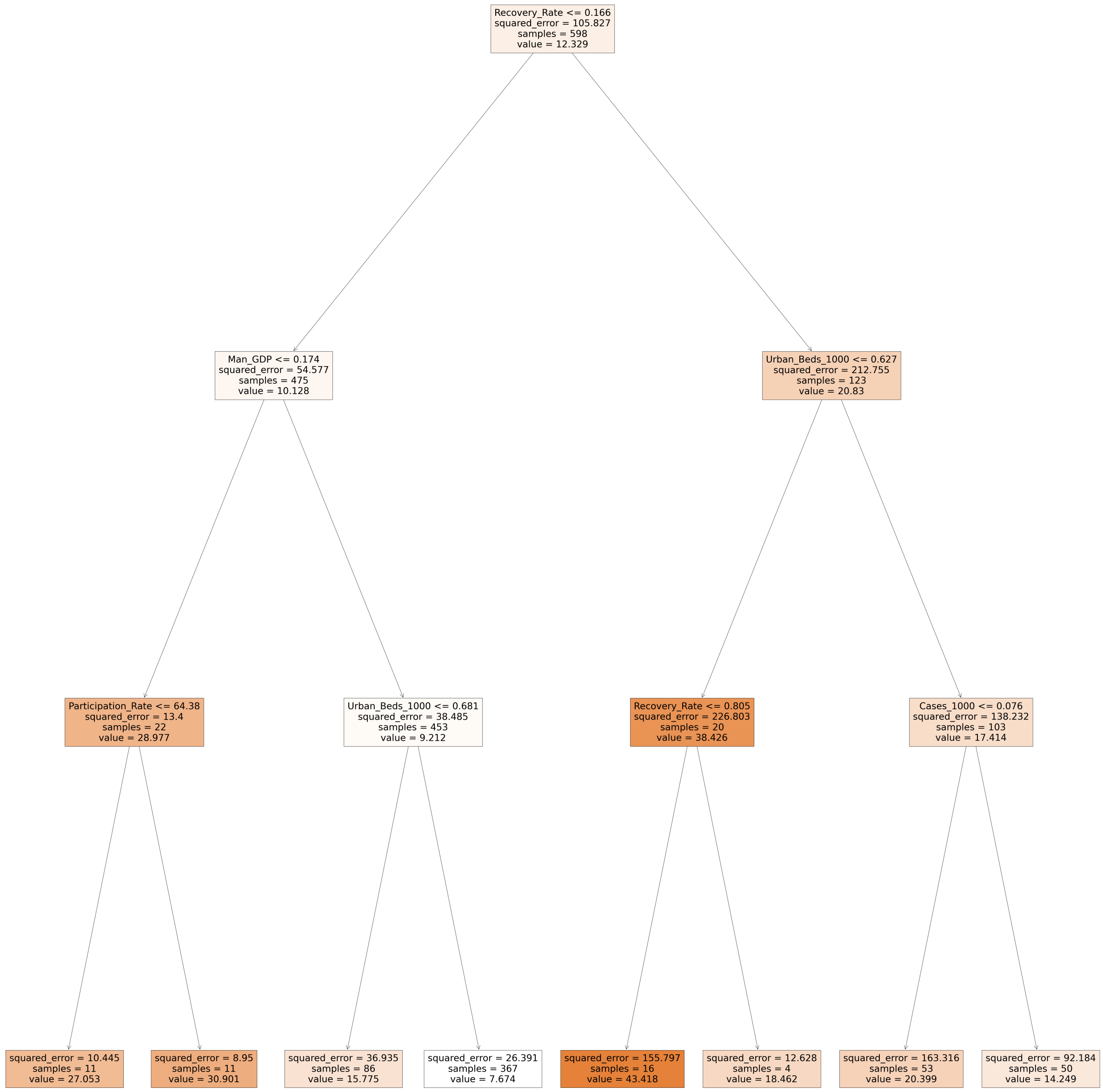
This positive coefficient means that in regions classified as having low healthcare status, each unit increase in the recovery rate is associated with an additional increase of 8.014 units in the unemployment rate, compared to the baseline category (medium healthcare status).

This result is particularly insightful as it implies that in regions with poor healthcare infrastructure, improvements in recovery rates (which indicate successful medical outcomes for COVID-19 patients) are still associated with significantly higher unemployment rates.

Machine Learning

In our regression tree analysis, we carefully select variables that provide a comprehensive understanding of the interplay between healthcare infrastructure and economic activity in relation to unemployment rates. We include healthcare-related variables such as healthcare expenditure, the number of beds per 1000 people, the number of doctors per 1000 people, the recovery rate, and the number of COVID-19 cases per 1000 people. These variables are critical for assessing the capacity and effectiveness of healthcare systems during the pandemic. Additionally, we incorporate sectoral GDP variables from services, manufacturing, and agriculture to evaluate the economic impact across different sectors.

To ensure the model's simplicity and relevance, we exclude categorical and time variables such as region, area, healthcare status, month, date, and frequency. These variables could introduce unnecessary complexity and risk overfitting, which might detract from the model's ability to generalize to broader contexts. We also exclude the number of people employed because it closely correlates with the unemployment rate, offering little additional insight and potentially leading to redundancy and overfitting in our model. By streamlining the input variables in this way, we aim to construct a robust model that can provide clear, actionable insights into how healthcare infrastructure and economic sectors influence unemployment during significant disruptions like a pandemic.



Our regression tree analysis has yielded insightful results regarding the factors influencing unemployment. At the top of our model, the recovery rate stands as the pivotal variable, forming the root node from which the tree splits. A recovery rate at or below 0.166 directs us down the left branch, pointing to its critical role in predicting unemployment rates.

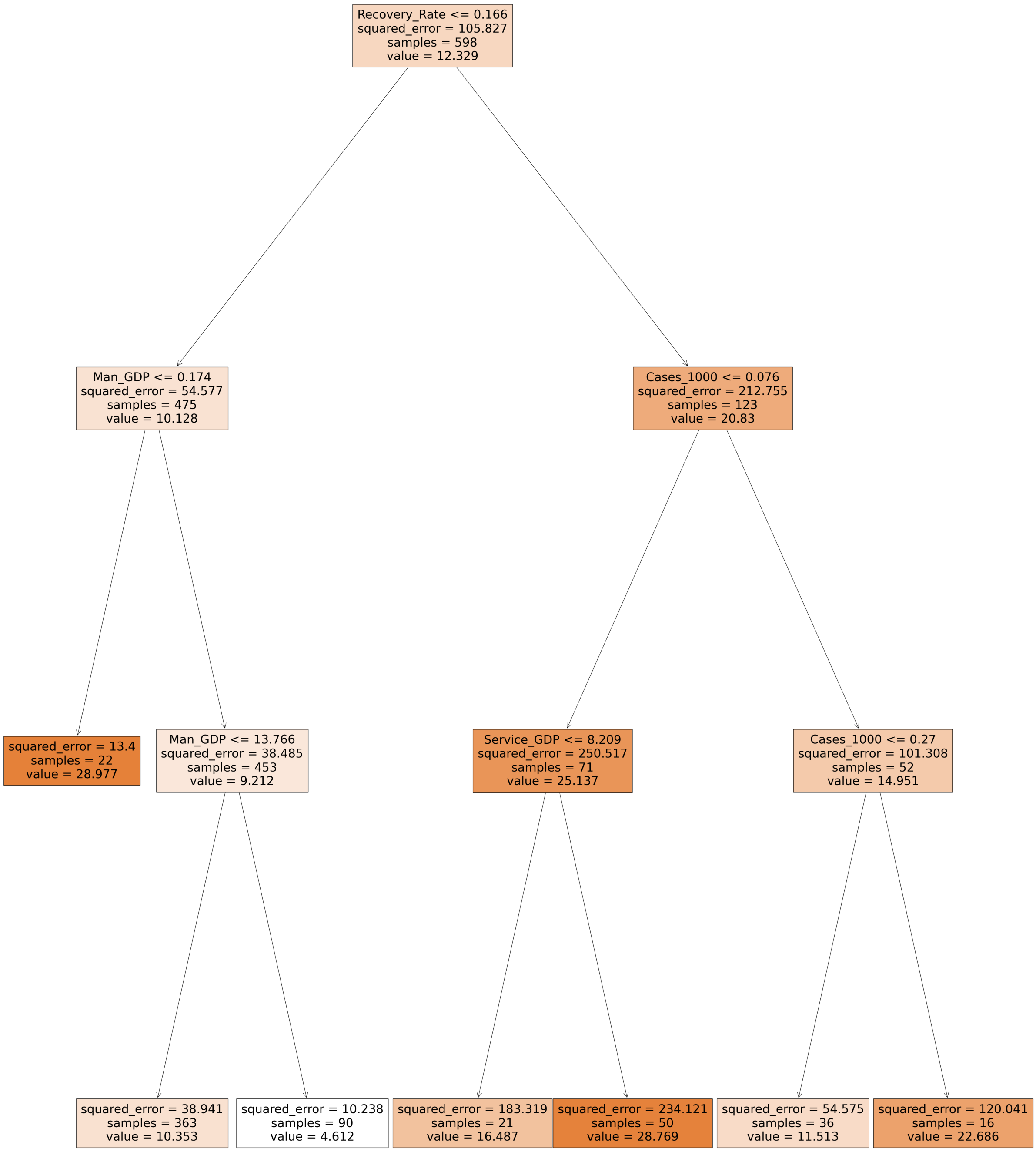
When faced with a lower recovery rate, the tree's subsequent decision relies on the GDP contribution from the manufacturing sector. An interesting observation emerges here; a larger GDP share from manufacturing leads us to consider the number of urban beds per 1000 as the next predictor. This sequence implies a strong link between manufacturing activities, predominantly situated in urban areas, and healthcare infrastructure, as measured by urban beds per 1000, highlighting their combined effect on unemployment. Particularly, when the count of urban beds is on the lower side, we observe higher unemployment rates at this terminal node, signaling the influence of healthcare accessibility in urban centres on employment.

Conversely, where the manufacturing sector's contribution falls below 0.174, the tree advises us to turn our attention to the labor force participation rate to predict unemployment, reinforcing the importance of active workforce engagement in shaping economic outcomes.

On the other branch of our tree, where the recovery rate surpasses 0.166, the number of urban beds per 1000 guides the next split. If the availability of urban beds fall below approximately 0.6, the tree further partitions based on the recovery rate. Within this sub-branch, a recovery rate under 0.805 culminates in a notably high unemployment rate, reaching approximately 43.418% at this terminal leaf. This unveils a nuanced interaction: regions with better lesser access to healthcare facilities are grappling with recovery challenges, exhibit significantly elevated unemployment, highlighting the intricate interplay between health outcomes and unemployment levels.

In summary, our decision tree underscores the importance of the recovery rate as a key determinant of unemployment, while also spotlighting the interconnected roles of healthcare infrastructure and economic activity as measured through sectoral GDP and workforce participation.

Comparing OLS and Machine Learning Results



OLS Regression Analysis In OLS regression, each predictor has an assumed linear and additive effect on the outcome variable. For instance, the significant recovery rate with a coefficient of -2.33 suggests that, holding all else equal, a one-unit increase in the recovery rate is associated with a 2.33-unit decrease in the unemployment rate. This method provides clear quantitative insights but operates under the assumption of linearity and does not capture more complex, non-linear relationships between variables.

In regression analysis, although cases per 1000 were not statistically significant and manufacturing had a low coefficient, agriculture GDP had a negative coefficient, indicating a significant impact on reducing unemployment. These results suggest that, within the confines of a linear framework, certain predictors like recovery rate and agriculture GDP are important for understanding unemployment dynamics, while others like manufacturing GDP and cases per 1000 may not be.

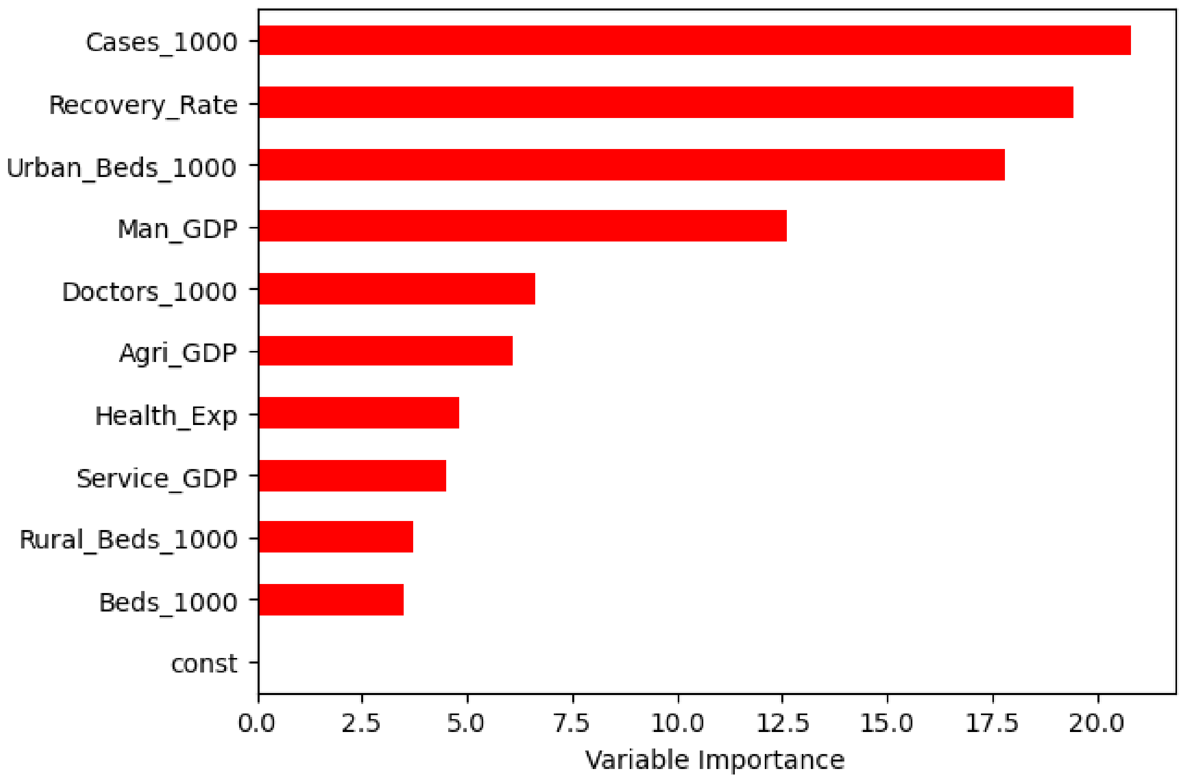
Regression Tree Analysis A regression tree, however, does not assume linear relationships and can uncover more complex interactions between variables. It can highlight non-linear patterns, such as thresholds or tipping points, that are not evident in OLS regression. For example, the regression tree identified cases per 1000 and manufacturing GDP as important splits after recovery rate, indicating their critical roles in predicting unemployment rates in a non-linear manner that OLS regression could not detect. This suggests that these variables may affect unemployment rates differently at different levels or in conjunction with other variables.

The regression tree also shows us how different variables come into play conditional on the values of other variables. It didn't prioritize agriculture GDP as a node, but did consider service GDP when the recovery rate and cases per 1000 were at specific levels, which differs from the linear model's estimation of service GDP's impact.It shows that for service levels below 8.2, the unemployment rate is lower comapre to when it is above thsi threshold confirming our economic intuition.

Furthermore, the regression tree did not use control healthcare variables like beds per 1000 or healthcare expenditure to predict unemployment, while these were statistically significant in OLS regression. The tree's reliance on continuous healthcare variables might suggest that these factors interact with other variables in a non-linear way to influence unemployment, a relationship that the linear model might miss. Economically, the regression tree's findings can indicate more dynamic and possibly more realistic relationships. For example, the importance of manufacturing GDP in the tree but not in the regression could reflect that the impact of manufacturing on unemployment only becomes pronounced under specific conditions, which the regression tree can capture but the OLS regression cannot. Similarly, the non-selection of agriculture GDP in the tree might hint that its effect on unemployment is more uniform and doesn't vary much across different levels, which a linear model like OLS regression would capture through its significant coefficient.

In summary, while OLS regression provides a valuable baseline understanding of how various factors may linearly predict unemployment, the regression tree enriches this understanding by revealing the conditional and non-linear relationships between variables

Importance Matrix



From the plot, it appears that Cases_1000 is the most significant predictor, suggesting that the number of COVID-19 cases per 1000 has the strongest relationship with unemployment rates in the model. This might reflect economic intuition that regions with higher infection rates experience greater economic disruptions, potentially due to stricter lockdowns or reduced consumer and business activity, thus leading to higher unemployment. Interestingly, it appears to be highly significant in the Random Forest mode but was statistically insignificant in the regression analysis. This discrepancy could be due to the non-linear and complex interactions captured by the Random Forest that are not accounted for in a traditional regression framework.

Recovery rate and Urban Beds per 1000 also show substantial importance, indicating that the speed of recovery from COVID-19 and the healthcare capacity in urban areas are significant factors in predicting unemployment. These variables are likely proxying the effectiveness and responsiveness of healthcare systems and their ability to mitigate the economic fallout from the pandemic.

The high importance of GDP from manufacturing in the variable importance plot indicates that the manufacturing sector has a substantial impact on unemployment rates. Economically, this suggests that regions with a strong manufacturing base may experience more pronounced changes in employment due to the pandemic. The manufacturing industry, often characterized by its reliance on physical labor and supply chains, may be particularly susceptible to disruptions caused by health crises and associated restrictions.

5 Conclusion

Our research seeks to explore the intricate question: "How do variations in healthcare infrastructure and economic sector composition influence unemployment rates across Indian states during the COVID-19 pandemic?" This inquiry is aimed at understanding the differential impact of healthcare capabilities and economic structures on regional employment outcomes amid a global health crisis.

Our research delves into the multifaceted relationship between healthcare infrastructure, economic sector composition, and unemployment rates across Indian states during the COVID-19 pandemic. The study brings to light the pivotal role that healthcare infrastructure plays in mitigating the economic impact of such global health crises. Specifically, states with robust healthcare systems like Goa and Himachal Pradesh have demonstrated resilience, managing to keep unemployment rates relatively low. This contrasts starkly with states such as Bihar and Jharkhand, where less developed healthcare frameworks have struggled to contain the repercussions, resulting in heightened unemployment rates.

To address this, our research delved into the influence of sectoral composition on unemployment rates during the pandemic. We hypothesized that the varying economic structures across states—specifically, the proportionate contributions of agriculture, manufacturing, and services sectors—could significantly impact how regional economies withstand or succumb to the economic disruptions caused by COVID-19. This line of inquiry aimed to uncover nuanced insights into the complex interplay between a state's economic makeup and its employment outcomes in the face of a global health crisis.

Further analysis highlights the significance of the sectoral economic composition in influencing unemployment dynamics during the pandemic. Our regression models pinpoint the recovery rate as a critical determinant, showing a robust negative relationship with unemployment rates. This suggests that higher recovery rates, indicative of effective healthcare responses, are associated with lower unemployment, presumably by shortening the duration of economic disruptions caused by the pandemic. Moreover, we observed that urban healthcare resources, quantified through metrics such as the number of beds per 1000 people and the availability of medical professionals, significantly predict unemployment outcomes. These variables underscore the importance of healthcare access and capacity in urban areas, which are often economic hubs, in cushioning the workforce against the impacts of COVID-19.

The sector-specific analysis revealed nuanced insights. While the manufacturing sector emerged as a significant predictor of unemployment, indicating that regions with substantial manufacturing activities faced greater employment challenges during the pandemic, the agricultural sector presented a contrasting scenario. States with a strong agricultural base such as Punjab despite having a pooere healthcare structure appeared less affected in terms of job losses, likely due to the sector's lower susceptibility to lockdown measures and social distancing norms.

Interestingly, our regression tree analysis, which allows for the exploration of non-linear relationships and interactions, identified that variables such as cases per 1000 and GDP contributions from manufacturing were critical nodes for predicting unemployment. This was in contrast to the linear regression models where cases per 1000 were not statistically significant, and manufacturing had a relatively low impact. This discrepancy highlights the complex and possibly non-linear interplay of these factors in affecting employment rates.

The significance of the service sector GDP in the regression tree analysis, particularly under specific conditions of recovery rate and cases, was another critical finding. This suggests that the service sector's vulnerability to the pandemic could be conditional on other economic and health-related dynamics, which linear models might not fully capture.

By explaining the possible sources and reasons for the variation and approaching it in a multifaceted way helps our research to discover findings that distinguish it from existing literature.

Limitations and Future Steps

Despite these insights, our study faces several limitations. Firstly, the high error rates in our machine learning models suggest that the predictive power could be improved. The low perdictive power also highlights the importance of considering other variables that affect unemployment rate. The limited data scope—capturing the pandemic's impact only up until June 2020—restricts our understanding of the full economic consequences, as the situation evolved significantly thereafter, especially around the peak period in May 2021.

To enhance the robustness of our findings and extend our analysis, future research should incorporate a longer timeline, ideally including data up to December 2021 or beyond. This extended dataset would allow a more accurate assessment of the prolonged impact of COVID-19 on unemployment and enable us to capture the recovery phase post-peak periods.

Moreover, considering other influential factors like the informal sector's role in employment and additional economic indicators could enrich our analysis. Implementing alternative econometric approaches, such as polynomial regression or even non-parametric methods, may also unveil more complex relationships and interactions that our current linear models may overlook.

In conclusion, while our study provides significant insights into the dynamics between healthcare infrastructure and unemployment during the pandemic, there is a clear pathway for further research. By expanding the dataset, employing diverse analytical techniques, and incorporating broader economic factors, future studies can offer more definitive conclusions and stronger policy recommendations to mitigate the effects of such global health crises on employment.

6 Work Cited

Goswami, B., Mandal, R., & Nath, H. K. (2021). Covid-19 pandemic and economic performances of the states in India. Economic Analysis and Policy, 69, 461–479. https://doi.org/10.1016/j.eap.2021.01.001

Sundararaman, T., & Ranjan, A. (2020). Challenges to India's Rural Healthcare System in the Context of Covid-19. Review of Agrarian Studies, 10(1).

Forbes India. (2023). Unemployment rate in India. Forbes India. Retrieved March 1, 2024, from https://www.forbesindia.com/article/explainers/unemployment-rate-in-india/87441/1

Chand, R. (2022). Changes in Labour Force and Employment in Rural and Urban India: 2017-18 to 2020-21. Presidential Address at the 105th Annual Conference of the Indian Economic Association, Bengaluru.

Hooda, B.S. (2022, January 18). Unemployment in Haryana needs to be addressed. The Tribune India. https://www.tribuneindia.com/news/comment/unemployment-in-haryana-needs-to-be-addressed-362208

Barman, P. D., & Ray, M. (2020, May 20). Tripura has best Covid-19 recovery rate with no deaths, claims law minister. Hindustan Times. https://www.hindustantimes.com/india-news/tripura-has-best-covid-19-recovery-rate-with-no-deaths-claims-law-minister/story-ECso6eYkZeWrxPNqA8EtMM.html

Gupta, V., Santosh, K.C., Arora, R., Ciano, T., Kalid, K.S., & Mohan, S. (2022). Socioeconomic impact due to COVID-19: An empirical assessment. Information Processing & Management, 59(2), Article 102810. https://doi.org/10.1016/j.ipm.2021.102810

Wijayaningtyas, M., Lukiyanto, K., Nursanti, E., & Laksmana, D. I. (2022). The effect of economical phenomenon on informal construction workers earnings within Covid-19 pandemic: A mixed method analysis. Heliyon, 8(8), e10321. https://doi.org/10.1016/j.heliyon.2022.e10321

Covid strongly impacted India's manufacturing sector, study shows. (2023). The Economic Times. https://economictimes.indiatimes.com/news/economy/indicators/covid-19-strongly-impacted-indias-manufacturing-sector-study-shows/articleshow/96936348.cms?from=mdr