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Benefits of Improved Cook Stoves: Evidence from Rural Bangladesh

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Reduction of biomass fuel consumption, improved health outcomes of household members and time savings for households are the key intended benefits of Improved Cook Stove (ICS). This paper attempts an empirical verification of these targeted benefits of the ICS, named *Bondhu Chula,* in rural Bangladesh. Propensity score matching (PSM), a quasi-experiment econometric method, has been applied using the 2018 household survey data of Bangladesh Institute of Development Studies (BIDS) that collected information from 600 users of *Bondhu Chula* and 396 users of traditional cook stoves. The analysis reveals that the use of *Bondhu Chula* on the average saves about 50 kg of biomass fuel consumption per month per household, i.e. 30-37 per cent of biomass fuel consumption compared to households using traditional cook stoves. *Bondhu Chula* was also found to have provided improved health outcomes by reducing indoor air pollution and led to reduced household cooking time. Despite the observed benefits of the use of ICS, the progress towards the adoption of ICS across the country is not satisfactory and there is a large opportunity to scale-up the use of ICS. The evidence provides justification for such a policy move.

Keywords: Impact of *Bondhu Chula*, Propensity Score Matching (PSM), Fuelwood Consumption, Traditional Cook Stoves

JEL Classification: D12, Q53, O13, Q54, Q55

I. INTRODUCTION

Biomass combustion within households is considered to be the main cause of indoor air pollution in developing countries (Smith 2000, Ezzati and Kammen 2001, Ezzati *et al*. 2004, Amegah and Jaakkola 2016). Around 80 per cent of Bangladesh's population relies on solid fuel for their household cooking and heating needs. According to estimates of the World Health Organization (WHO 2009), exposure to smoke from solid fuel combustion contributes to nearly 50,000

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deaths in Bangladesh every year, placing women and children at the greatest risk. At this backdrop, Improved Cook Stove (ICS) can potentially help to alleviate the negative implications of biomass fuel use because an ICS lowers the biomass fuel consumption per meal and thus lowers indoor air-pollution in the kitchen compared to traditional stoves (Sarkar, Akter and Rahman 2006, Zaman *et al*. 2017).

Initiatives to promote innovation and use of ICS in Bangladesh are aimed at enhancing the efficiency of energy use, reducing the adverse health impacts of indoor air pollution from traditional stoves and improving the quality of life. As the use of traditional cook stoves by rural people of Bangladesh results in negative health and environmental impacts, numerous efforts have been made by government and some non-government organisations (NGOs) during the 1980s and 1990s to develop and distribute ICS among rural people throughout the country (Sarkar, Akter and Rahman 2006, World Bank 2010, Mobarak *et al.* 2012). Though these efforts started as grant initiatives, commercial initiatives also evolved over time for the development and marketing of ICS (World Bank 2010).[1] Various initiatives to expand the use of ICS have generated interest among researchers to explore their impacts. The experiments by Sarkar, Akter and Rahman (2006) have noted that users of ICS are benefited by less smoke in the kitchen, less time to cook, lower energy requirements, etc. The experimental study by Zaman *et al*. (2017) has found lower incidences of respiratory illness among the mothers in rural Bangladesh who use ICS compared to the mothers who use traditional stoves. After conducting experiments on the efficiency of traditional cook stoves and ICS in terms of fuel use, Ahmed and Ahamed (2018) have concluded that ICS can save more than 50 per cent of traditional fuel compared to traditional stoves. Islam *et al*. (2014) have noted the importance of the structure of the ICS for better performance. World Bank (2010) has observed that many household energy problems can be solved by using ICS. The study has also mentioned the importance of a national publicity campaign to promote health and efficiency benefits of improved cook stoves. Mobarak *et al*. (2012) have noted that in rural Bangladesh, household preference for the adoption of an ICS over traditional cook stoves depends vastly on operating costs and cooking time rather than health and environmental benefits of improved stoves.

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[1]The commercial initiatives are coming from private entrepreneurs, NGOs, microfinance providers and various agencies like German International Cooperation (GIZ), United States Agency for International Development (USAID) and Infrastructure Development Company Limited (IDCOL).

The majority of the existing studies, as discussed above, investigated different benefits of ICS applying scientific experiment and a few using socioeconomic experimental methods. And the findings of this literature are mixed. Our study contributes to this literature using a quantitative method which takes into account the possible influence of different observable household characteristics on the decisions to adopt ICS and the outcomes of ICS use simultaneously. In doing so, the current study has used an econometric method and an observational data to estimate the impacts of ICS by comparing certain variables of user households with those of non-user households having similar characteristics. In particular, the study analyses the impacts of '*Bondhu Chula*' (a brand of ICS) on biomass fuel consumption, cooking time, and women's health by comparing the situation of these outcome variables in comparable user and non-user households.[2] Thus, the contribution of this paper is to show these three benefits of ICS use methodologically and empirically. Current attention to ICS focuses on the "triple benefits" they provide, and the triple benefits are improved health and time savings for households, the preservation of forests and reduction of emissions caused from the reduction of biomass fuel consumption (Jeuland and Pattanayak 2012).

Our empirical analysis first focuses on estimating the potential impact of ICS use on household biomass fuel consumption. There are three key rationales behind this. First, the immediate impact of ICS use is the savings of household energy cost, given that the use of ICS lowers the household biomass fuel consumption. Second, if the use of ICS reduces household biomass fuel consumption, then that indicates a reduction of overall demand for fuelwood or other biomass, and consequently, there will be lower pressure on deforestation. Third, the reduction of biomass fuel consumption would be associated with the reduction of smoke emissions, savings of time for cooking, and fuel collection. A reduction of smoke emissions is likely to lower the frequency of smoke–related diseases household members suffer from. Considering these possibilities, we have also looked into the impacts of ICS on cooking time and women's health.

The rest of the paper is organised as follows. Section II provides a brief discussion of *Bondhu Chula* programme in Bangladesh. Section III discusses the empirical methods and data. Section IV provides empirical results and a discussion on the impact of ICS *Bondhu Chula* and section V concludes.

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[2] In this paper, we use *Bondhu Chula and* ICS interchangeably.

II. THE CHARACTERISTICS OF *BONDHU CHULA*[3]

Bondhu Chula is a locally designed stove which was developed by the Institute of Fuel Research and Development (IFRD) of the Bangladesh Council of Scientific and Industrial Research (BCSIR) in the early 1980s. This evolved as a part of BCSIR's initiatives for efficient energy usage to save trees and the environment (World Bank 2010).[4] During the 1980s and 1990s, the ICS programme of BCSIR was expanded by various local NGOs (termed as partner organisations). Till 2001, direct subsidy was provided to customers in building the stoves (households provided the mud only). Additional supports were provided through training costs and programme costs to the partner organisations. During 2004-2010, German Technical Cooperation Agency (GTZ), later known as German Corporation for International Cooperation (GIZ), supported a programme of Ministry of Power, Energy and Mineral Resources for countrywide installation of ICS. This programme supported commercial initiatives, where no subsidy was given to customers, rather the partner organisations provided micro-credit support for purchasing ICS and the customers could return the credit in two to three installments (with interests). However, GIZ supported its partner organisations and manufacturers in the areas of finance, training, and business development. USAID (through Winrock, VERC, Concern Worldwide) supported a programme to install improved cook stoves in few northern districts of Bangladesh. This also supported commercial ventures of ICS through micro-credit to customers.

In 2010, Sustainable Energy for Development (SED) programme of GIZ developed a concrete version of the ICS, *Bondhu Chula*. During 2012 to 2014, GIZ and Department of Environment under the Ministry of Environment and Forests of Bangladesh jointly implemented the project "Market Development Initiative for *Bondhu Chula"* for developing a system for marketing and maintenance of ICS through local capacity building, but there was no credit component. The project has mobilised more than 4,300 sanitary shops to produce prefabricated standardized stoves and install them in the kitchen of the customers. The cook

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[3]Information regarding *Bondhu Chula* has been drawn from https://energypedia.info/images/e/ef/GIZ_HERA_2013_Bondhu_Chula_Bangladesch.pdf (as cited on 24 March 2019) and Project Completion Report "Market Development Initiative for Bondhu Chula" of Ministry of Environment and Forests of Bangladesh (2014).

[4]The initiative piloted different types of ICSs, such as (a) one-pot portable cook stoves; (b) one-pot semi-submerged stoves; (c) one-pot portable stoves for use with sawdust or rice husk; (d) one-pot fixed stove with chimney; (e) two-pot fixed household-sized stoves with chimney; and (f) two-pot fixed institutional stoves with chimney.

stoves were sold commercially, though SED provided training on making and installation of the stoves.[5] Average price of domestic *Bondhu Chula* is about BDT 800-BDT 1,200. *Bondhu Chula* is a fixed one, two or three pot prefabricated concrete stove with a chimney. Types of fuels that can be used in this cook stove include fuelwood, cow-dung stick/cake, twigs, jute sticks, and other agricultural residues. This cooking stove is mostly used in suburban and rural households where natural gas supply is unavailable. Under the project "Market Development Initiative for *Bondhu Chula,"* 500,000 stoves were installed throughout the country. The study by Arif *et al*. (2011) has noted that this ICS can burn the firewood more effectively than the traditional stove and thus reduces the quantity of firewood required for cooking. It is also noted that time for cooking can be less than the traditional stoves. Moreover, the chimney of *Bondhu Chula* channels smokes to the roof-top smoke cap leaving the kitchen smoke free.

III. EMPIRICAL METHODS AND DATA

3.1 Empirical Framework

In a study with observation data like ours, the causal estimation of the ICS (treated unit) on outcome variable is likely to be biased if we apply ordinary least squares (OLS) estimator. This is because of the selection bias, i.e., households are assigned to the ICS (treatment) and traditional cook stoves (control) users non-randomly and confounding effects are present. When the association between treatment and outcomes is distorted by the presence of an unobservable variable, then the confounding effects are present.[6] Without accounting for this bias, the observed differences in outcomes between treatment and control cannot be attributed to treatment effect (Austin 2011). In this case, the PSM is an effective technique that accounts for selection and confounding bias in an observational study and provide reliable estimates of the treatment effect. Thus, we use the PSM method to estimate the causal impact of ICS use.

The PSM calculates propensity score from the standard logit or probit model and tries to find for every participant (in our case household with an ICS) a non-participant (household with traditional cook stoves) similar in characteristics to the

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[5]NGO called Bangladesh Bondhu Foundation, established with the support of GIZ, continues supporting entrepreneurship development and installation of *Bondhu Chula*.

[6]A relevant omitted unobservable variable is efficiency in fuel use which affect the adoption of ICS positively and use of energy negatively. Or, the awareness about smoking problems that affect the adoption of ICS positively and health outcomes negatively.

participant from the surveyed. The difference in the mean outcome of matched participants between both groups is attributed to the impact of treatment or intervention (use of ICS) under the assumption that the use of an ICS is based only on observables. Let T denotes binary treatment variable (1=Households with ICS and 0=Households with traditional cook stoves), Y denotes outcome variable (e.g., energy use), and X is the vector of covariates. Then we write the propensity score equation as (Rosenbaum and Rubin 1983):

$$p(x) = e(X = x) = \Pr(T = 1 \mid X = x) \tag{1}$$

Given the propensity score, we want to estimate the impact of treatment T for an individual i, or, in other words, the average treatment effect on the treated (ATT) as follows:

$$\tau_{ATT} = E(\tau \mid T = 1) = E[Y(1) \mid T = 1) - E[Y(0) \mid T = 1) \tag{2}$$

Our aim here is to identify and consistently estimate the ATT defined in equation (2). In order to identify the equation (2), two assumptions are required to hold (Rosenbaum and Rubin 1983). They are conditional independence assumption (CIA) and overlap or common support condition. In this paper, the CIA assumption implies for a given set of observable covariates X which are not affected by treatment (ICS user), potential outcomes are independent of ICS user. The overlap condition implies that persons with the same X values have a positive probability of being both participants and non-participants (Heckman, Lalonde and Smith 1999). Given the CIA and overlap condition hold and $p(x)$ is known, the ATT is identifiable and the PSM estimator for the ATT can be written as:

$$\tau_{ATT}^{PSM} = E_{p(x)|D=1}\left\{E[Y(1) \mid T = 1, p(x)] - E[Y(0) \mid T = 0, p(x)]\right\} \tag{3}$$

Matching Method(s) and Selection of Covariates

Various matching methods have been proposed in the literature to estimate the equation 3 (Becker and Ichino 2002). We use three matching methods, namely a nearest-neighbour, caliper, and kernel matching, to estimate the ATT and examine the robustness of the results.[7] The consistency and/or robustness of ATT estimation depends on whether the covariates included in the propensity score estimation satisfy two conditions (Caliendo and Kopeinig 2008). They are (i) the covariates

[7]Caliendo and Kopeinig (2008) discuss the details of these methods.

satisfy conditional independence assumption (CIA) and (ii) the covariates affect both the decision to opt in the programme/treatment and the outcome variable(s). We include maximum education level achieved by a male member of a household; household head's age, gender, education, and self-employment status; household with the brick-built house; household with improved toilet and improved water facilities; per capita income; own land; and assets as covariates. It is less likely that these variables would be affected by the adoption of ICS and is highly likely that they will affect the adoption of ICS, which we will discuss using the probit model later in this paper.

After conducting the matching between those in the control and treatment groups using the three matching methods, we examine i) common support condition required to define the estimates of ATT,[8] ii) the balancing test of covariates across treatment and comparison groups, and iii) the sensitivity of ATT matching estimates by departing from CIA assumption. If there are unobserved variables which affect assignment into treatment and the outcome variables simultaneously, a "hidden bias" might arise (Rosenbaum 2002).

3.2 Data

One of the main objectives of the project titled "Market Development Initiative for Bondhu Chula" (noted in section II) was to expand the use of *Bondhu Chula* in all parts of Bangladesh and thereby reduce biomass fuel consumption and indoor air pollution. This project, supported by GIZ, compiled a list of *Bondhu Chula* users which was used by Bangladesh Institute of Development Studies (BIDS) for a household survey in 2018 under our supervision. This study uses 2018 BIDS household survey data to provide an analysis of the benefits of ICS relating to key socio-economic variables such as energy use, cooking time, and health.[9] The sampling was drawn to understand the effects of ICS which are due to market development initiative for ICS. A multi-stage purposive sampling approach was undertaken to design the sampling frame. In stage one, we select 11 districts in a way so that it covers all divisions of the country to account for geographical variations. In stage two, we randomly selected 31 *upazilas* from the list provided by GIZ. From each Upazila, we randomly selected one treatment and one control villages. From each treatment village, a range of 15 to 20 *Bondhu Chula* user

[8]To avoid evaluation bias, only the subset of the comparison group that is comparable to the treatment group should be used in the analysis (Dehejia and Wahba 1999).
[9]The distribution of sample has been shown in Table A.1 in appendix.

households were selected randomly. From these treatment villages, we also randomly selected a range of 3 to 4 households who use traditional *chula* (control). A range of 8 to 11 control households (households with traditional chula) were selected from each control village. The treated sample had 600 households, while the control sample had 396 households.

Though different types of ICSs (developed by different organisations) are available in different areas of Bangladesh, *Bondhu Chula* has the highest coverage throughout the country. Therefore, the present study represents more broad-based data source. We did not compare performance of *Bondhu Chula* with the performance of other available ICSs, as the purpose of this study is to enquire the impact of ICS methodologically and empirically and for that we have covered the variety of ICS which has country-wide coverage and that variety is *Bondhu Chula*.

3.3 Variables and Descriptive Analysis

Table I presents descriptive statistics of the variables used in the propensity score estimation. Outcome variables used in the PSM estimation are (1) per capita biomass energy consumption (kg/month), (2) rice cooking time (minutes/per meal per capita), (3) women's eye irritation (number of times/month), and (4) women's respiratory problem (number of times/month). The treatment variable is a dichotomous variable that takes the value 1 if a household uses *Bondhu Chula* and 0 if a household uses a traditional cook stove. Columns 1a and 2a present means for the households with *Bondhu Chula* and for those with traditional cookstoves, respectively, whereas columns 1b and 2b show the corresponding standard deviations for both groups of households. Column 3 reports the statistical differences of the variables between households with *Bondhu Chula* and households with traditional cook stoves.

The descriptive statistics reveals that there exist significant differences between household groups for most of the matching variables, as indicated by the results of column (3) in Table I. For example, the mean of the household head education, per capita income, and total own land is significantly higher for households with *Bondhu Chula* as compared to households with traditional cook stoves. This means households with traditional cook stoves are not a proper comparison group and are not exactly comparable to the households with *Bondhu Chula*. Thus, we cannot make any causal statement on the differences of the outcome variables, as evident in panel A of Table I, i.e., whether these differences due to the adoption of *Bondhu Chula*. Thus, there is a scope for the use of propensity score matching to make the households with ICS and traditional cook stoves sample comparable and to establish the causal association between outcome variables (e.g., per capita biomass energy consumption or per capita rice cooking time) and the adoption of *Bondhu Chula*.

TABLE I

DESCRIPTIVE STATISTICS

	Households with *Bondhu Chula*		Households with traditional cook stoves		
	(1a)	(1b)	(2a)	(2b)	(3)
	mean	Standard Deviation (SD)	mean	Standard Deviation (SD)	Mean Difference
Panel A: Outcome variables					
Per capita biomass energy use (kg/month)	32.75	7.83	43.08	13.73	10.334***
Per capita rice cooking time (minutes)	6.67	2.73	8.07	3.41	-1.406***
Women eye irritation (number/month)	0.10	0.72	5.64	7.35	-5.54***
Women respiratory problem (number/month)	0.09	0.49	1.45	3.78	-1.37***
Panel B: Explanatory or matching variables					
Household head age (years)	44.93	12.45	44.55	11.82	-0.382
Household head gender (1=male)	0.94	0.24	0.94	0.23	0.00800
Maximum education level (years) by a male member	9.67	4.63	7.44	4.23	-2.228***
Household head education (years)	7.70	5.10	5.09	4.61	-2.610***
Household head self-employed (1=yes)	0.15	0.36	0.18	0.39	0.0300
House with brick (1=yes)	0.70	0.46	0.44	0.50	-0.265***
House with improved toilet (1=yes)	0.59	0.49	0.32	0.47	-0.268***
Household with improved water (1=yes)	0.52	0.50	0.55	0.50	0.0360
Per capita income	3991.53	1643.32	3166.92	1274.43	-824.615***
Own land (decimals)	41.87	59.19	19.03	27.39	-22.842***
Log of own land	2.78	1.51	2.29	1.17	-0.486***
Log of assets	11.36	1.20	10.87	1.07	-0.491***
N	600		396		

Note: *** denotes significant at the 1% level of alpha.

We provide further details on the nature of biomass energy consumption because the main focus of this paper is to measure the causal impact of ICS use on biomass energy consumption. The nature of the biomass energy use by fuel type in households with ICS and traditional cook stoves can be observed from Table II. About 90 per cent households depend on fuelwood for their energy need for cooking, whether they use ICS or not. Other fuels used by both groups of households include tree leaves, hay or jute cake, dung (mainly cow-dung) and wooden powder. Except for cow dung, the energy consumption is much less among households using *Bondhu Chula* compared to the households using traditional cook stoves. This indicates the efficiency of an ICS in terms of fuel need. The efficiency of ICS in fuel use is also observed by comparing the energy use of households before and after the installation of ICS (Table III). The statistics in Table III shows that energy use significantly dropped after the installation of

ICS. This is observed for all types of fuel used by ICS users. From these results, we conclude that the use of ICS significantly lowers the biomass energy consumption, which we show methodologically later in this paper. We can also infer that this reduction of energy use significantly reduces air pollution and deforestation because 91 per cent of the sampled households use fuelwood for the purpose of cooking and the sources of fuelwood are mainly trees.

TABLE II
AVERAGE ENERGY CONSUMPTION FOR COOKING PER HOUSEHOLD (HH) BY TYPES OF FUEL

Fuel type	HHs with ICS (*Bondhu Chula*)		HHs with traditional cook stoves	
	% of HH consume	Energy consumption (kg/month)	% of HH consume	Energy consumption (kg/month)
Fuel wood	91	149.27	85	194.27
Tree leaves	12	49.75	29	75.77
Hay/jute cake	7	42.49	11	137.93
Dung	6	120.27	12	119.92
Wooden powder	3	37.00	2	77.50

TABLE III
AVERAGE ENERGY CONSUMPTION PER HOUSEHOLD (HH WITH ICS) BY TYPES OF FUEL

Fuel type	Before the use of ICS (kg/month)	After the use of ICS (kg/month)
Fuelwood	185.48	149.27
Tree leaves	76.09	49.75
Hay/jute cake	52.87	42.49
Dung	149.86	120.27
Wooden powder	54.00	37.00

Note: The data on use of fuel before installing "*Bondhu Chula*" have been collected by applying recall method on the respondents.

IV. RESULTS AND DISCUSSIONS

4.1 Propensity Score Estimation

We estimate the PSM using a probit model. Our goal in this paper is not to explain the adoption of ICS using relevant socioeconomic variables rather estimate propensity scores both for treatment and control households. Thus, we briefly discuss the coefficients obtained from the probit model. Table IV shows the individual coefficients of the model. The results show that household head gender and education, employment status, household with brick and improved toilet, per capita income, and own land significantly affect the adoption of ICS. Based on the sign of these coefficients, we find that i) a female-headed household is likely to buy an ICS, ii) a household with brick and improved toilet is a sign of wealthy household and, therefore, positively affect the adoption of ICS, and iii) as expected, an increase in per capita income and total own land raises the chance of using an ICS.

TABLE IV

PROBIT ESTIMATES OF THE DETERMINANTS OF ICS ADOPTION (1=YES)

Explanatory variables	Coefficient	Standard error
	(1)	(2)
Household head age (years)	0.003	(0.005)
Household head gender (1=male)	-0.235^{+}	(0.141)
Maximum education level (years) by a male member	0.011	(0.013)
Household head education (years)	0.039**	(0.010)
Household head self-employed (1=yes)	-0.159	(0.148)
House with brick (1=yes)	0.409**	(0.130)
House with improved toilet (1=yes)	0.330**	(0.117)
Household with improved water supplies (1=yes)	-0.053	(0.081)
Log (per capita income)	0.596**	(0.098)
Log (own land (decimals))	0.117**	(0.045)
Log (asset)	0.059	(0.057)
N	996	
Wald chi-square	221.51	
p-value	0.000	
MaFadden's Pseudo R-square	0.165	

Note: Standard errors are in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Overlap Condition/Common Support

Now, using the estimated propensity score, we check whether our data satisfy the overlap condition. The overlap condition ensures that each individual could receive any treatment level. Figure 1 shows the estimated density of the predicted probabilities that a household with traditional cook stoves owns a traditional stove and the estimated density of the predicted probabilities that a household with *Bondhu Chula* owns a traditional stove. The plots show that the two estimated densities mostly overlap each other and there is not too much probability frequency near 0 or 1.[10] Thus, we can conclude that there is not enough evidence that the overlap assumption is violated. Figure 2 also confirms this finding even after imposing common support restriction.

Figure 1: **Testing Overlap Condition**

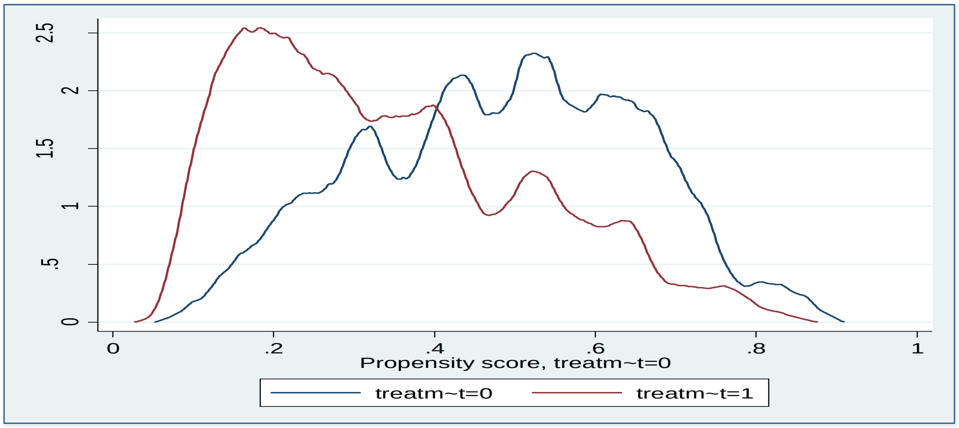
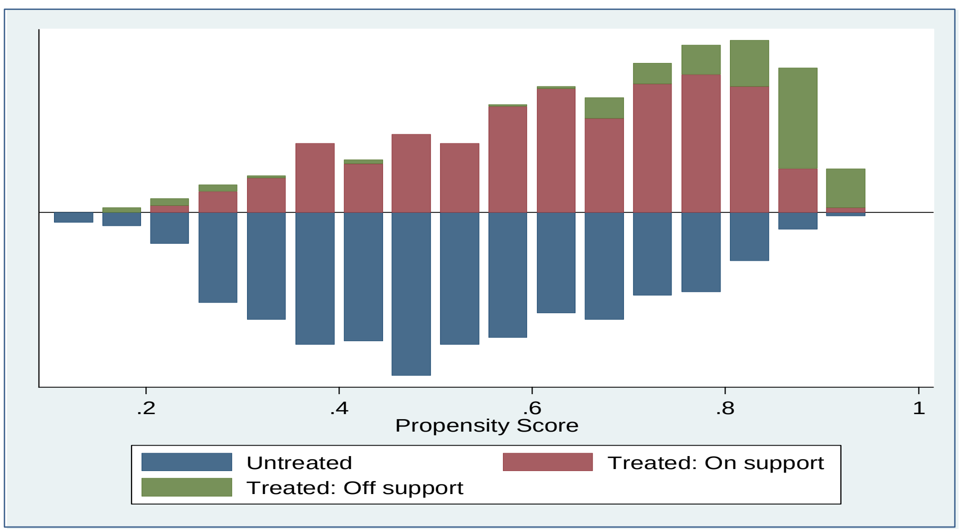


Figure 2: **Testing Overlap with Common Support Restriction**

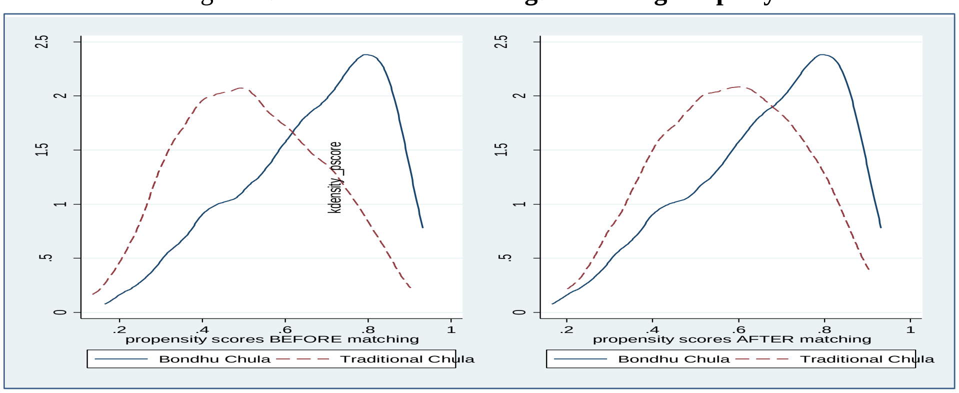


[10]The overlap assumption is violated when an estimated density has too much mass around 0 or 1 (Busso, DiNardo and McCrary 2011).

Balancing Test

Our estimates of ATT would be biased if there are differences in covariates or distribution of covariates is imbalanced between ICS and traditional cook stove using households even after a matching method is applied. To check the matching quality, we conduct several balancing tests. First, we show a simple graphical presentation of the distribution of propensity score before and after the matching. Figure 3 depicts the distribution of pre- and post-matching propensity scores for both households with traditional and *Bondhu Chula*. From Figure 3, we see that the differences between households with *Bondhu Chula* and households with traditional cook stoves have shrunk after the matching, which is indicated by a closer match of the distribution. This means the distribution of propensity score is more balanced, indicating that the application of PSM has potential gain in terms of removing selection bias compared to other regression methods. Second, to confirm this visual inspection, we perform four statistical balancing tests following the literature Caliendo and Kopeinig (2008). They are: (i) a two-sample t-test to check if there are significant differences in covariate means for both treatment and control groups (Rosenbaum and Rubin 1985), (ii) an assessment of standardized bias of the marginal distribution of covariates as suggested by Rosenbaum and Rubin (1985), (iii) comparison of pseudo-R^2 before and after matching (Sianesi 2004), and (iv) a likelihood ratio test on the joint significance of all covariates in the probit model.

Figure 3: **Estimates of Matching: Balancing Property**



Tables V and VI show the results of the balancing test obtained using several statistical measures. As we can see in Table V, the difference between the treatment and control groups has shrunken significantly once we match participants by replacing the hypothetically control group (HHs with traditional cookstoves) from the control area. The results in tables show that the covariates are well balanced because after the matching there are no significant differences in covariates between a household with ICS and a household with traditional stove, which was not the case before the matching (column 1 in Table V). After matching the standardized bias (SB) difference, as shown in Table VI, is about 5, which is well below 20, indicating that the distribution of covariates is well balanced.[11] Other balancing tests such as the very low pseudo-R^2 and LR chi^2 (joint significance of all covariates) as well as the acceptable value of Rubin's B and Rubin's R indicates proper balancing.[12] To summarise, all the tests, as shown in Tables V and VI, pass the post matching balancing test, indicating that the households with traditional cookstoves are well comparable to the ICS user households and thus our counterfactual estimates of the causal impact of the ICS use would well replicate the experimental method.

TABLE V

BALANCING BETWEEN HHS WITH BONDHU CHULA AND TRADITIONAL COOK STOVE-MEASURES OF THE EXTENT OF BALANCING OF THE VARIABLES

	Difference between HHs with *Bondhu Chula* and traditional cook stoves: before matching	Difference between HHs with *Bondhu Chula* and traditional cook stoves: after matching[a]	% bias after matching
	(1)	(2)	(3)
Household head age (years)	-0.382	0.960	7.90
Household head gender (1=male)	0.008	0.000	0.00
Maximum education level (years) by a male member	-2.228**	-0.159	-3.60
Household head education (years)	-2.610**	-0.495	-10.20
Household head self-employed (1=yes)	0.030	-0.015	-4.00
Household with brick (1=yes)	-0.265**	0.008	1.80
Household with improved toilet (1=yes)	-0.268**	0.023	4.80
Household with improved water (1=yes)	0.036	0.038	7.60
Log (per capita income)	-0.226**	-0.006	-1.50
Log (own land (decimals))	-0.486**	0.002	0.10
Log (asset)	-0.491**	0.117^{+}	10.30

Note: Matched samples are constructed using nearest neighbour with replacement and common support. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. [a]The matching process drops 125 treated observations which fall off-support region.

[11] Rosenbaum and Rubin (1985) suggest that a standardized difference of 20 or more should be viewed as large.

[12] For the sample to be considered sufficiently balanced, Rubin (2001) recommends that B should be less than 25 and R should be between 0.5 and 2.

TABLE VI

BALANCING TEST: OVERALL MEASURES OF COVARIATE IMBALANCE

Sample	Pseudo R^2	LR chi^2	$p>chi^2$	Mean Standardized Bias	Median Standardized Bias	Rubin's B	Rubin's R
Unmatched	0.114	152.61	0.00	33.5	43.2	84.5*	1.19
Matched	0.008	10.07	0.524	4.7	4.0	20.7	1.32

Note: * if B>25%, R outside [0.5; 2].

4.2 The Causal Impact of ICS Use or the Estimates of ATT

Table VII reports the estimates of ATT obtained using NN, caliper, and kernel matching. Columns 1 and 2 show ATT estimates obtained using NN 1-to-1 and 1-to-5 matching with replacement, whereas columns 3 and 4 show caliper matching with distance (d) equals 0.01 and 0.001, respectively. Columns 5, 6 and 7 show kernel matching with bandwidth (*bw*) of 0.06, 0.1 and 0.2, respectively.[13] As mentioned in section 3.1, we choose different matching methods to check the robustness of our ATT estimates. Within each matching method, we also vary caliper distance and bandwidth relating to the range of propensity score. A lower value of caliper distance means more similar values of covariates. A smaller *bw* lowers the bias and increases the variance of the estimates, as compared to large *bw*.

We now start our discussion by describing the impact of ICS on biomass energy consumption. The estimated results show that the impact of ICS use on household biomass energy is significant and is evident in all matching methods (Table VII). The impact is highest under kernel matching with *bw*=0.06 and lowest under caliper matching with d=0.001. From the table, we find that the use of ICS reduces the per capita biomass fuel consumption on average, with a range of 9.75 kg to 12.25 kg per month. In terms of percentage reduction, this is about 30-37 per cent compared to the amount of biomass fuel used by traditional cook stoves. The laboratory test, as conducted in Bangladesh by BCSIR, claims that ICS saves 50 per cent fuel compared to traditional cook stoves.[14] The difference between claimed fuel reduction and empirically obtained reduction is perhaps due to varying cooking habit practiced by the surveyed households.

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[13]Following Caliendo and Kopeinig (2008), we choose both small and large values of caliper and bandwidth.

[14] https://bondhufoundation.org/campaigns/bondhu-chula-new/ (accessed on 25 February, 2019).

We next turn our discussion to the impact of ICS on health outcomes. It is very common that women in Bangladesh are responsible for cooking and thus they are mostly affected by indoor air pollution, which is likely to affect the health outcomes related to indoor air pollution. Household air pollution (emission of particulate matter and carbon monoxide) caused from cooking with biomass fuel has negative impacts on health (WHO 2009). Smith (2000), Smith *et al.* (2007), Smith and Peel (2010), and Yu (2011) show the association between exposure to particles (caused from burning fuelwood) and respiratory diseases such as pneumonia or asthma. In this respect, the ICS users were asked whether the use of ICS reduces indoor air pollution. About 99 per cent households reported that the use of ICS reduces indoor air pollution. Thus, it is likely that the frequency of health problems associated with air pollution will reduce in the households with ICS. The estimated results also show that the use of ICS significantly reduces the air pollution-related health problems of women (Table VII). The health outcomes in this paper are self-reported and measured in terms of number of eye irritation and number of respiratory problems a woman suffers per month. For both eye related and respiratory problems, all models show significant negative effects (i.e., health improving effects). From the table, we find that women with ICS have on average 5.55-6.66 times lower eye irritation compared to the women who use traditional stoves and the same women have on average 0.90-1.28 times lower respiratory problems (cough, asthma, breathing difficulties) relative to women who cook using traditional stoves. Overall, our findings suggest that positive and significant health improving outcomes are associated with the use of ICS.

The use of ICS is likely to affect the time allocations of women who are involved in cooking through two channels: first, ICS may have an effect on the cooking duration by speeding up the cooking process and second, a reduction of fuel consumption may imply time savings in obtaining the fuel, be it in terms of collecting or buying it (Bensch *et al*. 2013). In case ICS has triggered time savings, households may then reallocate the freed-up time to other activities in a second-round effect (Wodon and Blackden 2006). The results in Table VII show that the use of ICS reduces the household cooking time and this is evident in all models. This means the ICS affects the time savings of women through the first channel, i.e., speeds up the cooking process by efficiently using the fuel and therefore cooking time reduces. Thus, women have more time to do some other activities. Our results in the table also show the effect of the second channel on time savings.

We can see from the table that the use of ICS reduces the biomass fuel consumption and, therefore, the fuel collection times reduces.[15]

TABLE VII

IMPACTS OF *BONDHU CHULA* ON ENERGY USE, HEALTH OUTCOMES, AND COOKING TIME: ESTIMATED USING PSM METHODS

Outcome variables		(1) Nearest neighbor	(2) Nearest neighbor	(3) Caliper	(4) Caliper	(5) Kernel	(6) Kernel	(7) Kernel
		(NN1)	(NN5)	d=0.01	d=0.001	bw=0.06	bw=0.1	bw=0.2
Per capita energy consumption(kg/ month)	ATT	-10.964	-12.149	-10.705	-9.740	-12.241	-11.659	-11.012
	SE	1.405	1.190	1.353	1.253	1.080	0.969	0.849
Women eye irritation (number/month)	ATT	-6.570	-5.838	-6.665	-6.320	-5.575	-5.573	-5.568
	SE	0.776	0.621	0.745	0.665	0.553	0.489	0.422
Women respiratory problem (number/month)	ATT	-0.908	-1.180	-0.950	-1.289	-1.215	-1.228	-1.245
	SE	0.369	0.318	0.354	0.339	0.285	0.252	0.218
Rice cooking time (minute per capita)	ATT	-1.678	-1.583	-1.703	-1.623	-1.484	-1.464	-1.512
	SE	0.409	0.302	0.395	0.388	0.282	0.256	0.226

Note: 1. ATT is average treatment effects on the treated, that is, the average effects of *Bondhu Chula* compared to traditional cook stoves, SE is standard error. 2. Upazila fixed effects have been controlled for in all matching estimates. In all matching methods, we improve the quality of the matching by imposing the common support restriction.

Estimates of Biomass Fuel Savings at the National Level

Using the household level reduction of biomass fuel consumption resulted by the use of ICS, we calculate aggregate reduction due to GIZ ICS programme as well as reduction at the national level. From the estimates of Table VII, we find that the use of ICS saves about 11 kg biomass fuel consumption per member per month, which is about 600 kg per household per year. As of 2018, the GIZ improved cook stoves component has facilitated access and the sales of about 2.6 million stoves, reaching more than 5.4 million people. This means that at the aggregate level, the intervention of GIZ saves about 1.54 million tons per year, which is about 2.6 per cent of national fuelwood consumption. Bangladesh has a great market potential for ICS, estimated at more than 29 million households. With 67 per cent of households using more than one stove, this could increase the total

[15] From the data, we find that households with ICS spend about 200 minutes' lower time in collecting fuel wood compared to households with traditional cook stoves, mainly due to the reduction of biomass energy caused from ICS use.

number of stoves to over 50 million.[16] Taking this potential market into account, we calculate that potential fuelwood consumption saving is about 30 million tons per year, which is about 51 per cent of the country's total fuelwood consumption. When converting this biomass fuel saving into the potential reduction of carbon dioxide emission, we obtain that the use of ICS would potentially reduce 50.49 million tons of carbon dioxide emission per year nationally.

4.3 Robustness Check

As we mentioned earlier, the PSM estimation is based on CIA, i.e., unconfoundness or selection on observable assumptions. Any deviation of from this assumption may lead to bias treatment effects estimates. For example, if a household is aware of the waste of fuelwood, it can affect the ownership and use pattern of *Bondhu Chula* as well as the outcome variable biomass consumption. This violates the assumption that potential outcomes are independent of our treatment status. Unfortunately, we cannot statistically test this violation or magnitude of selection bias with non-experimental data. But what we can do is to check the sensitivity of the estimates of causal impact by relaxing the unconfoundness assumption. For this, we use Rosenbaum (2002) bound test and Ichino, Mealli and Nannicini (2008) simulation-based sensitivity test. Rosenbaum (2002) bound test measures to what extent the estimates of ATT changes if unobserved variables that affect treatment and the outcome variables simultaneously, i.e., a hidden bias arise. Ichino, Mealli, and Nannicini (2008) simulation-based sensitivity test simulates a potential confounder to assess the robustness of the estimated ATT with respect to deviations from the CIA.

Table VIII shows the sensitivity of the estimates of ATT obtained using Rosenbaum (2002) bound test. If gamma (Γ) equals one, there is no hidden bias. We increase the value of gamma by 0.2 to see at what values of gamma the statistical significance of the estimates of ATT turn out to be insignificant. The results in Table VIII show that the estimates of ATT for both health outcomes are insensitive to selection bias arises from unobserved variables. These are evident for all level of gamma values (up to 5). The estimates of ATT for per capita biomass energy use turns out to be insignificant for gamma equals 4.8. The gamma value in this case for per capita rice cooking time is 2.4. The results suggest that

[16]Source: *2013 Country Action Plan for Clean Cookstoves*, Power Division, Ministry of Power, Energy and Mineral Resources, Government of the People's Republic of Bangladesh. http://www.sreda.gov.bd/d3pbs_uploads/files/policy_5_cap_final.pdf

the estimates of ATT are insensitive to biases caused by unobservable factors which would cause the odds ratio of treatment assignment to differ between treatment and control cases by a factor of about 4.8 and 2.4 for biomass energy use and rice cooking time, respectively. Overall, we can conclude that the results are in general not sensitive to bias due to unobservable.

TABLE VIII

ROSENBAUM BOUND SENSITIVITY ANALYSIS TEST FOR HIDDEN BIAS

Gamma (Γ)	*p*-critical			
	Per capita energy use	Women eye irritation (number per month)	Women respiratory problem (number/month)	Per capita rice cooking time
1	0.0000	0.0000	0.0000	0.0000
1.2	0.0000	0.0000	0.0000	0.0000
1.4	0.0000	0.0000	0.0000	0.0000
1.6	0.0000	0.0000	0.0000	0.0000
1.8	0.0000	0.0000	0.0000	0.0003
2	0.0000	0.0000	0.0000	0.0062
2.2	0.0000	0.0000	0.0000	0.0516
2.4	0.0000	0.0000	0.0000	0.2006
2.6	0.0000	0.0000	0.0000	0.4544
2.8	0.0000	0.0000	0.0000	0.7111
3	0.0002	0.0000	0.0000	0.8814
3.2	0.0006	0.0000	0.0000	0.9615
3.4	0.0018	0.0000	0.0000	0.9899
3.6	0.0046	0.0000	0.0000	0.9978
3.8	0.0103	0.0000	0.0000	0.9996
4	0.0205	0.0000	0.0000	0.9999
4.2	0.0370	0.0000	0.0001	1.0000
4.4	0.0616	0.0000	0.0002	1.0000
4.6	0.0954	0.0000	0.0003	1.0000
4.8	0.1388	0.0000	0.0004	1.0000
5	0.1914	0.0000	0.0007	1.0000

Tables A.2-A.5 in the appendix show the sensitivity of the estimates of ATT obtained using Ichino, Mealli, and Nannicini (2008) simulation-based sensitivity test. In this test, we simulate an unobservable covariate U that affects both our outcome variables and the selection into treatment and then we see to what extent the estimates of ATT vary due to U after adding as a covariate in matching estimates. We simulate different values of U in a way so that its association with the outcome and the treatment varies from low to high. The results in Tables A.2-

A.5 show that for all values of the association between U and outcome variables and treatment, the estimates of ATT effect are always negative and closer to the baseline estimate.[17] Hence, we can conclude that the results are robust to the presence of potentially omitted variables.

V. CONCLUSIONS

Using the 2018 BIDS household survey data and employing PSM methods, this study estimates the causal impact of an ICS named *Bondhu Chula* on household biomass consumption, cooking time, and women's health outcomes in Rural Bangladesh. To the best of our knowledge, this is the first study that estimates the causal impact of *Bondhu Chula* by applying PSM methods in a non-experimental data. The PSM is a quasi-experimental impact evaluation method and makes an attempt to replicate the experimental setting.

Based on the PSM methods, we find that on average ICS using households save 30-37 per cent (about 50 kg per month or 600 kg per year) of biomass fuel per cook stove if compared to households using traditional cook stoves with this difference being statistically significant. We also obtain that at the aggregate level, the intervention of GIZ saves about 1.54 million tons fuelwood consumption annually and the future potential market for ICS in Bangladesh would save about 30 million tons fuelwood consumption per year, which is about 51 per cent of the country's total fuelwood consumption. This would potentially reduce 50.49 million tons of carbon dioxide emission per year nationally. We also find that the use of *Bondhu Chula* reduces household cooking time and improves women's health condition. A reduction in the cooking time means women can enjoy more leisure time or allocate their time to some other productive activities.

The findings of this study have several important implications. First, the use of ICS would help in preserving trees and forests as well as in reducing CO_2 emissions that contribute to addressing global climate change concerns (Sustainable Development Goal (SDG) 13: Climate Action).[18] Second, an

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[17]We assume positive association between U and outcome variables and treatment so that s>0 and d>0. If s>0, then U has a positive effect on T and if d>0, U has a positive effect on Y. A relevant omitted variable or U is efficiency in fuel use which affects the adoption of ICS positively and use of energy negatively. Or, the awareness about smoking problems that affects the adoption of ICS positively and health outcomes negatively.

[18] More about SDGs could be found at https://www.un.org/sustainabledevelopment/sustainable-development-goals/ (accessed on 10 May 2019).

improvement of women's health outcome resulted from the lower indoor air pollution means an improved work environment in the kitchen, indicating that the use of ICS contributes to progress towards achieving SDG 8 (Decent Work and Economic Growth).[19] Third, as the use of ICS reduces time spent on cooking and firewood collections, the household members can use more time on leisure and income generating activities and thereby improve household welfare. Despite the abovementioned benefits of the use of ICS, the progress towards the adoption of ICS across the country is not satisfactory and there is a large opportunity to scale-up the use of ICS. Thus, the analysis and findings of our study would contribute to motivating policymakers to promote ICS throughout the country. The reduction of solid fuel use through some targeted interventions in developing countries provides opportunities for both reducing climate-warming emissions and improving the health situation (Kumar and Viswanathan 2011).

Our analysis of the impact of *Bondhu Chula* on household biomass energy consumption, health outcomes, and cooking time has some limitations. One primary limitation of the use of PSM is that it accounts for only the observed covariates. Unobservable variables such as the efficiency in fuel use or cooking habit or awareness about air pollution related problems might be correlated with both ownership of an ICS and our outcomes of interest and thus can affect our estimates of ATT. The second limitation is that the adoption of *Bondhu Chula* is nonrandom, i.e., a person can opt in *Bondhu Chula* programme if he or she wishes to and so there is an endogeneity problem, which may bias our results. Another limitation is that our study had access to post ICS programme data collected in 2018, whereas the GIZ ICS project activities occurred between 2012 and 2014. This means there is a possibility that our outcomes of interest variables (e.g., health outcome) may have been affected by some other factors such as precautionary measure taken by households or women's age or women's food habit/intake that protect them from the respiratory diseases. Taking account of these issues, perhaps, would minimize the bias associated with estimating the causal impact of *Bondhu Chula* on our outcomes of interest. However, our study has set an important example of how a quasi-experimental model like PSM can be utilised in assessing the impacts of ICS. Future research may address the limitations of our study while estimating the causal impacts of *Bondhu Chula* on household biomass energy use, cooking time, and health outcomes.

[19]More about SDGs could be found at https://www.un.org/sustainabledevelopment/sustainable-development-goals/ (accessed on 10 May 2019).

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APPENDIX

TABLE A.1

SAMPLE DISTRIBUTION BY DISTRICT

District	HH with *Bondhu Chula*	HH with traditional chula
Bandarban	60	40
Barishal	20	13
Narsingdi	60	36
Dinajpur	60	40
Habiganj	60	40
Mymensingh	60	40
Chattogram	60	40
Patuakhali	40	27
Rajshahi	60	40
Satkhira	60	40
Tangail	60	40
Total	600	396

TABLE A.2

SENSITIVITY ANALYSIS FOR PER CAPITA ENERGY CONSUMPTION: EFFECT OF CALIBRATED CONFOUNDERS U

	No confounder	Neutral confounder	s=0.05	s=0.15	s=0.25	s=0.35
	-12.20	-13.02				
SE	0.00	0.89				
Outcome effect		1.03				
Selection effect		1.02				
d=0.1			-13.14	-13.18	-13.36	-13.66
SE			1.02	1.19	1.33	1.60
Outcome effect			1.65	1.70	1.73	1.81
Selection effect			1.24	1.92	3.01	4.68
			s=0.13	s=0.23	s=0.33	s=0.43
d=0.2			-13.26	-13.65	-13.83	-14.22
SE			1.13	1.23	1.37	1.66
Outcome effect			2.95	3.02	3.15	3.35
Selection effect			1.77	2.69	4.30	7.10
			s=0.05	s=0.16	s=0.26	s=0.36
d=0.5			-13.39	-13.92	-14.55	-15.13
SE			0.87	1.06	1.15	1.31
Outcome effect			14.34	14.19	14.95	15.02
Selection effect			1.22	2.06	3.67	7.66

Note: d and s are two parameters depending on which we obtain several possible effects on outcome and the effects on selection into treatment, respectively.

TABLE A.3

SENSITIVITY ANALYSIS FOR WOMEN'S EYE IRRITATION: EFFECT OF CALIBRATED CONFOUNDERS U

	No confounder	Neutral confounder	s=0.07	s=0.17	s=0.27	s=0.37
	-6.47	-5.79				
SE	0.00	0.50				
Outcome effect		1.04				
Selection effect		1.02				
d=0.1			-5.67	-5.58	-5.64	-5.76
SE			0.52	0.54	0.68	0.78
Outcome effect			1.70	1.73	1.76	1.86
Selection effect			1.36	2.07	3.24	5.21
			s=0.16	s=0.26	s=0.36	s=0.46
d=0.2			-5.77	-5.98	-6.11	-6.27
SE			0.64	0.77	0.85	0.98
Outcome effect			3.01	3.05	3.34	3.73
Selection effect			2.06	3.22	5.22	8.67
			s=0.13	s=0.23	s=0.33	s=0.43
d=0.5			-6.16	-6.45	-6.73	-6.87
SE			0.64	0.70	0.76	0.84
Outcome effect			16.63	15.94	15.61	16.79
Selection effect			1.82	3.13	5.64	12.44

TABLE A.4

SENSITIVITY ANALYSIS FOR WOMEN'S RESPIRATORY DISEASES: EFFECT OF CALIBRATED CONFOUNDERS U

	No confounder	No confounder	s=0.08	s=0.18	s=0.28	s=0.35
	-0.87	-1.11				
SE	0.00	0.18				
Outcome effect		1.03				
Selection effect		1.02				
d=0.1			-1.14	-1.17	-1.19	-1.25
SE			0.21	0.23	0.28	0.35
Outcome effect			1.68	1.66	1.72	1.75
Selection effect			1.42	2.20	3.41	5.52
			s=0.19	s=0.29	s=0.39	s=0.43
d=0.2			-1.22	-1.29	-1.35	-1.47
SE			0.25	0.36	0.31	0.47
Outcome effect			2.82	2.88	3.10	3.30
Selection effect			2.28	3.53	5.71	9.71
			s=0.18	s=0.28	s=0.38	s=0.48
d=0.5			-1.32	-1.46	-1.62	-1.62
SE			0.23	0.25	0.30	0.30
Outcome effect			13.87	13.56	13.67	13.57
Selection effect			2.30	3.92	6.97	6.91

TABLE A.5

SENSITIVITY ANALYSIS FOR PER CAPITA RICE COOKING TIME: EFFECT OF CALIBRATED CONFOUNDERS U

	No confounder	Neutral confounder	s=0.06	s=0.16	s=0.26	s=0.36
	-1.71	-1.59				
SE	0.00	0.19				
Outcome effect		1.04				
Selection effect		1.02				
d=0.1				-1.58	-1.64	-1.68
SE				0.24	0.27	0.34
Outcome effect			1.70		1.73	1.80
Selection effect			1.30	1.99	3.09	4.94
			s=0.15	s=0.25	s=0.35	s=0.45
d=0.2			-1.65	-1.72	-1.84	-1.89
SE			0.23	0.25	0.31	0.35
Outcome effect			2.88	2.95	3.15	3.41
Selection effect			1.89	2.98	4.69	7.87
			s=0.09	s=0.19	s=0.29	s=0.39
d=0.5			-1.70	-1.90	-2.09	-2.19
SE			0.20	0.23	0.26	0.28
Outcome effect			14.43	14.08	14.32	14.66
Selection effect			1.50	2.54	4.52	9.55