Appendix C

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प्रयास

आरोग्य, ऊर्जा, शिक्षण आणि पालकत्व

या विषयांतील विशेष प्रयत्न

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Appendix C: Additional Analyses

C.1 Stacking analysis

The stacking analysis assumes that the solid fuel being used for stacking is biomass, since the bulk of solid fuel use (SFU) in the country is biomass in any case.

C.1.1 Estimation of health impacts with stacking

The estimation of DALYs for stacking follows the same approach as the health benefits assessment described in Appendix B.3, but with some modifications. The health benefits estimation in Appendix B.3 works when the population can be split into just two categories: those who are exposed to solid fuel combustion and those who are not. In the stacking case, households are split into three categories: those with no exposure (no SFU), limited exposure (partial SFU) and full exposure (full SFU), each of which is exposed to different 24-hour $PM_{2.5}$ concentrations. Because of this, the relative risk for each disease is calculated for each exposure level. Thus, the population attributable factor needs to take into account all relative risks arising from varying levels of exposure. The modified PAF formula adopted to account for such polytomous exposure is as below:

$$\text{PAF} = \frac{((\sum(p_{i \times RR_i})) - 1)}{(\sum(p_{i \times RR_i}))}$$

where p_i is the share of the population exposed to an exposure level i, ranging from 1 to n, which has a relative risk RR_i (Zapata-Diomedi, Barendregt and Veerman 2016, Hanley 2001)[1]. The risk ratios are estimated as in the main analysis, based on $PM_{2.5}$ concentrations arising out of partial use of biomass for cooking, depending on the particular stacking case.

This formula has also been used to estimate health impacts of smoking for populations with varied levels of exposure (Tanuseputro, et al. 2015). The PAF thus derived for a particular disease is then multiplied by the background DALYs as before to get the disease burden due to a combination of full SFU and partial SFU due to stacking.

C.1.2 Estimation of costs with stacking

The connection, stove and fuel costs also change with stacking, as now multiple connections, fuels and stoves are being used by a household. Cost calculations have been done only for the Baseline and PMUY scenarios in which the dominant fuels are LPG and biomass. In addition to the costs in the original analysis, costs of LPG stacking by primary biomass users and biomass stacking by primary LPG users are computed for the two scenarios.

Since the number of LPG connections is significantly higher than the households that use the fuel (due to the provision of subsidised connections under programmes such as PMUY which don't necessarily translate to use), we assume that the households primarily using biomass but stacking with LPG are from this set of households that have an LPG connection but do not use it as a primary

1. Note that the unexposed population (i.e. with zero exposure) has an RR of 1.

fuel. Since the LPG connection costs (and stove costs, since stoves come with connections) for such households are already estimated in the base analysis, no additional LPG connection costs are calculated for such households, while LPG usage costs are calculated depending on the quantity of LPG used. For primary LPG households stacking with biomass, additional cost of stoves and biomass (with the same percentage of purchasing biomass users as in the main analysis) is estimated. The methodology and assumptions for estimating costs in the presence of stacking are the same as the overall cost assessment. Table 1 summarises the additional cost related estimations which need to be made in the presence of stacking for the Baseline and PMUY scenarios.

Table 1: Stacking cost estimation

Stacking scenario	Additional costs estimated
Biomass users stacking with LPG	Fuel and distribution costs of LPG based on the stacking case (High, Moderate, Low)
LPG users stacking with biomass	• Biomass stove costs • Fuel (biomass) costs based on the stacking case

C.2 ICS analysis

Two kinds of analyses are undertaken to understand the potential role of improved biomass cookstove (ICS) in the cooking transition. In the first analysis, an 'ICS scenario' is developed to understand the role ICS can play as a primary cooking fuel by assessing the cost and health implications of such a scenario. In the second analysis, the role of ICS as a potential bridge fuel in a complete transition to modern fuels is assessed, where ICS is stacked with biomass and modern fuels.

For both these analyses, the ICS used is the tier-4 Mimi Moto stove[2], one of the best available ICS. However, field performance of ICS stoves usually does not match up to the lab performance. Since there is no publicly available data about field performance of the Mimi Moto stove, CEFTI assumes that the field performance of the ICS would be about 80% of known laboratory values.[3] Based on this, field $PM_{2.5}$ emissions from the Mimi Moto stove are assumed to be about 1.6 mg / minute, and its field efficiency is assumed to increase from 31% in 2015 to 41% in 2030. Based on data from some wood pellet suppliers, the cost of fuel for the Mimi Moto stove is assumed to be Rs 8 per kg in 2015, gradually falling to Rs 6.8 per kg in 2030 as the market for pellets deepens.

C.2.1 ICS scenario

The ICS scenario is different from the other scenarios in the model in that it is specifically introduced to study the role of ICS in the cooking fuel transition. This scenario is developed as a variant of the Multi-Fuel scenario, in which ICS penetration in rural India[4] gradually increases from 0% in 2015 to 17% in 2030. The penetration of ICS implies that there is a reduction in penetration of other fuels than that in the Multi-Fuel scenario. Thus, rural biomass penetration in 2030 is only 16% in the ICS scenario as against 22% in the Multi-Fuel scenario, while rural LPG penetration in 2030 is only 59% as against 65% in the Multi-Fuel scenario. Similarly, penetration of biogas and electricity in rural India in 2030 is 5% and 3% respectively as against 7% and 6% respectively in the Multi-Fuel scenario. CEFTI calculates the costs and health impacts of the ICS scenario similar to the calculation of costs and health impacts of other scenarios.

2. See http://catalog.cleancookstoves.org/stoves/434.
3. For comparison, a field performance test of the tier-3 Philips HD4012 stove resulted in emissions that were 6–9 times the lab emissions, i.e. 11%–16% of laboratory performance. See http://catalog.cleancookstoves.org/test-results?permalink=1&stoves=47 .
4. We do not consider ICS use in urban areas since, even in the Baseline scenario, usage of traditional fuels almost disappears in urban areas by 2030.

C.2.2 ICS as a bridge fuel

The analysis of ICS as a bridge fuel examines two cases using an analysis methodology similar to the stacking analysis (Appendix C.1). In the first case, it analyses the health impacts on 40% of households primarily using biomass in the Multi-Fuel scenario using ICS to meet 40% of their cooking needs. In the second case, it analyses the health impacts of 40% of households using modern fuel in the Multi-Fuel scenario using ICS to meet 40% of their cooking needs. The estimation of DALYs in these two cases is done similar to the stacking analysis, where different quantities of biomass use and hence different levels of exposures to emissions from biomass combustion and ICS are considered. The DALYs thus computed for these two cases are then compared with the DALYs for the original Multi-Fuel scenario in which all households use only one fuel to meet all their cooking needs, in order to understand the potential role of ICS.

C.3 Sensitivity analysis

In order to evaluate the robustness of our analysis, certain key parameters were varied within a range relevant to that parameter to see how it affects the cost effectiveness of a scenario. If the main results of the analysis are not significantly affected by changing the key assumptions, then the analysis may be considered robust, primarily with respect to cost-effectiveness of various scenarios. The sensitivity of the model results was tested against the following key assumptions being varied:

1. **Fuel prices:** Since fuel prices form the biggest component in the total costs, the model was tested against different fuel prices. Modern fuel prices were increased by 20% every year compared to the values in the primary analysis, while prices of biomass and cow dung were increased as well as decreased by 20% every year compared to the primary analysis.
2. **Useful energy required for cooking:** The CEFTI model assumes a fairly high value of 1046 MJ for the useful cooking energy required per person per year (Sanga and Jannuzzi 2005). As this is the fundamental assumption underlying all calculations for costs as well as benefits, this was varied to a lower, but older, value of 947 MJ found in the literature for the Indian context (ABE 1985).
3. **Emissions from solid fuel combustion:** There are multiple values in literature about the particulate emissions from solid fuel combustion, and the primary analysis was based on an assumption of 5.2 g / kg. Sensitivity analysis was done to see the impact of using a different value of 3.9 g / kg available in literature (Preble, et al. 2014).
4. **Increasing the share of PNG imports:** The Multi-Fuel and SDG scenarios require high penetration of PNG, which may require additional imports. This sensitivity test involved increasing the share of imports of natural gas used for cooking in these scenarios by 20 percentage points every year compared to the primary analysis.

Table 2 summarises the cost-related and health-related parameters that have been varied to check for sensitivity along with the range of variation tested.

Table 2: Sensitivity analysis parameters

Parameter	Upper bound	Lower bound
Annual per capita useful energy required (MJ/annum)	N.A.	947 MJ/annum
Fuel prices of LPG (Rs/kg), Natural Gas (Rs/scm) and Electricity (Rs/kwh)	+20%	N.A.
Price of biomass and cow dung for biogas (Rs/kg)	+20%	-20%
Emissions per kg of solid fuel (g/kg)	N.A.	3.9 g/kg
Share of imports in PNG	+20 percentage points	N.A.

The results of the different sensitivity tests — measured as their impacts on the cost per aDALY for each scenario — are given in Table 3. These results are for the entire country, i.e. including all states and rural and urban areas.

Table 3: Percentage change in Cost per Averted DALY for various sensitivity tests

Sensitivity test	Change	PMUY	Multi-Fuel	SDG
Changing annual per capita useful energy required for cooking from 1046 MJ to 947 MJ	-9.5%	-9%	-7%	-6%
Increasing LPG, PNG and electricity prices	+20%	46%	38%	36%
Changing biomass and cow dung price	+20%	-32%	-30%	-30%
Changing biomass and cow dung price	-20%	32%	30%	30%
Changing PM 2.5 emissions per kg of solid fuel from 5.2 g/kg to 3.9 g/kg	-25%	3%	4%	5%
Increasing the share of PNG imports	+20 percentage points	0%	4%	3%

The price sensitivity scenarios affected only costs, while reducing solid fuel emissions only brought down the DALYs. Variability in cooking energy requirement affected both costs and DALYs.

Although the cost per averted DALY changed with the assumptions, the important point is that all the scenarios continued to remain very cost effective over the entire analysis period even with the changed input assumptions, i.e. the changed cost per averted DALY continued to be less than the average per capita GDP for all years from 2019 to 2030. Moreover, the SDG scenario retained its position as the most cost-effective scenario at the national level in all sensitivity cases. Thus, the sensitivity analysis shows the robustness of our analysis since changing crucial model parameters or assumptions does not affect the principal conclusions drawn from the analysis about the cost effectiveness of interventions to increase modern fuel usage.

Looking more closely at the results of the sensitivity analysis, since fuel prices are the driving factor behind costs, increasing the prices of LPG, PNG and electricity by 20% resulted in a significant (up to 46%) increase in costs per aDALY. The cost increase reduces with increasing diversity of fuels as seen with the Multi-Fuel and SDG scenarios. This is possibly because of a combination of two factors: firstly, electricity and PNG, which have a greater presence in these scenarios than PMUY, are cheaper than LPG, which is the predominant fuel in PMUY. And secondly, the price of biogas, whose price does not increase in this sensitivity analysis case, has a greater role to play in Multi-Fuel and SDG scenarios than the PMUY scenario. This suggests that fuel diversity could perhaps also be a good risk mitigation strategy against price rises, since it is less likely that the prices of all fuels would increase simultaneously.

Increasing the price of biomass and dung leads to a reduction in cost per aDALY (and vice-versa) because of greater biomass use in the Baseline scenario and hence higher costs for this scenario. Reducing the emissions per kg of solid fuel increases the cost per aDALY since the health impacts of exposure to solid fuels reduces. There is hardly any change in the cost per aDALY when the share of PNG imports is changed, since it forms a very small part of the overall costs in the model.

References

ABE. “Towards a perspective on energy demand and supply in India 2004-05.” Report of the Advisory Board of Energy. Government of India, May 1985.

Hanley, J A. “A heuristic approach to the formulas for population attributable fraction.” Journal of Epidemiology & Community Health . 2001. http://jech.bmj.com/content/jech/55/7/508.full.pdf (accessed May 9, 2017).

Preble, Chelsea, Odelle Hadley, Ashok Gadgil, and Thomas Kirchstetter. “Emissions and climate-relevant optical properties of pollutants emitted from a three-stone fire and the Bekeley-Darfur stove tested under laboratory conditions.” Environmental Science and Technology, 2014.

Sanga, G. A., and G. D. M. Jannuzzi. Impacts of efficient stoves and cooking fuel substitution in family expenditures of urban households in Dar es Salaam, Tanzania. International Energy Initative, Latin America, 2005.

Tanuseputro, Peter , et al. “Improving the estimation of the burden of risk factors: an illustrative comparison of methods to measure smoking-attributable mortality.” Population Health Metrics. 2015. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4339639/ (accessed May 9, 2017).

Zapata-Diomedi, Belen, Jan J Barendregt, and Lennert J Veerman. “Population attributable fraction: Names, types and issues with incorrect interpretation of relative risks.” British Journal of Sports Medicine. March 8, 2016. https://www.researchgate.net/publication/297549582_Population_attributable_fraction_Names_types_and_issues_with_incorrect_interpretation_of_relative_risks (accessed May 9, 2017).