



Optimizing Food Subsidy Distribution in India

A Stochastic Model Using NSSO Household Data



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Understanding the Problem

Food Insecurity and Inequitable Subsidy Allocation in India

- **Paradox of Plenty:** Despite leading in food production, India faces widespread undernourishment and food insecurity among low-income households.
- **Ineffective Subsidy Targeting:** Current PDS and subsidies fail to equitably reach the most food-insecure populations due to static policy design.
- **Complexity of Price and Needs:** Random price fluctuations, household diversity, and budget limits necessitate a stochastic and need-based policy model.



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Modeling the Challenge: Stochastic Optimization Approach

Formulating Equitable Food Subsidy Allocation under Price Uncertainty



Stratified Household Modeling

Households are grouped into 12 fractile classes for rural and urban sectors using MPCE and food share data.



Random Price Simulation

Food prices are modeled as normal distributions (mean 1.0, SD 0.1) to reflect volatility, ensuring non-negative prices.



Objective: Minimize Shortfall

Optimization targets minimum expected weighted per capita shortfall using nonlinear constraints under a fixed budget.



Convex Optimization Problem Formulation

Stochastic Subsidy Allocation Model

- **Objective Function:**
$$\min \mathbb{E}_p \left[\sum_i w_i \cdot \max \left(0, \theta_i - \frac{e_i + x_i}{p_i h_i} \right) \right]$$

—expected weighted food shortfall across groups
- **Constraints:**
$$\sum_i x_i \leq B, \quad x_i \geq 0 \quad \forall i$$

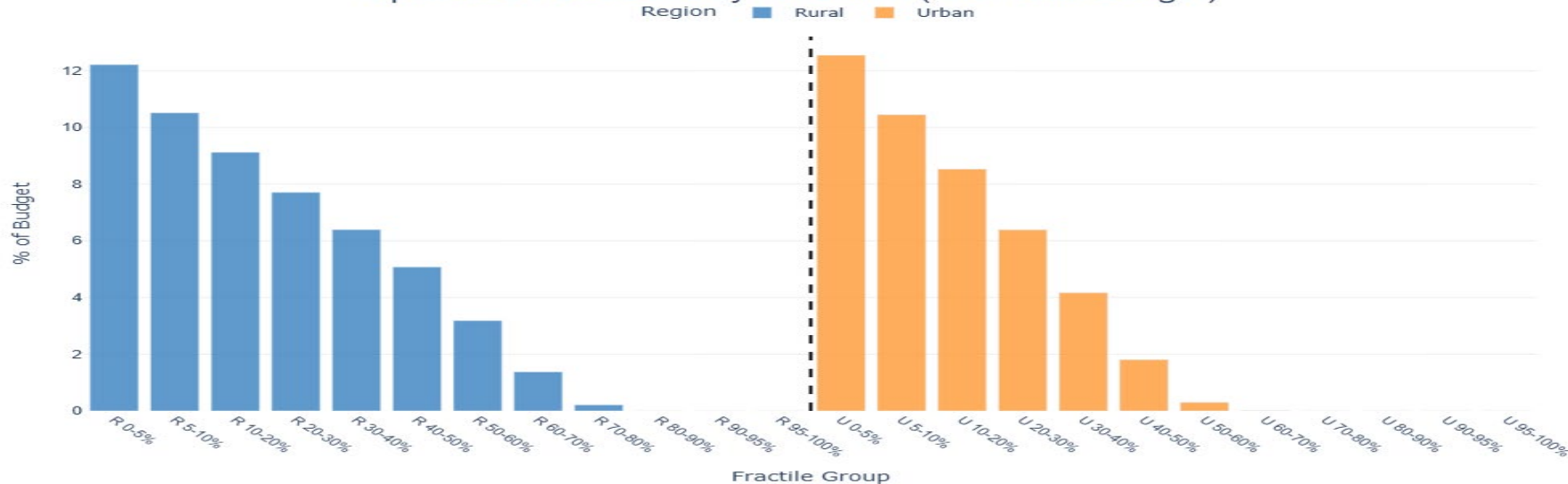
—total subsidy must not exceed budget and must be non-negative
- **Model Features:** Incorporates group weights w_i , stochastic prices p_i , and consumption thresholds θ_i for realistic targeting

Where, x_i : Subsidy allocated to MPCE group i	$\left \begin{array}{l} \theta_i: \text{Nutritional threshold (1891 for rural, 2078 for urban)} \\ w_i: \text{Weight of group } i, \text{ proportional to initial shortfall and population share} \\ B: \text{Total subsidy budget available} \end{array} \right.$
p_i : Random price of food (simulated from a normal distribution for group i)	
h_i : Average household size in group i	
e_i : Current per capita food expenditure in household i	



Simulation and Results

Optimized Food Subsidy Allocation (% of Total Budget)



Subsidy Allocation Results

Higher allocation observed among lower MPCE groups under weighted optimization strategy.



Targeted Allocation

Top 30–40% poorest households receive majority of funds, reflecting need-based allocation.



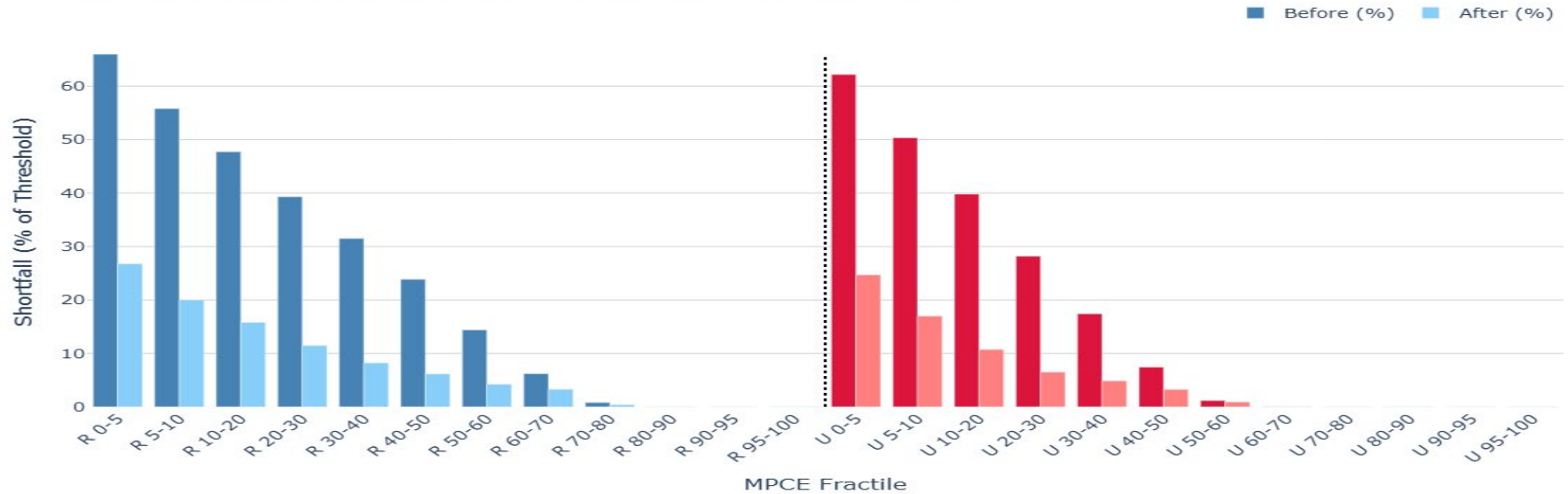
SLSQP Performance

Algorithm converges reliably within constraints; computational results implemented using Python's SciPy.



Impact of Subsidy on Food Shortfall

Shortfall Before vs After Subsidy (as % of Consumption Threshold)



Graphical Insights

Visuals indicate substantial shortfall reduction in low-MPCE groups post-subsidy optimization, confirming efficacy.



Shortfall Reduction

Shortfall as a percentage of nutritional threshold significantly drops post subsidy.



Group-Level Improvements

Bottom 30% of MPCE fractiles in both rural and urban sectors experienced the greatest gains in consumption adequacy.



Policy Implications and Recommendations

Translating Model Outcomes into Actionable Strategies

- **Data-Driven Targeting:** Adopt optimization-based subsidy design at state/district levels using real-time household and price data.
- **Integration with Existing Schemes:** Leverage infrastructure of PDS and integrate model-guided allocations to minimize inefficiencies.
- **Flexible Budgeting:** Allow dynamic adjustment of subsidy allocations under price shocks and inflation to retain effectiveness.
- **Institutional Adoption:** Recommend implementation through NITI Aayog or MoSPI for robust, empirically grounded policy frameworks.



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Acknowledgments



Faculty Support

Prof. Kaushik Jana provided key insights bridging theory and policy, guiding the optimization model design.



Teaching Assistance

Subhajit Pramanick assisted with technical guidance and troubleshooting during model implementation.



Data Provision

NSO and MoSPI provided access to HCES 2022–23, forming the empirical backbone of the study.



Team Contributions

Ridhwan led plotting, handled data processing and Rajneesh wrote the code and handled presentation.



Summary and Future Directions

- **Empirical Effectiveness:** Model successfully allocates subsidies with focus on lower fractiles, reducing food shortfall significantly.
- **Policy Viability:** Framework can be adopted by policymakers using stratified administrative data for effective regional targeting.
- **Suggested Enhancements:** Future work can incorporate individual-level risk indicators, inflation effects, and dynamic modeling over time.



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References

Sources Cited in the Project

- **HCES 2022–23:** Household Consumption Expenditure Survey by the National Statistical Office, MoSPI, Government of India.
- **NSS 68th Round:** Household Consumer Expenditure survey by MoSPI providing historical data context.
- **Boyd & Vandenberghe (2004):** Seminal text on convex optimization used for formulating and solving the subsidy problem.



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