Program Evaluation: Smart Cities Mission

Brief Description of Policy Intervention

The Smart Cities Mission is an urban renewal program launched by the Government of India to enhance the quality of life for citizens by implementing smart solutions that address core infrastructure, sustainability, and a clean environment. A total of 100 cities have been distributed through India, chosen through a two-stage selection process. Some of these cities include New Delhi, Pune, and Jaipur. Although these cities are more advanced than other urban centers, they were unprepared to manage the pandemic outbreak. Many of the smart cities had actually reported some of the highest positive cases, positivity rates, and deaths despite utilizing technological infrastructures.

In immediate response to COVID-19, smart cities in India implemented various technological solutions and data-driven approaches to combat COVID-19. Approximately 45 cities transformed their Integrated Control and Command Centres (ICCC) into COVID-19 War Rooms following the outbreak to monitor emergency responses, implement lockdowns effectively, and establish database monitoring platforms for virus containment. Below are key actions taken by cities in response to the pandemic.

The War Room plays a crucial role in monitoring city activities, identifying lockdown violations, and enforcing necessary actions for compliance. It also focuses on tracing and tracking suspected and positive COVID-19 cases, ensuring quarantine protocols, and facilitating treatment. A GIS-based COVID-Tracker dashboard is developed, offering key parameters such as hotspots, disease heat maps, and detailed information on cases, recoveries, daily case counts, trends, and affected age groups.

In addressing the needs of economically weaker sections, cities have implemented various initiatives. They developed mechanisms to identify individuals in need of food and shelter and set up food banks and canteens with support from civil societies and NGOs. Special provisions have been made to accommodate migrant laborers and homeless individuals in separate community halls with food facilities.

Plans have been made to manage lockdowns and ensure essential item delivery, including establishing a strong food supply chain for uninterrupted availability, transportation, and delivery. Food supply control rooms track and manage doorstep deliveries, while web portals offer details on ward-wise vendors for food and medicine. Some cities provide online delivery services to citizens.

Sanitization measures for streets and public spaces, including spraying disinfectants through fire tenders are implemented throughout cities. Drones are employed for city surveillance and disinfection. Sanitization tunnels have been installed at the entrances of crucial locations. Additionally, public taps with wash basins have been provided in slum areas to facilitate handwashing.

Cities have established health facilities to address the challenges posed by the pandemic. This includes converting hotels, hostels, and schools into temporary quarantine centers. Dedicated Rapid Response Teams and Mobile Action Units are deployed in specific wards to quickly address issues. Cities also provide remote digital medical consultations (Tele-medicine) for citizens and establish virtual training centers for healthcare professionals.

Brief Literature Review

The research (Mullick et al., 2022)[1] investigates the role of pandemic IT initiatives in shaping citizen responses within Indian smart cities, combining the theoretical perspectives of the digital divide and the right to the smart city. The study identifies digital exclusion factors for marginalized residents and informal migrants, revealing a selective focus on the digitally included, upwardly mobile citizens during pandemic combat. It introduces the concept of 'chatur citizenry,' operational in certain smart cities, emphasizing politically engaged communities capable of mitigating socio-economic and digital divides. The findings underscore the limited rights of the marginalized and digitally excluded within smart cities, perpetuated by the technologically-driven pandemic management. Despite this, the study emphasizes the essential inclusion of citizens in crisis management. Recommendations include local decentralization, mediating agencies, and the incorporation of 'chatur citizens' to bridge digital divides and enhance citizen-centric crisis management in smart cities. This research contributes to understanding and addressing socio-economic and digital disparities within smart cities during pandemics and the technologically-driven smart solutions.

The publication (Deloitte, 2020)[2] explores India's Smart Cities' response to the COVID-19 pandemic. The paper outlines the initial measures implemented by the Government of India in its efforts to curb the virus's spread before delving into the specific initiatives undertaken by smart cities. It underscores multiple key initiatives: the creation of War Rooms, food and shelter for economically vulnerable populations, delivery of essential services, sanitization of public areas, and the creation of healthcare facilities. Through analysis of case studies, this review seeks to document and evaluate the effectiveness of these smart city initiatives. Structured around three themes—ICCC as a COVID-19 War Room, Managing the Lockdown - Social Inclusion, and Managing the Lockdown - Essential Citizen Services—the case studies aim to contribute insights into the advanced responses of smart cities to the COVID-19 crisis. The paper highlights different strategies employed by smart cities and examines their effectiveness and the associated challenges in future considerations. The publication seeks to shed light on the efficacies of these initiatives towards the pandemic.

Overview of Research Design

In our research design for evaluating the impact of smart city initiatives in India's response to COVID-19, we adopt a nuanced cross-sectional analysis. The primary focus is on cities selected for the Smart Cities Mission, a cohort of 100 cities equipped with Integrated Command and Control Centers (ICCC). This group is contrasted with a carefully chosen control group of 100 other Indian cities not included in the mission. By comparing key metrics like infection rates, hospitalization, and response times across these groups, our design aims to unravel the specific contributions of smart city technologies. This methodological approach allows us to discern the distinct impact of these interventions on pandemic outcomes, providing a detailed understanding of their efficacy and implications in public health crisis management.

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[1] Mullick, M., & Patnaik, A. (2022, August 17). *Pandemic management, citizens and the Indian Smart cities: Reflections from the right to the smart city and the digital divide*. Available at: https://www.sciencedirect.com/science/article/pii/S1877916622000352

[2] Deloitte India. (2020, August 28). *India smart cities COVID-19 response*. Available at: https://www2.deloitte.com/in/en/pages/public-sector/articles/smart-city-2020.html

In our research design, the identifying assumption is that the cities selected for the Smart Cities Mission and those not selected are comparable in all aspects except for the implementation of smart city technologies. This assumption underpins our cross-sectional analysis, enabling us to attribute observed differences in COVID-19 responses to the presence or absence of smart city initiatives like ICCCs.

To implement our research design, we will collect current COVID-19 data from Indian cities within and outside the Smart Cities Mission. We will source data from government health departments and smart city reports to ensure comprehensive coverage. Our analysis will focus on comparing these cities' current health metrics, especially regarding ICCCs' influence. We'll also engage with local authorities for insights into each city's smart technology implementations. This approach, emphasizing statistical rigor and controlling for confounding variables, enables our group to robustly assess smart city interventions' impact on COVID-19 outcomes, comparing current illness and death rates across the two groups.

In interpreting our cross-sectional analysis results, if we find significant differences in COVID-19 metrics such as infection rates and hospitalizations between cities with and without ICCCs, this will indicate the effectiveness of smart city interventions. A lack of significant differences would suggest minimal impact. Our group’s research methodology is grounded in comparing these specific groups, recognizing that variables other than ICCC implementation might influence outcomes. In our analysis, we closely examine how smart city technologies, like ICCCs, influence pandemic responses. For instance, if cities with ICCCs show consistently lower infection rates compared to those without, this underscores the effectiveness of such technologies. Similarly, faster emergency response times in ICCC-equipped cities would further validate their impact. By contrasting these specific outcomes, we gain insights into the practical benefits of smart city interventions, shedding light on their role in enhancing public health infrastructure and crisis management capabilities.

We can enhance the statistical power of our analysis if we integrate a theoretical framework that correlates smart city technologies with public health outcomes. This framework, derived from literature on urban tech interventions, guides our non-parametric data analysis. This method strongly captures the complexities of the data reported by the Indian government and other bodies during the pandemic. We recognize potential confounders, like concurrent policy shifts, and plan to incorporate diverse data sources to mitigate their impact. Ultimately, our comprehensive, theory-based, and methodologically robust approach is designed to accurately evaluate the effects of smart city initiatives on COVID-19 in Indian cities.

Identification of Outcome Variables

The outcome variables that we will be examining in this research are COVID-19-caused death rates and the total number of positive cases, which can both be collected from government databases.

Description of Data Requirements and How This Data Will Be Collected

The objective is to prove that being part of the Smart Cities mission does lead to better COVID-19 response in terms of lower death rates and fewer positive cases. All data will be collected at the end of the year of 2020, except for the scores from 2015 when the cities were chosen to be smart cities. In terms of the treatment and control group, the 100 cities that participated in the Smart Cities Mission will enter as the treatment group; another 100 cities will be selected based on random selection in the rest of the cities in India to avoid selection bias. On account of data collection, all data will be collected through secondary data sources including government databases and industry reports. We will use multiple sources to confirm the accuracy and consistency of data. If we locate a significant difference between data from government databases and other authorized sources (e.g. industry reports on average income), we would delve into it more and take all kinds of biases into account. For example, there is a chance that the government reports lower death rates and positive cases to assure the general public.

To test the objective, we set the dependent variables to be 1) death rates due to COVID-19 on city-level (numerical continuous) 2) the total number of positive cases on city-level (numerical discrete). The control variables that will collected to contribute to the regression analysis are as follows:

- Scores received during the selection process to enter the Smart City Initiative in 2015 (numerical continuous)
  - Since the smart cities were not chosen randomly but were competition-based, we include the scores as a factor to capture the original difference between the treatment and control group when the Smart Cities Mission started.
- Average income (numerical continuous)
- Population density (numerical continuous)
- Government funding (numerical continuous)
- Proportion of the population that received education higher than high school (numerical continuous)
- Vaccine coverage rate (numerical continuous)
- Average age (numerical continuous)
- Gender distribution (numerical continuous)
- Binary variables
  - Lockdown policy
  - Social-distancing policies
  - Mask mandates

Main Regression Equations and How to Interpret

We elect a difference-in-difference model to compare the outcomes between cities with and without the Smart Cities Mission.

Our main regression equation reads:

$$Y\_i = \beta 0 + \beta 1\text{SmartCity}\_i + \beta 2\text{Scores}\_i + \beta 3\text{AverageIncome}\_i + \beta 4\text{PopulationDensity}\_i + \beta 5\text{GovernmentFunding}\_i + \beta 6\text{EducationProportion}\_i + \beta 7\text{VaccineCoverage}\_i + \beta 8\text{AverageAge}\_i + \beta 9\text{GenderDistribution}\_i + \beta 10\text{LockdownPolicy}\_i + \beta 11\text{Social-DistancingPolicies}\_i + \beta 12\text{MaskMandates}\_i + \varepsilon\_i$$

For easier readability, the regression equation can be simplified to:

$$Y\_i = \beta 0 + \beta 1\text{SmartCity}\_i + \sigma\_\text{c} + \varepsilon\_i,$$

where σ_c is a vector of control variables for city c.

σ_c includes all the factors listed in the section above, including scores during selection for the Smart City project, average income, population density, government funding, education levels, vaccine coverage rate, average age, gender distribution, and binary variables for lockdown policies, social-distancing policies, and mask mandates. σc would effectively act as the city-fixed effect variable.

Our outcome variable Y_i represents the total positive cases in the city i. $\beta 0$ is the intercept term, representing the expected value of the outcome variable when all other variables in the equation are zero. $\beta 1$ is the average difference in the outcome variable between cities in the Smart Cities Mission and those not in the mission, before the onset of COVID-19. The term SmartCity_i is a binary variable indicating whether the city is part of the Smart Cities Mission. Each coefficient from $\beta 2$ to $\beta 12$ captures the average impact of their respective controls, where $\beta 2$ would indicate the average impact of the scores received during the selection process on the total positive cases, β3 indicates the average impact of average income, β4 of population density, β5 of government funding, β6 of education proportion, β7 of vaccine coverage, β8 of average age, β9 of gender distribution, β10 of lockdown policy, β11 of social-distancing policies, and β12 of mask mandates. ε_i is the error term that captures the unobserved factors that affect the outcome variable but are not explicitly modeled.

Description of Any Other Analyses

In our further research, we will conduct a sensitivity analysis to assess the robustness of our RD findings. This involves systematically varying the bandwidth around the cutoff point and experimenting with different polynomial orders in our regression model. By adjusting these parameters, we aim to test the stability of our results under different conditions, ensuring that our findings are not artifacts of specific model choices. This thorough examination will bolster the reliability and validity of our conclusions, affirming the integrity of our research design.

Next, our group will incorporate a cost-benefit analysis that meticulously evaluates the economic efficiency of smart city interventions against COVID-19. We will quantify the costs, including technology implementation, maintenance, and operational expenses, against tangible benefits like reduced infection rates and improved response efficiencies. This analysis will involve discounting future benefits to present value, allowing for a comprehensive assessment of the interventions' long-term economic impact. By analyzing these cost and benefit streams, we can determine the net economic value of smart city technologies, providing crucial insights into their overall efficacy and sustainability.

In our time-series analysis, we will scrutinize trends such as the evolution of infection rates and hospitalization numbers over time, alongside the persistence of effects like changes in public health response efficiency. We thus aim to uncover any latent impacts of smart city interventions, distinguishing short-term fluctuations from long-term trends. By identifying these patterns over time, we gain a richer understanding of the interventions' sustained influence on COVID-19 outcomes. This rigor in our methodology is essential for a robust evaluation of policy effectiveness.

Together, these additional analyses will provide a comprehensive view of the effectiveness of smart city initiatives, enhancing the credibility and depth of our research.

Brief Policy Discussion

In a policy context, a positive and significant treatment effect ($\beta 3$) would imply that the Smart Cities Mission, with its integrated technologies and infrastructures, has a discernible impact in mitigating the spread of COVID-19 in India. Policymakers can leverage these findings to advocate for continued investment in smart city initiatives and further integration of technology-driven solutions in urban planning, emphasizing their role in crisis management.

On the other hand, if the treatment effect is minimal or statistically insignificant, it prompts a reevaluation of current smart city interventions. Policymakers may need to reassess resource allocation and consider alternative strategies to address the challenges posed by pandemics. Rather than outright cessation of smart city initiatives, policymakers can identify insights uncovered in this study to refine their plan for managing COVID-19 threats.