Does the Adoption of Solid Cooking Fuel Contribute to Adverse Child Health Outcomes? A Propensity Score Matched (PSM) Analysis from Bangladesh Demographic and Health Survey, 2011-2018

by

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A thesis submitted to the Department of Economics and Social Science in partial fulfillment of the requirements for the degree of
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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. I/We have acknowledged all main sources of help.

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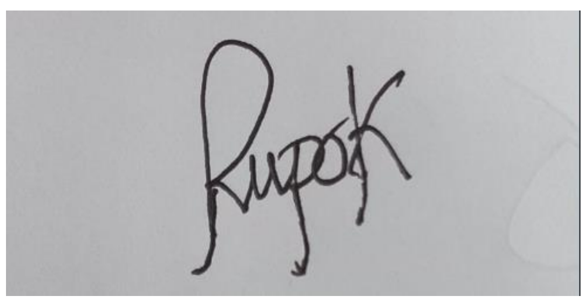

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Approval

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Ethics Statement

There is no potential ethical conflict while submitting this paper. The author has taken full consent and agree with the policy of Demographic Health Survey, while accessing their data from there data.

Abstract

Low birth weight and severe respiratory infections in children are just two of the acknowledged negative health impacts of household air pollution caused by the use of solid fuels for cooking, which is still a serious public health concern in underdeveloped nations. Using data from Bangladesh demographic and health census 2011-2018, the paper evaluates the effects of dirty fuels on health. The application of propensity score-matching method by year unadjusted and later unbiased year adjusted estimation with average treatment effect on the treated (ATT) shows that dirty fuel households have a 37.8% greater incidence of stunting than clean fuel households and no link with having ARI with solid fuel use, which is biased result for unadjusted matching. However, this ATT estimate after year-specific match shows 33-35% rise of malnutrition and 2.8 to 5.6% increase in respiratory illness because of solid fuel adoption. Due to the shortcomings of this study, more research is needed to better devise strategies to discourage households from using solid cooking fuel and encourage the use of more affordable, healthier alternatives.

Keywords: Bangladesh; Stunting; Acute Respiratory Infections; Solid Fuel; Propensity Score Matching; Average Treatment Effect on the Treated

Dedication

My dear parents have always been there for me, and I want to thank them for that by dedicating this thesis to them.

Acknowledgement

I would want to begin by thanking the Almighty, for granting me the strength and wisdom to write this thesis.

I would like to convey my unending gratitude to my esteemed thesis supervisor, Dr. Wasiqur Rahman Khan, Professor and Acting Chair at Economics and Social Science department, BRAC University, for approving the topic of my thesis and providing the necessary supervision. His consistent support, valuable recommendations, and essential corrections enabled me to successfully complete this thesis.

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expressing any dissatisfaction or remorse, which made it possible for me to finish my master's thesis.

Contents

List of Acronyms

ARI	Acute Respiratory Infections
PSM	Propensity Score Matching
ATT	Average Treatment Effect on the Treated
HAP	Household Air Pollution
LPG	Liquified Petroleum Gas
WHO	World Health Organization
UNDP	United Nation Development Program

Glossary

Nearest Neighbor	This procedure randomly arranges the treatment and control patients, chooses the first treatment, and locates the closest-scoring control(Lalonde, 1986)

Chapter One

Introduction

1.1 Background and Motivation

While many developing nations are in the midst of a transition to cleaner cooking energies like electricity and gas, around 2.4 billion people worldwide still lack access to these options(WHO, 2022). About half of the global population and as many as 90% of rural families rely on fuels derived from biological material, such as firewood, agricultural residues, and animal waste for their home energy needs whereas in underdeveloped nations, solid fuels used for cooking and heating create the most indoor air pollution and violate permissible standards. (UNDP-WHO, 2004). According to estimates provided by the World Health Organization (WHO), approximately seven million people die annually as a direct consequence of being exposed to air degradation. Twelve percent of the deaths that were caused by household air pollution (HAP) which contributes 3.3 million children died from acute lower respiratory complications in many Asian regions(WHO, 2014). Indoor air pollution generated by the combustion of biomass fuel has been identified as one of the world's major health concerns, with women and children, who spend the bulk of their time indoors, being especially susceptible to the health impacts of air contamination during fuel burning(Albalak et al., 1999).

It is argued that solid fuels are safer for human health since they are less polluting than solid energy sources such as coal, wood, and other organic material whereas there is evidence in the published literature to suggest that having a baby with a premature births is more likely if mothers consume solid fuels., developing respiratory infections, and passing away in infancy(Epstein et al., 2013). When people cook with solid fuels, it is also obvious that they have a more pessimistic outlook on the state of their own health(Liao et al., 2016).

Since a couple of decades, malnutrition in children has been a major public health and global health policy concern, especially in poor nations; malnourishment is a major contributor to mortality in children under the age of five; the number is estimated at 45 percent where 149 million are stunted (WHO, 2020). With a view to cutting the burden of stunting by almost half in 2025, the World Health Assembly set a goal of a 16% prevalence rate in 2012 and since then, this objective has been formalized as a Sustainable Development Goal (De Onis et al., 2013). Stunting is one of the most common types of malnutrition, and kids who suffer from it have a far higher risk of dying young and developing mental disabilities(Black et al., 2008). Globally, 150 million children under the age of five are undersized, with a prevalence of 23.2% in Asia(OMS, 2018). The prevalence of stunting varies not only between different continents but even between different regions within the same country. In Bangladesh's slums, the rate of stunting is double the national norm(NIPORT, 2013). It is estimated that almost 4% of the entire disease poses a great pressure in the country is attributable to the pollution of the air found indoors(WHO, 2007). Another adverse health outcome, acute respiratory infection (ARI) is linked to the mortality of around one quarter of children (Baqui et al., 1998) and causes severe illness to the under five years infants in developing countries(Walker et al., 2013). The most affected regions are those with large child populations; acute respiratory infections account for one-fourth of all pediatric hospital admissions worldwide(Alemayehu et al., 2019).

Bangladesh, located in South Asia's region, through April to September brings hot and moist temperatures, whereas November to February delivers cold and dry winters which is one of the determinants to use biomass fuel, a primary source of energy for 92% of Bangladesh's population (NIPORT, 2013). Since biomass fuel is thought to produce more pollution, the use of fossil fuels is advocated(Kamijima, 2010). In previous study it was found that there is lack evidence to support the fact that there is no significant improvement in child health associated with smoke induced biomass fuel in Bangladesh and replacing biomass with fossil sources for a better health condition is needed to explored(Khalequzzaman et al., 2007).

Till now, many studies have tried to determine the effect of household use of various cooking fuels on childhood malnutrition. (Ahmed et al., 2021; Islam & Mohanty, 2021) and respiratory illness(Duflo et al., 2008; Gordon et al., 2014; Khan & Lohano, 2018; Ranathunga et al., 2019). This study has tried to bring both the adverse outcomes in an one umbrella and replicate the study design, propensity score matching, which minimize the selection bias arises due to the systematic differences between who use solid fuel and who do not use according to their socio-demographic status(Capuno et al., 2018; Liu et al., 2020a; Rahut et al., 2017).

The goal of this research is to examine the effects of the adoption of smoke induced solid fuel on child malnutrition and respiratory health status. The paper is prepared in the following stages: chapter 1 introduces the background of the study, in chapter 2 compiles the existing literatures, chapter 3 includes data sources and methodologies used in the paper; in chapter 4, analysis and results, chapter 5 provides discussions and chapter 6 draws conclusion.

Chapter Two
Literature Review

2.1 Low birth weight and fuel choice

There are numerous numbers of studies which have evident that more or less, there is significant association between child stunting and adoption of smoke induced fuel among households.

Both retrospective and observational research have produced evidence that there is a connection between air pollution and linear growth. These studies concentrated their attention primarily on effects of prenatal exposure to ambient air pollution and unfavorable pregnancy outcomes such low birthweight and premature birth. Prenatal exposure to fine particulate matter increases the likelihood of preterm birth and low birthweight., according to the findings(Li et al., 2017).

There have only been a handful of research that look at the connections between postnatal development and air pollution. There are some studies indicated stunting as a result, which was discovered through a meta-analysis and systematic review of research on the relationship between home air pollution and child survival. One of those meta-analysis found links between moderate stunting and severe stunting and exposure to home air pollution, which was defined as the use of solid fuel for cooking(Bruce et al., 2013).

In China, to assess the health impact there has been a published work where the observations were based on the choice of cooking fuel, which was a significant explanatory variable; the use of non-solid fuels like hydrocarbons, marsh gas, gasoline, and electricity and the use of solid such as coal, crop residues, and firewood. With the help of propensity score matching approach, it showed that the usage of non-solid fuels for cooking raised respondents' living activities without any assistance by between 1.33-1.42%, and their ability to deal with instrumental activities without assistance by between 3.02-3.40% (Liu et al., 2020b).

Evidence from India, the risk of childhood stunting was considerably increased by 16% for children under-5 years who stayed all the day at indoor where unclean cooking fuel was used, as comparison to the risk for the groups who lived in households where clean cooking fuel was used(Islam & Mohanty, 2021).

Finally empirical work based on Bangladesh DHS data 2011, the prevalence of undernutrition, underweight, and stunting among household consumers of biomass fuel was observed., which is a form of fuel that is prone to producing smoke, was 16.1% and 43.3%, respectively. Adolescents who used solid fuels exhibited greater rates of underweight and stunting than those who used cleaner energy. (Ahmed et al., 2021).

2.2 Acute respiratory infections and fuel choice

(Gordon et al., 2014) Examining the data linking indoor air pollution to respiratory illnesses like colds, lung cancer, and chronic bronchitis in children and adults. A number of respiratory illnesses have been linked to exposure to air pollution in the home, and it has long been known that low-cost fuel sources are typically the least efficient, emit the most smoke, and are utilized by people whose dwellings are the least well-constructed. From a large pooled analysis, it is estimated that people who have smoked and burned wood for fuel have a risk of developing lung cancer that is 22% higher than the risk faced by people who have never burned wood or smoked. The majority of findings on dirty fuels have solely concerned with inhalation of smoke from burning wood; therefore, additional research must be conducted utilizing smoke from different types of solid fuels in order to evaluate their association with the risk of lung cancer

(Capuno et al., 2018) Minimizing the selection bias with the help of different matching techniques, case young children living in households that use electricity, gasoline or biogas have a lower incidence of severe coughing that is accompanied by difficulty breathing by a margin of 2.4 percentage compared to kids who are not exposed kerosene or solid fuel, despite the fact that these children otherwise have similar observable characteristics, evidence from Philippines survey.

(Rahut et al., 2017) A similar study, which is based on the Bhutan Living Standard Survey from 2012 and adopts matching strategy, investigates the consequences of smoke generating fuels on health and the amount of money households spend on health care. According to the findings of the propensity score-matching method, homes who burn filthy households that burn dirty fuels have a 2.5–3% higher rate of respiratory illness than those that utilize modern technologies.

(Sk et al., 2019) An empirical study with 31,063 children, using Afghanistan DHS data, a multilevel logistic regression analysis was performed. Households utilizing clean cooking fuel inside the home, without a separate kitchen, had a 32% lower risk of having children under the age of five with ARI compared to those using dirty fuel in a separate building or outside. However, A kid under the age of five living in a home where polluting cooking fuel was used was 14% more likely to have acute respiratory infection (ARI) than a child living in a home where clean cooking fuel was used.

(Ranathunga et al., 2019) A Sri Lankan prospective study that tracked infants below five years found that the high exposure group, made up of those who cooked with biomass fuel and kerosene, had a significantly higher rate of infection-induced asthma than the low exposure group, made up of those who cooked with Liquefied Petroleum Gas (LPG) or electricity.

(Khan & Lohano, 2018) Acute respiratory infections (ARIs) affect 1.5 times as many children in homes where polluting fuels are burned as in homes where cleaner fuels are being used., according to Pakistan DHS 2012-13 data that utilized logistic regression model, fixed effects were used to account for unobserved confounders as well as covariates such as kid features, household characteristics, and maternal characteristics.

(Khalequzzaman et al., 2007) Results from a comparison of 49 biomass users and 46 fossil fuel users in Dhaka, Bangladesh's urban slums showed a significant odd ratio (OR) of 6.6

without controlling for confounders, but an adjusted OR showed no linkage between biomass fuel usage and respiratory problems.

Chapter Three

Methodology

3.1 Data Source

The most recent four waves of the Bangladesh Demographic and Health Surveys (BDHS) 2011, 2014, 2017 and 2018 survey rounds were used to assess the level of health complexities that children have faced. A nationally representative survey on nutrition, mortality, fertility, family planning, and mother and child health is the BDHS. Under the direction of various institutions, this cross-sectional data survey was carried out using a multistage cluster sampling technique to estimate factors at both the national and regional levels. The study collected 22,126 samples over 3 waves, using a pre-tested structured questionnaire, For the purpose of determining nutrition status, this study collected samples from never-married women between the ages of 15 and 49, as well as samples from their children between the ages of 0 and 59 months.

3.2 Sample Design

The sample that was used for the 2011–2018 BDHS is representative of the whole population that resides in non-governmental housing across the country. The Bangladesh Bureau of Statistics' list of enumeration areas (EAs) created for the 2011-2018 Population and Housing Census served as the survey's sampling frame (BBS). The survey's EA, or primary sampling unit (PSU), was designed to contain an average of roughly 120 dwellings. The assessment is based on a stratified household sample drawn in two stages. In this time frame (2011-2018), with more than 200 clusters in urban regions, 400+ clusters in rural areas, more than 600 EAs were chosen in the first round in each survey year, with a probability corresponding to the size of the EA. Then, to provide a sampling framework for the next step of home selection, a comprehensive household selection criterion was conducted in each of the chosen EAs. To get statistically accurate estimates of important demographic and health characteristics for the country as a whole, for urban and rural areas separately, and for each of the seven divisions, a systematic sample of 30 households on average was chosen each EA in the second round of sampling (National Institute of

Population Research and Training (NIPORT) et al., 2015; NIPORT, 2016; NIPORT et al., 2020).

3.3 Variables used in the study

3.3.1 Dependent variables

One of the outcome variables in this study is stunting which is proxy for child malnutrition. Based on existing Z-scores WHO child growth criteria are used to calculate standard deviations from the reference population median in the BDHS data (World Health Organization, 2006). A "Stunted" diagnosis is given to a child with a weight-for-height Z (WHZ) score of below -2. Acute respiratory infection (ARI), another adverse health indicator, is also taken into account in the study.

3.3.2 Defining the Fuel Pattern for Household Cooking

The key exposure variables of this study are based on what type of fuel a household chooses when it comes to cooking their food. Location of food cooking, fuel type, and smoke exposure risk are three indicators to predict exposure to child health. The location has been categorized into outdoor (=0) and indoor (=1). From numerous types of fuel sources, this paper has categorized fuel as non-smoke-producing (=0) and smoke-producing fuel(=1). Electricity, liquified petroleum gas (lpg, natural gas, biogas, coal, and charcoal were grouped as non-smoke-producing cooking fuel(=0) and kerosene, wood, straw, shrubs, grass, animal dung, and others were categorized as smoke-producing cooking fuel(=1The smoke exposure risk (SER) is another important metric that can be broken down into three categories: high SER (if smoke-producing cooking fuels = 1 and indoor cooking = 1), moderate SER (if smoke-producing cooking fuels = 1 and outdoor cooking = 0), and low SER (if non-smoke-producing cooking fuels = 0 and indoor cooking = 1).

3.3.3 Other Covariates

Our choice of confounders follows those of other studies (Jalan & Ravallion, 2003; Kumar & Vollmer, 2013) comprises indicators like- parent choices, individual and family socioeconomic features, and community-level factors like the availability of clean cooking fuel. Table 1 depicts the list of attributes and their respective definitions.

Table 1: Child, mother and location specific variables definition

Variable	Definition
Child's age (in Months)	0= if "0-12", 1= if "13-24", 3=if "25-36", 4= if "37-48", 5= if "48-below 60"
Male Child	1= if yes, 0=if no
Child Size during birth	0=if very large, 1=larger than average, 2=average, 3=smaller than average, 5=very small
Wealth index	(0= if poorest, 1= if poorer, 2=if middle, 3= if richer, 4=if richest
Mother's age at the time of her first delivery (in years)	0= if "below 21", 1= if "21-30", 3=if "31-40", 4= if "41-48"
Mother's education	0= "no education", 1="primary dropout", 2="primary completed, 3="secondary dropout", 4="secondary", 5="higher"
Mother's smoking status	1= if yes, 0=if no
Antenatal Care	1=if WHO recommended 8 or more visits, 0= if less than 8 visits
Region (Division)	7 divisions; Barisal=1, Chittagong=2, Dhaka=3, Khulna=4, Rajshahi=5, Rangpur=6 and Sylhet=7
Living Urban	1=if yes, 0=if no

Author’s Compilation, 2022

3.4 Statistical Framework

3.4.1 Bivariate Analysis

The bivariate analysis gives a rough notion of the relationship between the response variables and the covariates. The main statistic used to determine whether two or more variables are independent or not is the chi-square. The null hypothesis is tested by comparing an observed set of frequencies to a corresponding set. The chi-square test's proposed hypothesis is

H_0 : Adverse health events and the use of solid cooking fuel has no causal relationship

H_A : There is a significant relationship between adverse health events and the use of solid cooking fuel

First, one need to determine the expected value of the two nominal variables. The expected value of the two categorical variable can be calculated with the help of the given equations:

$$E_{i,j} = \frac{\sum_{k=1}^{c} O_{i,j} \ \sum_{k=1}^{r} O_{k,j}}{N}$$

Where $E_{i,j}$ = expected value

$\sum_{k=1}^{c} O_{i,j}$ = sum of the i_{th} column

$\sum_{k=1}^{r} O_{k,j}$ = sum of the k_{th} column

N = total observation

After finding mean value, value chi-sqaute test of independence can be obtained by the given formula:

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c} \frac{(O_{i,j} - E_{i,j})^2}{E_{i,j}}$$

Where, χ^2 = Chi-sqaure test of independence

$O_{i,j}$ = Observed value of two categorical variables

$E_{i,j}$ = Expected value of two categorical variables

3.5 Logistic Regression Model

All of the words and definitions of the logistic regression model that are given in this paper are primarily derived from the book " An Introduction to Generalized Linear Models"(Annette J. Dobson, 2018). The bivariate analysis does not provide any insight into the nature of the causal connection that exists between the response and the variables. Regression analysis is therefore necessary to evaluate the nature of their relationship. For binary data, logistic regression is the most widely used technique out of the three.

Let be the conditional mean Ψ and dependent variable Y given explanatory variable X.

$$E(Y|x) = \Psi(x)$$

Then assume the logistic regression model p(x) is,

$$\Psi(x) = p(Y = 1|X) = \frac{\exp{(\beta_0 + \beta_1 X)}}{1 + \exp{(\beta_0 + \beta_1 X)}}$$

And

$$1 - \Psi(x) = p(Y = 0|X) = \frac{1}{1 + \exp{(\beta_0 + \beta_1 X)}}$$

β_0 and β_1 are two parameters to estimate in logistic regression model
The appeal of the model is due to the logistic function (x), which has a range of 0 to 1.

3.6 Propensity Score Approach

The occurrence of confounds is a major barrier to isolating the impact of one's choice of cooking fuel on one's health(Liu et al., 2020a). There is a possibility of sample selection error occurring as a result of the systemic disparities that exist between a family that uses dirty fuel and one that does not use dirty fuel. Depending on needs of the individual or family, several forms of energy may be preferred(Rahut et al., 2017). By condensing all of the important components into an identical score, propensity scores matching address the dimensionality issue: People in the treatment and control groups are compared to one another based on propensity ratings. It can be viewed as a sophisticated matching method. For instance, one technique might be to distinguish people with comparable ages in both groups if one were worried that age would have an impact on both treatment selection and result. Finding precise matches for people gets harder and harder as more variables are included in the matching process (Garrido et al., 2014). When estimating items like the possible health benefits of improved cooking stoves in China, the PSM approach was utilized to take into consideration the possibility of selection bias present in the observational data. (Mueller et al., 2011) and implications of water quality and sanitation on the prevalence of diarrhea in Indian children (Fan & Mahal, 2011; Kumar & Vollmer, 2013)

In order to compare the negative health impacts between people who use solid fuel for cooking and those who do not (cleaned fuel), PSM approach was used. It can be mentioned that balancing the observed distribution of covariates between adopters and non-adopters is a key goal of propensity score calculation. In order to pair solid fuel adopters and non-adopters with similar propensity ratings, a number of strategies have been devised. It ensures that individuals with the equal features have a good chance of being both participants and non-participants. This simulates random assignment to treatment in order to generate random experiment conditions(Smith & Todd, 2003) with a view to reducing the effect of confounding variables. Commonly, balancing tests are conducted after matching to ascertain whether or not the variations in the variables between the two groups in the matched sample have been removed. If so, the control group serves as a valid proxy for the experimental group.(Caliendo & Kopeinig, 2008). As this study has considered different years of sample, it has matched propensity score adjusted by year (Hermans et al., 2019; Yamada & Bryk, 2016)

3.6.1 Model Specification

The propensity score, which is derived from a function of cooking fuel options, is the conditional probability of a household adopting solid fuels in the future. Specifically, the selection function was defined as follows:

$$Fuel_i^* = X_i\alpha + \varepsilon_i \ where \ Fuel_i = \begin{cases} 1 \ if \ Fuel_i^* > 0 \\ 0 \ otherwise \end{cases}$$

where $Fuel_i^*$ is a latent variable that represents the value that can be derived from a person's interests regarding the choice of fuel. For example, if the utility is positive, the person will prefer to cook with solid fuels ($Fuel_i = 1$), but if the utility is negative, the person will choose to cook with non-solid fuels ($Fuel_i = 0$). The exogenous variables X_i in the function affect the individual's utility, and an is a vector of parameters that must be estimated using some method, such as a probit model.. After that, the projected propensity scores from the selection function were utilized to execute matching using matching technique, nearest neighbor setting calliper at 0.001(Capuno et al., 2018; Rahut et al., 2017).

3.7 Assess the Average Treatment Effect on Treated (ATT)

According to the literature, the health outcome variables (undernourishment and respiratory infection) were treated as binary, i.e., let Y have a value of 1 or 0, denoted by Y_{1i} and Y_{0i}, respectively, to indicate whether or not an adverse health event occurred during the reference period for the i^{th} child. Additionally, we indicate the therapy status of the i^{th} child using another binary indicator, T_i, where $T_i = 1$ indicates that the child comes from a family that cooks with solid fuel and $T_i = 0$ indicates that the child comes from a household that doesn't cook with solid fuel. Let X also be a vector of observed traits that affect the availability of uncleaned cooking fuel but are unrelated to the consumption of solid cooking fuel. In this situation, the vector X can incorporate the mother's educational background, wealth index, and location of residence. The propensity score is the conditional probability of acquiring treatment given the reported covariates, known as the propensity index p(X). Using logistic regression on a collection of data containing kids under five, this paper estimates the propensity scores following the findings from the existing literatures(Baser, 2006; Capuno et al., 2018). Then, pairing each treatment child with a control child whose propensity score is within a certain predetermined distance of the treatment child's. The child who did not receive the therapy but otherwise has extremely similar traits as shown by the propensity scores serves as the counterfactual for the treatment child. Two assumptions must be fulfilled for the matching to be valid. The conditional mean independence (i.e., $E(Y_0|T = 1, p(X)) = E(Y|p(X)))$ is the first requirement. Essentially, this calls for balanced average features in both the treatment and matched control units. If this criterion is met, then each child in the subsample of paired treatment and control units is effectively assigned to treatment at random

Once the household with similar traits have been matched, this paper has computed the means of the outcomes for the treated children and their matched control counterparts, and then we take the difference between the two means. The distinction, also referred to as the average treatment effect on the treated

$$ATT(X) = E\{Y_{1i} - Y_{0i}|T_i = 1\},$$
$$= [E\{Y_{1i} - Y_{0i}|T_i = 1, p(X_i)\}],$$
$$= E[E\{Y_{1i}|T_i = 1, p(X_i)\} - E\{Y_{0i}|T_i = 0, p(X_i)\}|T_i = 1]$$

The ATT(X) estimates the likelihood that whether a child will experience a severe undernutrition and breathing difficulties. The STATA program psmatch2 is used to obtain our PSM and ATT(X) estimates(Leuven & Sianesi, 2003). This paper has adopted common matching technique following the previous works (Capuno et al., 2018; Rahut et al., 2017); Nearest Neighbor Matching.

In this paper, using nearest neighbor, we chose matching partners for each observation of solid fuels respondents (the treated) to make the most of the huge sample size. As a means of decreasing matching bias, we characterized all matching as occurring inside shared support and established a caliper of 0.001. Following pairing, the following formula was used to characterize the typical treatment outcome for the treated:

$$ATT = E(Y_1|Fuel_i = 1) - E(Y_0|Fuel_i = 1)$$

where Y_1 and Y_0 represent the health status of the consumers of solid fuel and non-solid fuel, respectively, who were matched.

Chapter Four

Analysis and Results

4.1 Graphical Analysis

A graphical analysis is carried out in order to establish which regions (divisions) have the highest stunting and ARI rates and to understand the factors that contribute to such rates. According to Figure 4.1(a) and Figure 4.1(b), the prevalence of stunting is highest in the both Chittagong and Sylhet divisions, while it is the lowest in the north and southern parts. Severity of ARI result shows Chittagong has highest number of respiratory cases.

Figure 4.1(a)

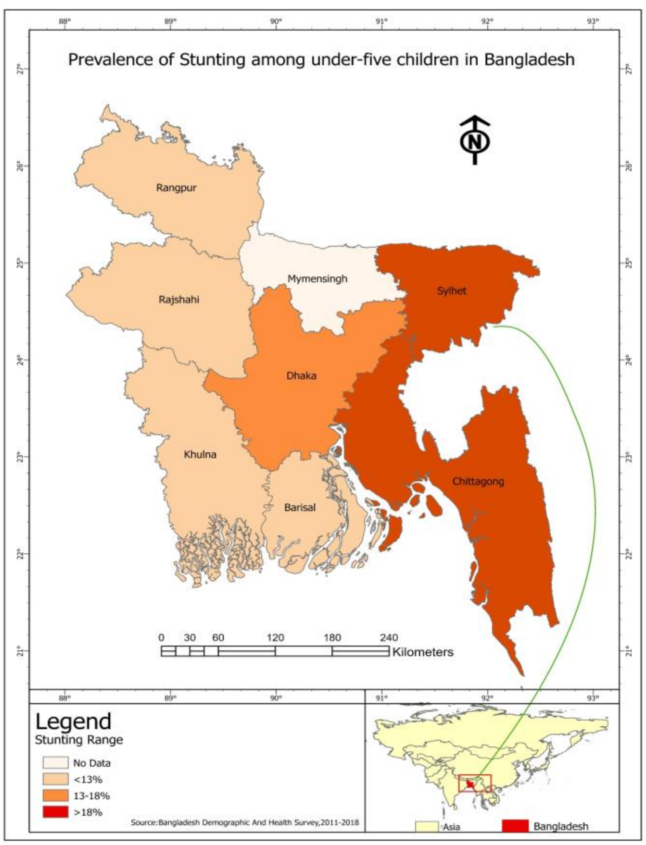
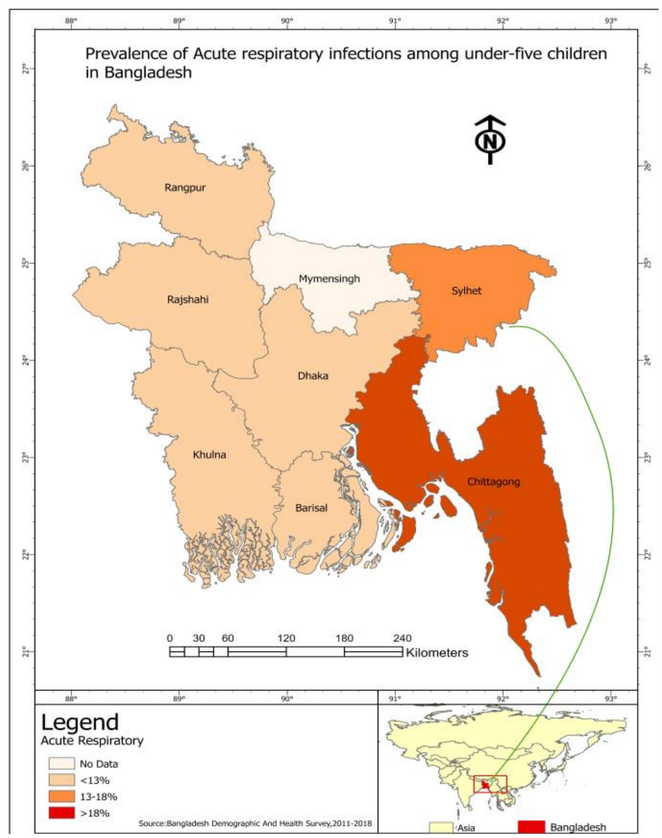
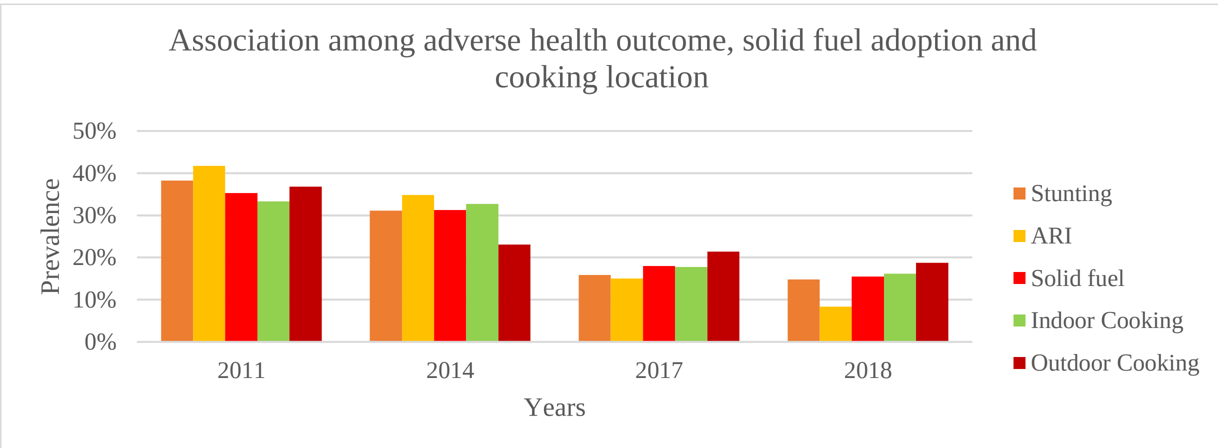


Figure 4.1 (b)



In figure 4.2, there bar graphs categorized by 4 years to show the trends of four different variables. Exhibiting bar plots, we see there is consistent fall of prevalence of each covariate. We also explore that, most importantly, even if ARI rises alongside the high prevalence of solid fuel uses but in 2017 and 2018 there is great fall of ARI (more than half) but still prevalence of solid fuel adoption is high but not that much amount like previous periods. It is also explored that level of stunting diminishes by half proportion since 2014 to 2018. Cooking in outdoor using typically biomass has remained higher in each year but only in 2014 it was recorded lowest. Thus, we can say there is no significant improvement in giving up the solid fuel approach.

Figure 4.2: Cross-linkage among outcome, treatment and cooking place, trend from 2011-2018



Data Source: BDHS data, 2011-2018

4.2 Descriptive Analysis

Brief statistical description has been exhibited to visualize the proportion of the sample that is used to assess malnutrition and respiratory complications among under-5 children. 36% of total sample has reported that there is low level of growth in comparison to their age (malnutrition) and 4.75% of child are having acute respiratory infections. The table 2 has explored the pattern of cooking fuel uses by different households, based on different income groups, regions and rural-urban categories. This paper has considered smoke producing fuel or solid fuel as treatment group which is almost 85% of the total sample and only 15% of the household are using clean fuel who are control group. There is also demographical information of both mother and child.

Table 2: Descriptive statistics of sample includes undernutrition, respiratory complications, demographic and socio-economic characteristics

Variables	Frequency(n)	Percent (%)
Outcome Variables		
Stunting		
No	14,176	64.05
Yes	7,955	36
Acute respiratory infections (ARI)		
No	21,076	95.25
Yes	1,050	4.75
Exposures		
Location of food cooking		
Outdoor	4,201	19
Indoor	17,912	81
Type of fuel		
Non-smoke-producing	3,351	15.18
Smoke-producing	18,700	84.71
Level of smoke exposure risk		
High SER	14,637	66.41
Medium SER	4,052	18.39
Low SER	3,350	15.20
Child's age category (in months)		
0-12	4,493	20.31
13-24	4,838	21.87
25-36	4,298	19.43
37-48	4,456	20.14
49-59	4,041	18.26
Child sex		
Male	11,411	51.57
Female	10,715	48.43
Child size at birth		
Very large	238	2.05

Larger than average	1,367	11.75
Average	7,976	68.57
Smaller than average	1,435	12,34
Very small	616	5.3
Mother's age at the time of 1st birth (in years)		
below 21	8,142	36.8
21-30	11,421	51.62
31-40	2,451	11.08
41-48	112	0.51
Mother's education		
No Education	3,062	13.84
Primary	6,418	29.01
Secondary	10,000	45.2
Higher	2,646	11.96
Mother's employment status (last 12 months)		
No	7,790	72.7
in the past year	192	1.79
Currently working	2,711	25.3
have a job but on leave last 7 days	22	0.21
Mother smoking frequency		
Never	1,659	45.3
Daily	1,749	47.52
Weekly	125	3.41
Monthly	37	1.01
Less than month	101	2.76
Currently breastfeeding practice		
No	3,947	36.86
Yes	6,760	63.14
Mother’s access to healthcare facility		
No	9,177	85.71
Yes	1,530	14.29
Antenatal care (ANC) visits	`	
No or less than 8 visits	13,848	62.64
8 or more visits	8,260	37.36
Wealth index		

Poorest	4,853	21.93
Poorer	4,296	19.42
Middle	4,190	18.94
Richer	4,410	19.93
Richest	4,377	19.78
Region (division)		
Barisal	2,430	10.98
Chittagong	4,057	18.34
Dhaka	3,542	16.01
Khulna	2,464	11.14
Rajshahi	2,674	12.09
Rangpur	2,602	11.76
Sylhet	3,198	14.45
Place of residence		
Urban	7,110	32.13
Rural	15,016	67.87
Total	**22,108**	**100**

Source: BDHS data, 2011-2018

As can be observed from the bivariate analysis of both outcomes, there are 7,092 cases of stunting among children whose households use solid fuel, but only 833 cases among those who have switched to using clean fuel. ARI has been detected in 944 children whose parents use filthy fuels, whereas just 102 cases have been found in children whose parents do not smoke.

Table 3: Bivariate analysis of Chi-square test for Stunting and ARI

Covariates	Stunting Status		Chi-square value	P-value	Acute Respiratory Infections (ARI)		Chi-square value	P-value
	No n	Yes n			No n	Yes n		
Cooking fuel type								
Smoke Induced (No)	2,518	833	210.99	0.000	3,249	102	25.29	0.000
Smoke induced(yes)	11,604	7,092			17,752	944		
Wealth index								

Poorest	2492	2360	912.76	0.000	4563	289	34.67	0.000
Poorer	2487	1,806			4072	221		
Middle	2665	1524			3990	199		
Richer	3036	1367			4219	184		
Richest	3471	890			4207	154		
Mother Age								
below 21	5116	3017	33.64	0.000	7712	421	7.75	0.000
21-30	7446	3959			10907	498		
31-40	1540	908			2327	121		
41-48	49	63			105	7		
Mother Education								
No education	1525	1536	944.75	0.000	2897	164	35.85	0.000
Primary incomplete	2125	1678			3604	199		
Primary complete	1508	1101			2453	156		
Secondary incomplete	5820	2890			8315	395		
Secondary complete	2697	618			3214	101		
Higher	476	124			568	32		
Mother Smoking Status								
No	4987	2584	16.79		7217	354	0.1	0.7532
Yes	9164	5363			13834	693		
Antenatal Care								
No or less 8 visits	8906	4934	1.57	0.7532	13086	754	41.36	0.000
8 or more visits	5245	3013			7965	293		
Urban residency								
No	9251	5760	13.31		14246	765	13.31	0.003
Yes	4900	2187			6805	282		

Source: BDHS data, 2011-2018 ***p-value<0.001 **p-value<0.05

The estimation of the PSM procedure's logistic regression is displayed in Table 4. Statistics show that the majority of the estimated coefficients are significant. Statistically significant determinants of use to solid cooking fuel include wealth quintile indicators, cooking place, educational qualification, mother smoking status, antenatal care, male children, child age, region and rural-urban status. These data imply that there are systematic differences between the treatment and control groups. These variables will confound the impact of smoke inducing fuel on child health if the estimate is based on a naive comparison of homes who use uncleaned fuels or solid fuels for cooking. Richer or richest group are expected to use less solid fuel compared to the poorest counterparts. It is also revealed household who are more inclined to indoor cooking less motivated to use solid fuel in comparison to the household who are habituated to cook outdoor. Mother's smoking interest will likely to encourage the use of smoke-inducing fuel for cooking and provision of antenatal care (WHO recommended; 8 or more days visit) will discourage the solid fuel adoption by the households than who don't. Urban households didn't show any affinity towards solid fuels compared to the rural individuals. Only Barisal and Chittagong showed interest to adopt solid fuels for cooking purpose compared to Dhaka division.

Table 4: Logistic regression and likelihood of using solid cooking fuel

Covariates	Coefficient	SE
Wealth Index (ref: poorest)		
Poorer	-0.195	0.216
Middle	**-1.165*** **	0.178
Richer	**-2.487*** **	0.163
Richest	**-4.189*** **	0.165
Place of cooking (ref: outdoor cooking)		
Indoor Cooking	**-1.111*** **	0.107
Mother age (ref: below 21 years)		
21-30	0.065	0.059
31-40	0.053	0.093
41-48	0.971	0.609
Educational qualification (ref: no education)		
Primary incomplete	0.047	0.120
Primary complete	**0.245** **	0.128
Secondary incomplete	**0.601*** **	0.107
Secondary complete	**0.230* **	0.115
Higher	0.023	0.155

Mother smoke (ref: don't smoke)	**0.646*** **	0.089
Antenatal care (ref: less than 8 visits)		
8 or more visits	**-0.273*** **	0.071
Child (ref: female)	**0.399*** **	0.082
Child age (ref: 0-12 months)		
13-24	0.091	0.083
25-36	0.144	0.086
37-48	**0.202** **	0.096
more than 48	**0.191* **	0.099
Region (ref: Dhaka)		
Barisal	**2.68*** **	0.127
Chittagong	**0.962*** **	0.077
Khulna	**-0.05*** **	0.108
Rajshahi	**-0.783*** **	0.106
Rangpur	**-0.194*** **	0. 125
Sylhet	**-1.484*** **	0.089
Place of residence (ref: rural)		
Urban	**-2.049*** **	0.059
Constant	6.770	0.255

Source: BDHS data, 2011-2018, SE= Standard Error ***p-value<0.01, **p-value<0.05, *p-value<0.001

4.3 Balance diagnostics

Considering that after matching using propensity scores, the treatment and control units should have similar average features, ensuring the validity of the impact estimations. In table 5 it shows the means of covariates for households who are using solid fuel or not, before and after matching. After the analysis, almost all variables matched which are previously differs in mean to both treatment and control groups. However, mother age and male child stayed as insignificant before and after matching. Mother smoking status is significantly associated before matching, but after matching they are not, and this procedure has reduced the bias more than 95%. Whereas child age becomes significant covariate after the matching.

Table 5: Tests of means and rate of reduced biased estimation, before and after matching of the treated and control groups

Variable		Mean			P-value
		Treated	Control	% Reduced bias	
Wealth Index	Unmatched	2.72	3.06	-31.2	0.000
	Matched	2.81	3.25		0.000
Mother Age	Unmatched	1.74	1.82	-53.4	0.173
	Matched	1.73	1.71		0.109
Mother Education	Unmatched	2.04	2.44	48.3	0.000
	Matched	2.16	2.95		0.000
Mother Smoking Status	Unmatched	0.998	0.512	100	0.000
	Matched	0.997	0.997		0.969
Antenatal Care	Unmatched	0.181	0.455	89.9	0.000
	Matched	0.198	0.171		0.000
Male Child	Unmatched	0.51	0.52	75.6	0.298
	Matched	0.43	0.52		0.847
Child Age	Unmatched	3.00	2.97	-184	0.000
	Matched	2.80	2.87		0.000
Urban	Unmatched	0.22	0.361	4.4	0.000
	Matched	0.25	0.383		0.000

Source: BDHS data, 2011-2018 ***p-value<0.001, **p-value<0.05, *p-value<0.01

The distributions of the treatment subsample and the matched control units significantly overlap along a shared range of propensity scores, as shown in figure 2 (Kernel density) which ranged between 0 to 1. In the left panel, there is a match between the entire sample and the two groups, treatment and control, assuming that different years will have similar characteristics for both groups. However, to adjust this issue, this study has matched propensity scores for different years to get an unbiased estimation (right panel).

4.4 Impact estimate

Table 6 answers the research question of this paper and demonstrates that the estimated effects of using uncleaned fuel for cooking or the ATT (X). It has displayed the treatment effect both for year unadjusted and adjusted propensity score matching. In upper table, using the nearest neighbor with the closest propensity score as the matched control unit, we estimate a 37.8% (at $p<0.001$) increase in the occurrence of child stunting. It is also revealed that whether there is any diverge from this estimate from this matching method to other. However, the hypothesis of the impact on acute respiratory infections among children due the treatment group who are using solid fuel has failed and it can be concluded that in propensity matching technique, reducing selection biases there is no significant association between child ARI and use of solid cooking fuel.

Adjusting for years in lower table, with a view to estimating unbiased impact estimate, this paper has evident different results for both the outcome variables. Becoming stunting due to solid fuel adoption did not reveal any significant association for year 2011 and 2014, however, for the year 2017 and 2018 adoption of solid fuel has increased the malnutrition among under-5 children increases by 33% and 33.9%, respectively. The ATT estimates for respiratory infection in 2011 likewise found no significant association with the use of solid fuels. Solid fuel adoptions are expected to raise ARI by 5.6%, 3.9%, and 2.8% in 2014, 2017, and 2018, respectively, according to the estimations.

Figure 2: Kernel density of propensity scores by treatment status: not adjusted by different years (left panel) and adjusted by different years (right panel)

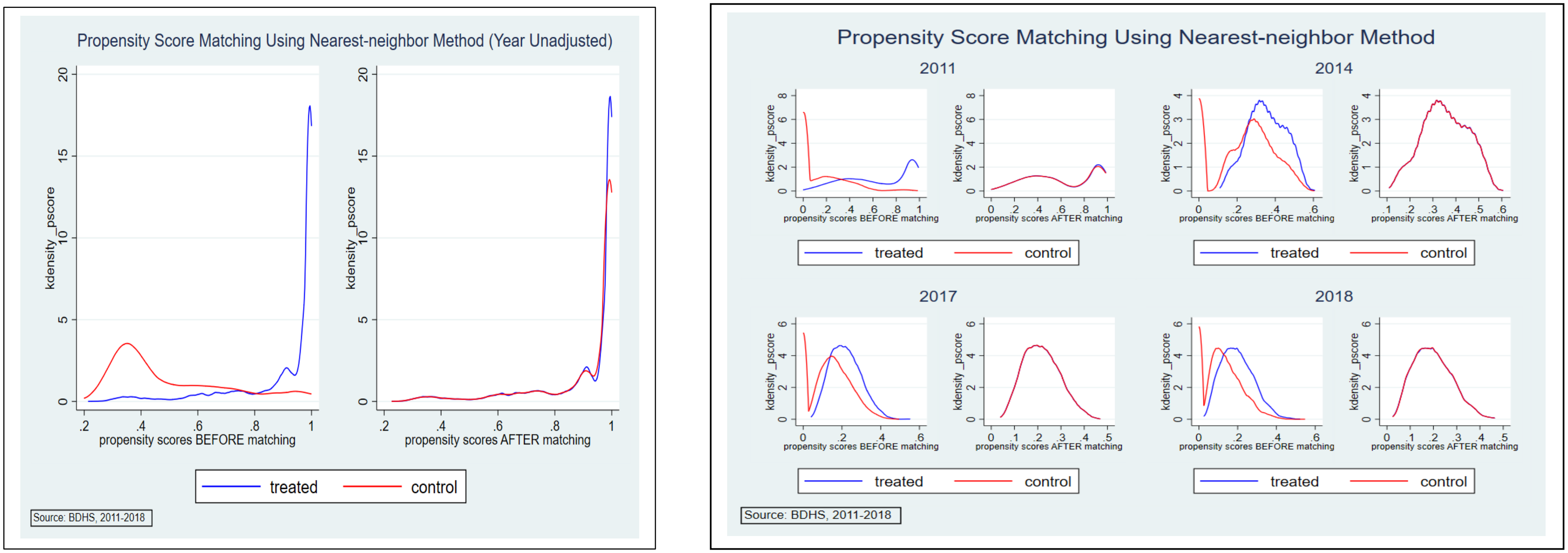


Table 6: Estimates of the average treatment effects on the treated (ATT(X))

Match propensity score without adjusting for different sample years

	Stunting					ARI				
	Nearest matching estimates ATT					Nearest matching estimates ATT				
	Treated	Controls	Difference	SE	T-stat	Treated	Controls	Difference	SE	T-stat
Unmatched	0.379***	0.251	0.128	0.0008	14.46	0.05	0.03	0.019	0.003	4.95
ATT	**0.378*** **	0.437	-0.058	0.026	-3.65	0.05	0.066	-0.016	0.01	-0.92

Source: BDHS data, 2011-2018 Caliper set at 0.001, ***p-value<0.01 (1% significance level), **p-value<0.05 (5% significance level)

Match propensity score adjusting for different sample years

	Stunting					ARI				
	Nearest matching estimates ATT					Nearest matching estimates ATT				
	Treated	Controls	Difference	SE	T-stat	Treated	Controls	Difference	SE	T-stat
2011										
Unmatched	0.420	0.334	0.087	0.007	12.34	0.061	0.042	0.019	0.003	6.2
ATT	0.411	0.367	0.044	0.023	1.9	0.061	0.045	0.017	0.010	1.69
2014										
Unmatched	0.376	0.353	0.023	0.007	3.17	0.056	0.044	0.012	0.003	3.62
ATT	0.377	0.361	0.015	0.011	1.35	**0.056*** **	0.040	0.016	0.005	3.38
2017										
Unmatched	0.330	0.365	-0.035	0.009	-3.92	0.040	0.049	-0.009	0.004	-2.32
ATT	**0.330*** **	0.378	-0.048	0.013	-3.66	**0.039*** **	0.054	-0.015	0.006	-2.57
2018										
Unmatched	0.349	0.361	-0.012	0.010	-1.21	0.028	0.050	-0.023	0.004	-5.37
ATT	**0.349*** **	0.392	-0.043	0.013	-3.18	**0.028*** **	0.053	-0.025	0.006	-4.54

Source: BDHS data, 2011-2018 Caliper set at 0.001, ***p-value<0.01 (1% significance level), **p-value<0.05 (5% significance level)

Chapter Five
Discussion

This piece of research has reveals not just the scenario of malnutrition and respiratory problem among children due to the adoption of solid fuel but it has incorporated PSM technique, a quasi-experimental method that mimics the randomization; solid fuel adopters (treatment) and clean fuel adopters (control) were assumed to be same on average by matching similar individual from both groups based on their characteristics to handle selection bias problem, treatment variable was not correlated with other covariates to avoid multicollinearity and shows average treatment effect on the treated (ATT) to estimate the actual causal effect on the treatment group eliminating the outcome of the treated observations if they had not been treated.

5.1 Findings

It is evident from PSM analysis there is significant increase in stunting among under 5 children in Bangladesh and the household who adopts solid fuel contributes child stunting by 39% compared to the control group who use clean fuel. This finding has supported previous works where similar PSM were introduced: (Boy et al., 2002)found pregnant women's exposure to different kitchen fuel types led low birth weights (less than 500 gram) among children; (Mishra et al., 2004) Babies whose mothers used firewood, compost, or crop residues to cook instead of LPG, natural gas, or electricity weighed, on average, 175 grams less than those whose mothers used any of those other fuel sources.

To measure the association of child respiratory illness with exposure to solid fuel, ATT estimate shows no significant result in year unadjusted matching estimation in this study. However, after adjusting for different years there is significant positive relationship has been found between ARI and solid fuel adoption, which supports the existing literatures: (Capuno et al., 2018) founds young children in houses that use electricity, LPG, natural gas, or biogas have a 2.4% lower incidence of severe coughing with difficulties breathing than young children in households that use kerosene or solid fuel but who otherwise have similar observable characteristics; (Rahut et al., 2017) states due to use of solid fuel child respiratory crisis increases up to 3%. However, there are also counterintuitive evidences that contradicts most of our findings, but support for insignificant result in 2011 estimation: (Shah et al., 1994) a southern India based study found no significant evidence to define use of smoke producing stove contributes ARI among children, (López Bravo et al., 1997) after studying 437 children who are not more than 18months revealed that there is no statistical significance to say that use of solid fuel is key risk factor of developing either upper ARI or lower ARI.

5.2 Limitation of the study

Despite the fact that the PSM method has some limitations, this paper has urged for the employment of the PSM approach in other nations having household survey data that is comparable to that which is found in the demographic and health surveys. Extending the scope of the study in a way it takes into account the different kinds of clean fuels and their individual effects, however it was not performed. In addition, this research did not take into account characteristics such as the average household income, out-of-pocket expenses, or pattern of taking loans.

Chapter Six

Conclusion

In concluding remarks from this matching analysis, it has been explored that the dwellers who adopt solid fuel are expected to give birth of malnourished baby than those who use clean and non-smoke cooking fuel for 2017 and 2018. Furthermore, there is significant relationship between average treatment effect on the treated group (solid fuel adopters) and child having acute respiratory infections except in the 2011. By estimating logistic regression, it can be concluded that wealth index, mother age, mother smoking status, child age and urban residency are the key determinants of choosing solid fuel sources after matching the propensity scores. All those findings have tackled with proper referencing of empirical works.

6.1 Recommendations

The outcomes of this research could have significant repercussions for public policy. There will be positive effects on the economy of Bangladesh as a result of the provision of clean and affordable sources of cooking process to reduce household air pollution, particularly among the rural population. This will particularly be the case because it will reduce the burden of the masses' health expenses on the government treasury as well as on the people themselves.

Some suggestion can be pointed based on the findings:

1. As most of the cooking places were found outside in the sample and out of which household, particularly in rural areas, adopted smoke generating fuel source like-biomass, it is advisable to the local government to manage household not to fully depend on the traditional sources of cooking fuel.
2. This paper reveals most of the key significant predictors of selecting solid fuel, policies could be designed based on those factors so that people can change their pattern of using cooking fuel and adopt cleaned fuel.

3. According to the findings of this study, there is a substantial association between ARI and the utilization of solid fuel. Therefore, policy should be prioritized on the premise of lowering the usage of solid fuel.
4. Other indicators of malnutrition like- wasting, underweight and obesity could be addressed to proper estimate the degree of overall malnutrition scenario and proper treatment should take place accordingly the magnitudes of the estimates.

As a result, these initiatives from the empirical findings lend credence to local and international initiatives to encourage the use of clean fuel for cooking as a public health intervention.

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