Do Social Safety Net Programs Increase Calorie Intake in Bangladesh? Evidence from Household Survey Data

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Abstract

Do Social Safety Net (SSN) programs increase household's calorie consumption? To answer this question, we employ *Household Income and Expenditure Survey* 2010 data from Bangladesh covering 12241 households. Our overall result is that the SSN programs do not significantly affect household's calorie consumption especially for the people whose calorie consumption is lower than required. This finding remains robust even after matching for economic and demographic factors. These results are not surprising since the SSN programs are highly fragmented and emerge as a somewhat ad hoc fashion to meet the needs of an ongoing economic or social crisis caused by an exogenous shock. This paper also finds that income is not robustly related to calorie consumption but living area and household's size are strongly linked to calorie consumption.

JEL Classification: H 55, C21, C31, H31

Keywords: Social Safety Net, Calorie Consumption, Treatment Effect Model, Household Behavior

1. Introduction

Social Safety Net (SSN) is a set of services such as health care, unemployment benefits, homeless shelters, etc. provided by state or government. The effectiveness of SSN programs has long been an important topic for academicians, social activists and policy advisers in Bangladesh. In 1974, the Government of Bangladesh (GOB) along with the United Nation's World Food Program, national Non-Governmental Organization and some International agencies was helping disadvantaged and vulnerable people to fight against poverty, malnutrition, and starvation for food. To do so, under the umbrella of SSN programs, the GOB provides cash, food for work, gratuity relief, freedom fighter allowance, old age allowance, widow allowance and much more. The GOB is very much concerned about SSN programs since every year it spends a significant portion of fiscal budget on SSN programs. According to UNDP (2016) "SSN programs have been an essential component in the fight against poverty. Initially focused only on protection goals, they are now increasingly combining promotional goals too."

In spite of 6.5% GDP growth for last decade, about 13 percent of the population in Bangladesh still live in extreme poverty and 25% people live under the poverty line (Ministry of Planning, 2015). Moreover, natural catastrophes such as drought, flood, and cyclone are also common in Bangladesh, and for these natural catastrophes people suffer from loss of their property and crop. These natural catastrophes force many individuals to live into a vulnerable situation. In the rural Bangladesh not only disadvantaged people, but also non-disadvantaged people whose income mainly depends on agriculture are heavily affected by these catastrophes. Sen (1982) argues that because of entitlement failure, after these natural catastrophes, these individuals face stark food security, which decreases their productivity and hence their income. In addition, increase in food price after these natural catastrophes add extra fuel to food insecurity (Ninno and Dorosh, 2001). Pitt et al. (1990) argues that after these catastrophes, because of entitlement failure, people's productivity decreases because of food insecurity and hence their income. However, each year GOB increases its national budget to protect its people, help them to fight against and safeguard their property from these natural catastrophes.

The importance of a well-designed system of SSN programs within a comprehensive approach to social security has found increasing acceptance within national and global policy circles. Worldwide, SSN programs are made up of various welfare programs which aim to help low-income people from hardship and poverty. For instance, in the United States, the objectives of the SSN programs are to help Americans facing a hard time (Federal Safety Nets, 2016). Similarly, in Canada one of the SSN is its universal health care system called *Medicare* and in UK one of her SSN is *National Health Care* service.

In the past decade, Bangladesh has lifted out 16 million people out of the poverty, a rather remarkable achievement. Still, 13 percent of the population lives in extreme poverty. To support these disadvantaged and vulnerable people, the GOB implements a number of SSN programs that involve allocation of BDT 45,293 crore taka in the fiscal year 2016-2017, which is 13.28% of the national budget and 2.31% of GDP of Bangladesh. At present, the GOB operates 54 SSN programs (excluding running development projects and new development projects). These programs fall under categories of 1) Social Protection programs, 2) Social Empowerment programs, 3) Cash Transfer (Special) Programs, 4) Food Security: Social Protection programs, 5) Micro-credits programs: Social Empowerment, 6) Miscellaneous Fund: Social Empowerment, and 7) Miscellaneous Fund: Social Empowerment (Ministry of Finance, 2016). These programs are designed to help disadvantaged and vulnerable people in different situations, and support them to get out of poverty.

Recently, SSN programs have been subject to criticism by national and international organizations. According to the World Bank (2016), the existing safety-net programs are marred by fragmentation, weak targeting and inefficiencies. One objective of SSN programs (especially food security programs) is to ensure that disadvantaged people consume a minimum amount of calorie every day. Quisumbing (2003) and Barrett (1999) show that any kind of food transfer and cash transfer to disadvantaged households increase their calorie consumption. Rahman (2012) finds that the SSN programs produce insignificant effect and argues that corruption weakens the effectiveness of the SSN programs. Khuda (2011) surveys the literature on SSN programs in Bangladesh and concludes that SSN programs for urban poor are limited and these programs should give more focus on those living in informal settlements in urban areas. Every year, the number of SSN programs and their benefits and coverage are increasing. Currently, there are sixty-six SSN programs being operated in Bangladesh.

The rest of the thesis is organized as follows. Section 2 provides a review of the related literature. Section 3 provides an overview of the various SSN programs that are being used in Bangladesh. Section 4 discusses the econometric methods used in the empirical analysis. Section 5 discusses the data, choice of variables, and model specification. Section 6 presents the main empirical results. Section 7 makes a comparison of findings between this thesis and that of Rahman (2012), who conducted a similar analysis using the 2005 HIES data. Section 8 concludes the thesis with some policy recommendations.

2. Literature Review

The relationship between SSN and calorie consumption is a subject of interest for researchers and policy makers alike. The SSN programs and calorie consumption literature has focused on the role of government in providing basic facilities to disadvantaged individual or household so that they do not perish and get out from the vicious cycle of poverty.

Khuda (2011) provides a comprehensive overview of the SSN programs in Bangladesh. He outlines several points to improve the function of SSN programs: high-level commitment of SSN officials to achieve their objectives, effective programme management and delivery of SSN programs to targated households, better identification of needy households, establishing a sound financial management and payment system for cash SSN programs, strengthening the monitoring system of how well SSN programs are working and supervision of SSN officials at different levels. He pointed out that most of the SSN programs are based in rural areas, but due to rapid urbanization an increasing proportion of the poor are living in informal urban settlements. So provisioning programs targeting the urban poor need to be taken into account.

Rahman (2012) uses the HIES 2005 data to examine the effectiveness of SSN programs in Bangladesh. He finds that when the mean difference model is applied on whole sample, the SSN programs dummy produces a significantly negative impact on households members' calorie consumption. However, when the nearest neighbour matching model is applied on a reduced sample, it produces an insignificant positive impact. Overall, his results suggest that SSN programs have a statistcally insignificant effect on calorie consumption among poor households in Bangladesh.

Tiffin and Dawson (2002) examine the long run relationship between per capita calorie intake, per capita income and food prices in Zimbabwe. They find a strong evidence of a long-run relationship between calorie and income. The results of impulse responses suggest that a shock to calorie (income) increases income (calorie) permanently and the effects remain significant up to four years.

Quisumbing (2003) uses panel data of Ethiopian Rural Household Survey for 1989, 1994/95 and 1997 to examine the determinants of participation and reception of food aid among Ethiopian households. She finds that shocks to households income increase the likelihood of participating in SSN programs. Moreover, food for work program has a positive impact on the weight and heights of younger children in low asset households.

Martin and Hulme (2003) study selected SSN programs such as Vulnerable Group Development (VGD) in Bangladesh. They find that VGD increases the number of meals of beneficiary households from 2 to 3 in a day. They conclude that programs like VGD are helpful in protecting the livelihood of disadvantage households and these programs provide a cushion against persistence food deprivation.

Subramanian and Deaton (1996) study the relationship between total expenditure and nutritional status among rural Indian households. Using the Indian Nation Sample Survey data for 1983 they estimates elasticities of calorie consumption with respect to total expenditure. The results show that nutrition is constrained by income in India. Sinha (2005) uses the Indian Nation Sample Survey data for 1987-88 and 1993-94 to estimate the effect of income (after controling for certain household characteristics) on per capita calorie consumption in rural India. Based on quantile regression he fiinds heterogenous effects of income on calorie consumption. The distribution of calorie consumption is affected differently at different levels depending on the household characteristics and their nutritional status. The effect of income is not uniform across the conditional distribution of calorie consumption. It is higher for individuals at a higher position in the calorie consumption distribution. These results suggest that when providing food subsidy, the *nature* of the food subsidy is very important.

The literature also reveals that generally food transfers to poor households increase their calorie consumption (e.g., Barrett 1999, Quisumbing 2003) and cash transfer improves calorie consumption (e.g., Bouis and Haddad 1992, Gibson and Rozelle 2002). However, there are a few studies examining the effect of the SSN programs on calorie (or nutrition) consumption of Bangladeshi households. For example, Ahmed and del Ninno (2002) find that Food for Education program increases nutrition level among the preschoolers of the beneficiary households. del Ninno et al. (2001) show that most households under the Cash Transfer program experienced an increase in income, which in turn improving the quality and quantity of their food intake. Khanum (2000) reports that 90 percent of the Rural Maintenance Program beneficiaries have benefitted from an improved consumption level.

3. Conceptual Framework

3.1 SSN Programs in Bangladesh

In Bangladesh, SSN gets significant attention because of her socio-economic condition. Since the independence in 1971, the main agenda of all ruling governments was the alleviation of poverty. To reduce poverty, the government uses SSN programs such as Social Protection and Food Security as their main tool. Details of these two programs are given below. SSN programs are deployed with several objectives including poverty reduction, human development and providing social protection to vulnerable people in the society (Ministry of Finance, 2016).

3.2 Social Protection

To ensure the well-being of the disadvantaged people, the GOB deploys a large number of social protection programs. These include old age allowance, educational stipend, maternity allowance, widow allowance, disability allowance, educational allowance for physically challenged students, one house one firm, oppressed and poor women allowance, food for work, dispute mothers' food assistance programs, TR, GR, VGD, Ashrayan Programs, etc. The GOB declared that it will continue these programs in the future. As criticisms of SSN are coming from different sides, the GOB is aware of the ineffectiveness of the SSN programs. Taking criticism and policy recommendations into account, the government is trying to improve its welfare operations by implementing National Social Security Strategy (NSSS). The GOB expects that this strategy will avoid duplication and will be more targeted.

3.3 Food Security

To ensure food security, the GOB recently put special emphasize on improving the food procurement system, processing and storage facility. The government aims to stock 13.25 lakh metric tons of food grains (rice and wheat) in 2016-2017 fiscal year, of which some will be used for Test Relief (TR) and Vulnerable Group Feeding (VGF) initiatives. The government also took some steps to introduce rural rationing packages in areas covered under TR and VGF programs.

The government also taken others programs such as: 1) welfare for elderly people that incudes palliative care center, formulate a service pool and organize life skill training and employment for elderly people in remote areas, 2) women development programs to train women engaged in different trades, distribute micro credits, rural and agricultural credits to enhance the scope of skill development and self-employment opportunity, and 3) constructing districts and upzilas rehabilitation complex for freedom fighters program and government also providing microcredits to freedom fighters for their self-employment.

Achieving these objectives is both difficult and complex. To achieve these objectives, each year the GOB not only allocate a large amount of money but also do some promotional activities for SSN programs. Annual budget allocation for the SSN programs from 2009-10 fiscal year to 2016-17 fiscal year is given in Table 1.

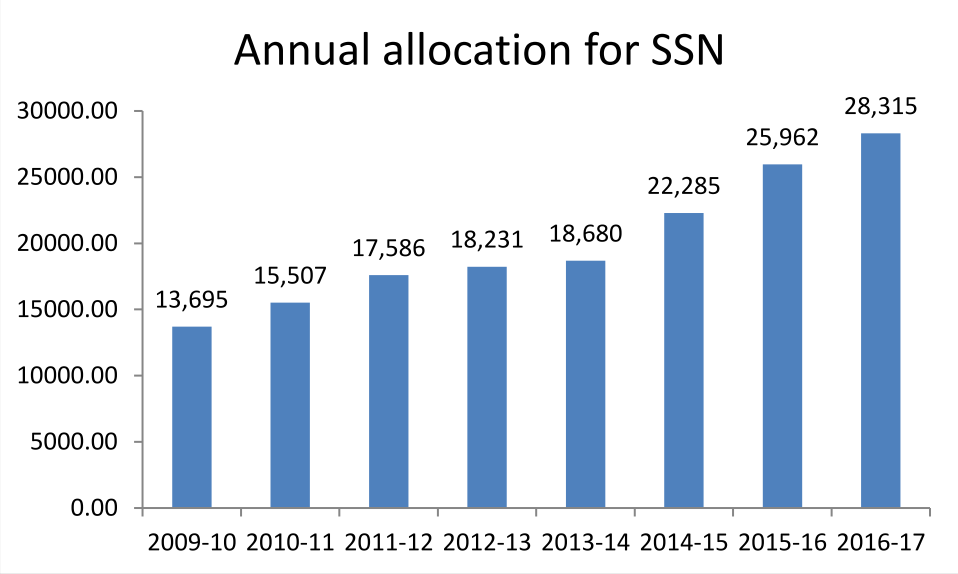
Table 1: Budget allocation for SSN programs

Fiscal year	BDT (in Crore)	Growth rate	% of Budget	% of GDP
2009-10	17327.33	..	15.22%	2.52%
2010-11	19496.99	12.52%	14.75%	2.50%
2011-12	22556.05	15.69%	13.79%	2.51%
2012-13	22750.55	0.86%	11.87%	2.18%
2013-14	25371.35	11.52%	12.40%	2.13%
2014-15	30767	21.27%	12.28%	2.01%
2015-16	37546	22.03%	12.72%	2.19%
2016-17	45230	20.47%	13.28%	2.31%
Average	27630.66	14.91%	13.29%	2.29%
Std. Dev.	8978.267	6.94%	1.13%	0.18%

Source: Ministry of Finance (2016)

As can be seen from Table 1 that every year the government is increasing its allocation for SSN. This conveys a message that the role of government’s support for disadvantaged people is increasing every year. The average allocation of budget for SSN programs from fiscal year 2009-10 to 2016-17 is Tk. 27,630.66 crore with a standard deviation is 8978.267. In the fiscal year of 2016-17, the GOB allocated Tk. 45,230 crore for SSN programs, which is roughly 13.28% of the national budget and 2.31% of the country’s GDP. The average growth rate of budget allocated for SSN programs from 2009-10 to 2016-17 is 6.94%.

Figure 1: Annual budget allocation for SSN programs



Source: Ministry of Finance (2016)

From a microeconomic perspective, we expect SSN programs to help people in two ways. First, those who receive cash transfer will experience a rightward shift of their budget line, helping them to obtain a higher utility level. Second, those that who are benefited from in kind transfers such as food will also be able to obtain a higher utility level. However, in the case of in kind transfer a portion of consumer surplus will lost (Varian, 2012, page – 29 to 31). Employment generation programs are design to create employment opportunity for unemployed people so that their income goes up, which in turn will improve their life standard. In Bangladesh, the SSN programs are so important that it is, in effect, enshrined in the constitution under Article 15 (D). It says "It shall be a fundamental responsibility of the State to attain, through planned economic growth, a constant increase of productive forces and a steady improvement in the material and cultural standard of living of the people, with a view to securing to its citizens – (a) the provision of the basic necessities of life, including food, clothing, shelter, education and medical care; (b)..;(c)..; and (d) the right to social security, that is to say, to public assistance in cases of undeserved want arising from unemployment, illness or disablement, or suffered by widows or orphans or in old age, or in other such cases (Bangladesh, 1972)." Throughout this research, we assume that cash transfer is used for the consumption of goods and services where a significant portion goes towards calorie consumption.

4. Econometric Methodology

Rahman (2012) employs mean difference and matching estimators for estimating the effect of SSN programs on per capita daily calorie consumption in Bangladesh using HIES 2005 data. He argued that using the full sample the unconfoundness and overlap assumption of matching estimator is failed to satisfy by treatment variable, which is a dummy variable of inclusion of SSN programs or not. To overcome this problem, he applied the same techniques on reduced sample. We follow Rahman (2012) and estimate the average treatment effect model using the mean difference and matching estimators. For matching estimator, we use the nearest neighbor matching estimator. Rahman (2012) also argue that treatment dummy has a serious endogeniety problem because of the choice of treated individual, which is likely to be determined by some other unobserved factors, for instance, corruption. In the following section, we will discuss the econometric methods in some details and the rationale behind using these methods.

4.1 Mean Difference and Matching Estimator

The mean difference (or difference in mean) is a simple standard method of measuring the absolute difference in mean between two groups. Suppose, we have *N* number of households, in which *K* number of households are treated in any SSN programs and *N-K* number of households are not. Let *T* be a dummy variable representing the difference in households; that is, if households benefit from any programs they are considered as treated and are assigned with a value of 1 and 0 otherwise. In this setting, we can write the outcome variable, per capita daily calorie consumption, Y_i, as follows:

$$Y_i = T_i Y_{1i} + (1- T_i)\, Y_{0i} = \begin{cases} Y_{1i} \; if \; Ti = 1 \\ Y_{0i} if \; Ti = 0 \end{cases}$$

In the above equation if a household *i* is treated in any SSN program then it is denoted as Y_{1i} and if a household is not treated then it is denoted as Y_{i0}. This model also assumes random selection of households covered in any SSN programs. Therefore, we can write the sample average treatment effect, $\hat{\tau}$, as follows (Nayman 1923):

$$\hat{\tau} = \frac{\sum_{i|T_i=1} Y_{1i}}{K} - \frac{\sum_{i|T_i=0} Y_{0i}}{N-K}$$

Using the Ordinary Least Square (OLS) method we can easily estimate the sample average treatment effect in the following manner:

$$Y_i = \hat{\alpha} + \hat{\tau}T + e, \tag{1}$$

where $\hat{\tau}$ is the coefficient of SSN programs dummy. If a household is entitled with any SSN programs then $\hat{\tau}$ shows the difference in calorie consumption between benefitted and non-benefitted household, that is, the sample average treatment effect of the SSN programs. This average treatment effect is said to be unbiased under the condition of random experiment, which is not found in social science/economics field. Even households who are benefitted from any SSN programs might be conditioned to some observed characteristics X_i, that are unaffected by T. In this case matching estimator is appropriate to estimate the average treatment effect (Abadie and Imbens 2011, Dehejia and Wahba 1999).

4.2 Matching Estimator

According to Khandker et al. (2010), matching estimator usually creates a statistical comparison group by modeling the probability of participating in the programme on the basis of observed characteristics unaffected by the programme. Participants are then match on the basis of this probability to non-participants. The average treatment effect of the program is then calculated as the mean difference in outcomes across the two groups. The necessary assumptions for quantifying the effect of programs (SSN in our case) on beneficiary households are i) conditional independence and ii) the presence of common support.

Different approaches are used to match beneficiary and non-beneficiary households based on their observed characteristics. These include nearest neighbor matching, caliper and radius matching, stratification and interval matching, and kernel and local linear matching. In this thesis, we employ Propensity Score Matching (PSM) and Nearest Neighbor Matching (NNM) estimator.

Nearest neighbor matching estimates the average treatment effect and average treatment effect on the treated. This method accepts continuous outcome, the one we have. Similarity between subjects is based on a weighted function of the covariates for each observation. The treatment effect is computed by taking the average of the difference between the observed and imputed potential outcomes for each subject.

4.2.1 Assumption of Conditional Independence

Conditional independence assumption states that given a set of independent variables, $\boldsymbol{X}$, that are not affected by SSN programs and the potential outcome Y are independent of SSN assignment (that is T, - treatment dummy). If Y_i^C refers outcome for nonparticipants, conditional independence implies:

$$\left(Y_i^T, Y_i^C\right) \perp\ T_i \middle| X_i$$

This assumption is also known as *unconfoundness*, implying that inclusion in the SSN program is based entirely on observed characteristics.

4.2.2 Assumption of Area of Common Support

The second assumption of area of common support implies that the probability of households- $X_i -$ benefiting from any SSN programs will remain between zero and one, 0 < P $(T_i = 1|X_i)$ < 1. This assumption implies that benefitted households can be compare with non-benefitted households (propensity score distribution of benefitted households have sufficient overlapping with the non-benefitted households' distribution). This condition warrants that the effectiveness of propensity score matching depends on having a large and roughly equal number of participant and non-participant households so that a significant region of common support can be established. Therefore, both groups of households have to be similar in terms of observed characteristics unaffected by program participation. Thus, households who do not receive any benefits from a SSN program are automatically dropped to ensure the comparability.

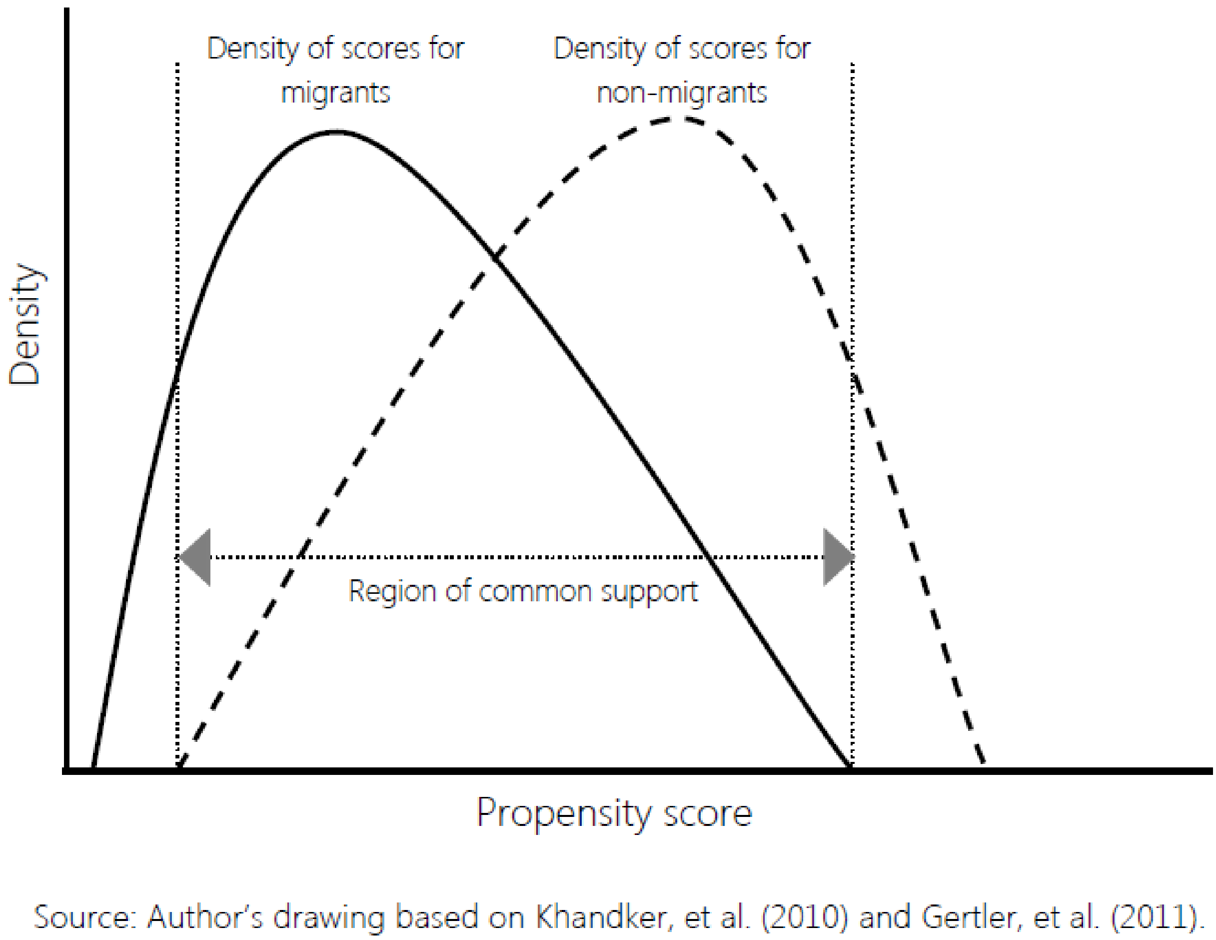


Figure 2: Propensity score distribution and area of common support

4.3 Instrumental Variable (IV) Regression

The role of IV regression takes place at the presence of endogeniety in casual relationship, the average treatment effect. As argued by Rahman (2012), treatment dummy has a serious endogeniety problem because of the choice of treated individual is determined by some other unobserved factors such as corruption. The IV regression is a method for estimating a consistent estimator of unknown coefficient of population regression function when at least one of the regressors is endogenous or correlated with the error term, ε (Stock and Watson 2011). The IV regression is essentially a two-stage regression model. Consider a population regression function relating Y to X, that is:

$$Y_i = \beta_0 + B_1 X_i + \mu_i,$$

where μ_i is error term representing omitted factors that determine Y_i. If X_i is correlated with μ_i, the OLS estimator is inconsistent. The IV regression uses an additional *instrument* variable Z

to separate that part of X that is uncorrelated with μ_i. There are two conditions for a valid instrument:

1. Instrument relevance: correlation between regressor and instrument is different from zero. That is corr($Z_i, X_i \neq 0$)
2. Instrument exogeneity: correlation between error term and instrument must be zero. That is corr($Z_i, \varepsilon_i = 0$)

The first stage of the two-stage IV regression involves running a regression model linking *X* and *Z*:

$$X_i = \lambda_0 + \lambda_1 Z_i + \nu_i,$$

where λ_0 is intercept, λ_1 is the slope of Z_i, and ν_i is the error term with zero mean and constant variance. This regression delivers the needed breakdown of X_i. One part is $\lambda_0 + \lambda_1 Z_i$, the part of X_i that can be predicted by Z_i. Because Z_i is exogenous, this component is uncorrelated with μ_i, the error term in the main equation. The other component of X_i is ν_i, which is the problematic component of X_i that is correlated with μ_i. From the first-stage regression we get the fitted value of X_i, that is $\widehat{X_\iota}$.

In the second stage of the two-stage least square regression we regress Y_i on $\widehat{X_\iota}$. The estimated result of second stage regression is the two stage least squares (2SLS) estimator.

$$Y_i = \beta^{TSLS}{}_0 + \beta_1^{TSLS}\widehat{X}_\iota + \mu_i,$$

Further details are provided in Stock and Watson (2011).

4.4 Quantile Regression

The percentile distribution of calorie consumption shows that the bottom one percent households consumes less than 1000 calorie per day, bottom five percent consumes less than 1350 calorie, bottom ten percent consumes less than 1550 calorie and bottom 25% consumes less than 1850 calorie. The remaining households in the sample consume more than 1850 calorie per day. This provides a strong motivation for employing quantile regression and we estimate regression at the 25 percentiles or first quartile.

Quantile regression is used to estimate the effect of Y_j on different parts of the distribution. For example, specifying quantile 0.25 estimates the parameters that describe the 25th percentile (first quartile) of the conditional distribution. Quantile regression allows for effects of the independent variables to differ over the quantiles. That is, the effects of the independent variables may vary over different quantiles of the dependent variable. Hence, the quantile regression has an important advantage over the mean regression. See Angrist and Pischke (2009) for further details.

Suppose we are interested in the distribution of a continuously distribute random variable, $Y_{i,}$ with a well-behaved density function. Then the conditional quantile function at the quantile τ given a vector of regressor $X_{i,}$ can be defined as:

$$Q_\tau(Y_i|X_i) = F_Y^{-1}(\tau|X_i)$$

where $F_y(\tau|X_i)$ is the distribution function for Y_i conditional on X_i. When $\tau = 0.10$, for instance, $Q_\tau(Y_i|X_i)$ describe the lower decile of Y_i given X_i, when $\tau = 0.50$, gives us the conditional median. By looking at changes in the conditional quantile function of calorie consumption as a function of SSN programs, we can tell whether the dispersion in calorie consumption goes up or down with SSN programs.

5. Data

Since 1991-91, Bangladesh Bureau of Statistics (BBS) has been conducting *Household Income and Expenditure (HIES)* survey. This is a nationwide representative survey which collects a large number of information including consumption (food and non-food), income, expenditure etc. The HIES survey collects data from all districts of Bangladesh. For this study, we used the HIES 2010 survey data, which is the latest available survey. Some summary statistics of the main variables used in the empirical model is presented in Table 2. The empirical model used in this study is given as follows:

$$PCDCC = f(x) = \beta_0 + \beta_1 ISSNP + \beta_2 INC + \beta_3 HHSIZE + \beta_4 \mathrm{EDUC} + \beta_5 AGE + \beta_6 RURAL + \beta_7 RURAL * SSN + \varepsilon$$

PCDCC	Per capita average calorie consumption of a household member (dependent Variable)
ISSNP	Dummy variable of household's inclusion in SSN programs. =1 if a household benefitted from any SSN programs; 0 otherwise.
INC	Average monthly Income of a household head
HOUSEHOLDSIZE	Size of the Household
EDUC	Highest class passed by household head
AGE	Age of the household head
RURAL	Dummy variable; =1 if household live in rural area; 0 otherwise
*Rural*ssn*	Interaction between rural dummy and ISSNP dummy
$\boldsymbol{\varepsilon}$	Stochastic error

Some summary statistics of the main variables used in the empirical model is presented in Table 3.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.
Income	2462	4979.84
Per Capita Daily Calorie Consumption	2313.17	776.54
Household size	4.54	1.89
Education of household head	3.86	4.49
Age of Household Head	46.00	13

Location of Household (Rural=1)	0.64	0.48
SSN Dummy (Treated household=1)	0.15	0.36
Interaction of location and SSN Dummy	0.12	0.32
N = 12240		

5.1 Dependent Variable

Our dependent variable is per capita daily calorie consumption by an individual. The average calorie consumption of an individual is 2313.17 with a standard deviation is 776.54. The main sources of calorie consumption are food grain, pulses, fish, eggs, meat, vegetables, milk and dairy, and fruits. HIES survey includes 200 food items that come from household’s private production, purchase, and in-kind transfer such as wages, and gifts. The units of account vary across products and they have been converted into a single measure, gram. The HIES 2010 survey collects 14 days food consumption using the recall method and we use the average of 14 days food consumption as our dependent variable. We then converted it into calorie consumption according to guideline set by the University of Dhaka’s food and nutrition’s department (BBS, 2010). The treatement group’s per capita daily average calorie consumption is 2318.66 with a standard deviation of 798.45 calorie. Whereas, the control group’s daily average calorie consumption is 2312.20 with a standard deviation of 772.67 calorie. The treatment group consumes only 6 calorie more compare to the control group.

The HIES 2010 survey shows that out of 12,241 households only 1,228 households are benefitted from SSN programs. Local government determines which households are eligible for any kind of SSN programs. This selection is based on households’ income, land holding, gender of households’ head, and age of households’ head etc. Unfortunately, the selection of households is not corruption free. For instance, recently the GOB lunched a program to sell rice at Tk. 10 per kg directly to poor households. A summary statistics of calorie consumption by each group is given below in Table 3.

Table 3: Summary statistics of dependent variable by group

Calorie Intake	**Obs.**	**Mean**	**St. Dev.**
Overall	12239	2313.17	776.54
Treatment Group	1828	2318.66	798.45
Control Group	10411	2312.20	772.67

Source: Author’s calculation using HIES 2010 data

5.2 Independent variables

5.2.1 Monthly Income

Income of a household's head is one of our regressor and is an important variable in determining daily calorie consumption because a household's consumption level to a large extent depends on income. A household's net income is derived as follows:

Table 4: Sources of income

Revenue:
1. Wage and salary income including in-kind benefits
2. Agricultural enterprise revenue
3. Farm crop sale
4. Farm livestock sale
5. Farm animal product sale
6. Farm fish sale
7. Farm forestry sale
8. Farm agriculture asset rent income
9. Other income
Expenses:
1. Farm input expense
Household net income = Revenue-Expenses
Further details are available in Section 7 of the HIES 2010 questionnaire.

All individual level data have been convert into household level. We divide net income by household size to get average per capita yearly income and then divide the amount by 12 to get monthly average per capita income of an individual. The average monthly per capita income of an individual is Tk. 2,665.24 with a standard deviation of 51.57. The maximum amount of monthly per capita income is Tk. 368,233 and the minimum monthly per capita income is Tk. -139,78.89. If we further differentiate monthly income for treatment and control households, monthly per capita income of an individual in treatment households is Tk. 1,626.13 with a standard deviation of 2058.83. On the other hand, monthly income of an individual in control household is Tk. 2,847.69 with a standard deviation of 6107.90. The treatment households' monthly income is 43.9% higher than control households, indicating income inequality between the groups.

5.2.2 Education

Education of a household represents the highest grade completed by the head of a household. In the HIES 2010 survey, the average education of treatment group household is 2.10 years of schooling with a standard deviation of 3.51. The control group household head average education is 4.16 years of schooling with a standard deviation of 4.57. In the HIES 2010 survey, there are 6,297 heads of households with zero year of schooling, which constitutes roughly 51.45 percent of the sample. After excluding the observations with zero year of schooling, the year of schooling of the treatment group household head jumps to 6.84 years with a standard deviation 2.75; while the year of schooling of the control group household head becomes 8 years with a standard deviation of 3. A histogram of years of education of households' head is shown in Figure 3.

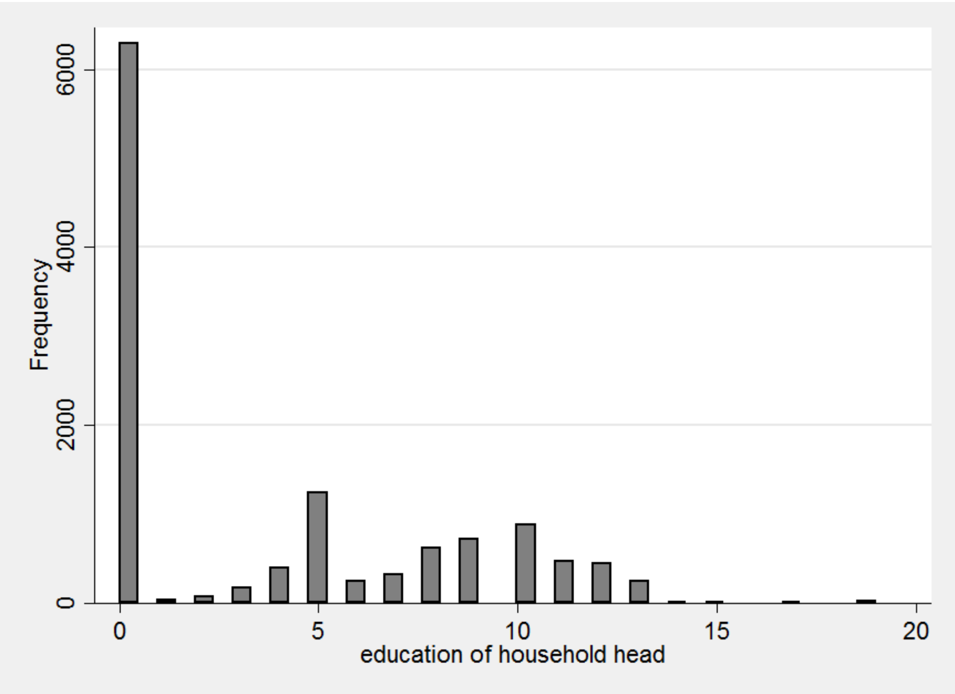


Figure 3: Year of schooling of household head

It is clear from Figure 3 that over 6,000 household heads have zero year of education and only a few household heads have studied beyond grade ten.

5.2.3 Age of Household Head

There is a widely known proverb that says '*with age comes wisdom.*' But the question is how the age of a household's head affects their calorie consumption? Many SSN programs such as *old age benefit* is designed to help elderly people, which are primarily used for consumption of goods that improves calorie intake. Similarly, in-kind transfer also increases the calorie intake of a household. The average age of a household head is 46 years with a standard deviation of 13.88. Age of the household head in the treatment group is 50.46 years with a standard deviation of 14.94. Age of control group household head is 45.22 year with a standard deviation of 13.53. It is clear from this statistics that, an average treatment group household head attended primary school before independence of Bangladesh. Although access to education was not easy as it is today and being in a disadvantaged group before the independence increases the probability of inclusion in SSN programs now.

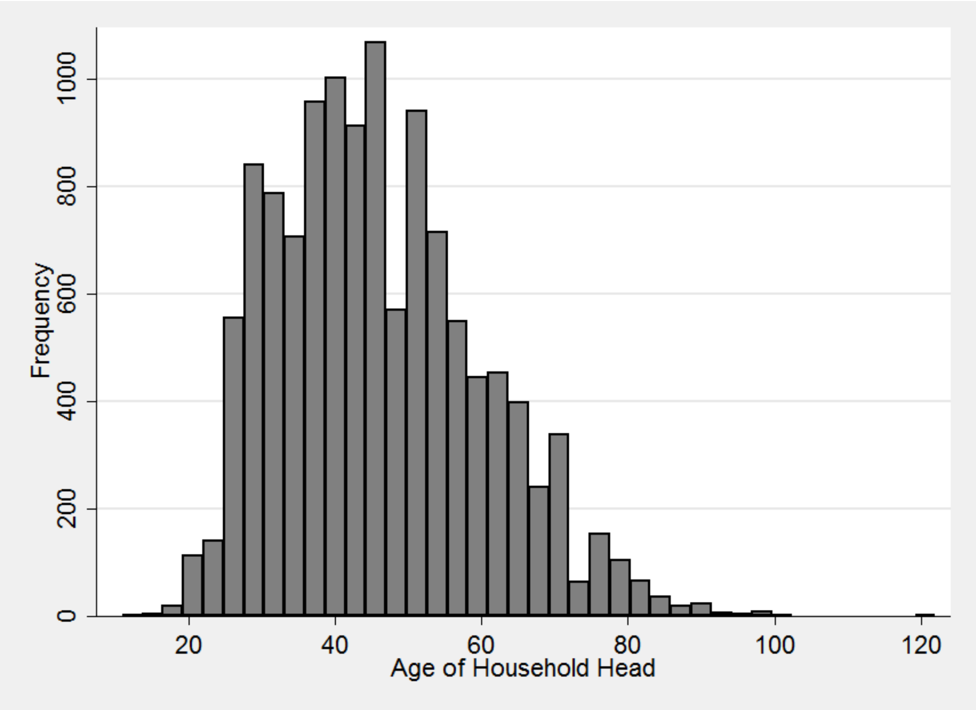


Figure 4: Histogram of age household head

5.2.4 Location of Household

Most of the SSN programs are especially designed for the people who live in rural areas. For example, the food for work program provides food grains in return for the benefitted person to work in an assigned project. In our data there are 4400 (35.95 percent) households living in urban/municipalities area and 7840 (64.05 percent) living in rural area. We also use the *interaction of living area of the households and SSN dummy* to show the effect of SSN programs when a household is under the coverage of SSN programs and living in the rural area. In the HIES survey, there are 1828 households benefitted from SSN programs and of which

1464 households (80.08 percent) live in the rural area. This shows that rural areas are the primary recipients of SSN programs as a means to support village people.

5.2.5 Divisional Dummies

To control for potential endogeneity, we use seven divisional dummies. These are, in alphabetical order, Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur, and Sylhet. In the regression mode, Sylhet is used as the benchmark category. These divisional dummy variables are used as instruments for the treatment variable in our IV regression. Some of the unobserved effect that are generally left out in regression estimation will be captured by these divisional dummies. For example, a city dweller in Sylhet has higher average income than individuals living in other divisions.

Table 5: Frequency of households by division

Division	Freq.	Percent
Barisal	980	8.01
Chittagong	2200	17.97
Dhaka	3540	28.92
Khulna	1800	14.71
Rajshahi	1580	12.91
Rangpur	1280	10.46
Sylhet	860	7.03
Total	12240	100.00

Source: BBS (2010)

5.3 Treatment Variable

The treatment dummy variable is weather the household head is getting benefit from any SSN programs or not. If the household head receives benefit from any SSN programs, it is denoted as 1 and 0 otherwise. Our primary hypothesis is that SSN programs help to increase calorie consumption of the recipient households. Programs such as *food for work* is expected to increase calorie consumption directly, while programs like *agriculture rehabilitation* would contribute to calorie intake indirectly. The data shows that the agriculture rehabilitation program has the highest coverage, followed by old age allowance and general relief activities. Table 6 presents the name and number of household's coverage by different SSN programs.

Table 6: List and frequency distribution of SSN program

Name of SSN Program	Freq.	Percent
Food Security Programs:		
1. Food for Work	3	0.16
2. Subsidy for open Market Sales†	6	0.33
3. Vulnerable group development	7	0.38
4. Cash for Work†	13	0.71
5. Test Relief	24	1.31
6. Vulnerable Group Feeding	101	5.53
7. Gratuitous Relief	410	22.43
Total	564	30.85
Social Protection Programs:		
1. Honorarium for Injured Freedom Fighter†	12	0.66
2. Allowance for beneficiaries in Ctg. Hill track†	14	0.77
3. Employment Generation for Hard-core Poor	14	0.77
4. Honorarium for Insolvent Freedom Fighter†	14	0.77
5. Allowance for the Financially Insolvent†	18	0.98
6. Allowance for Widowed, Deserted and Des. †	117	6.40
7. General Relief Activities	207	11.32
8. Old Age Allowance†	338	18.49
Total	720	39.39
Others	544	29.76
Total	1828	100

Source: BBS (2010). † Marks provide cash and rests provide in kind transfer.

6. Result and Discussion

6.1 Mean Difference IV Results

Table 7: **OLS and IV estimates: Baseline results**

	(1)	(2)	(3)
SSN dummy	6.33 (20.15)	-63.70*** (20.73)	-147.60 (172.87)
Age		10.09*** (0.59)	10.42*** (0.83)
Education		9.59*** (2.15)	11.25*** (2.27)
Household size		-100.23*** (4.49)	-95.78*** (4.89)
Income		0.015** (0.0075)	139.89 (19.14)
Rural		147.45*** (15.26)	0.006*** (0.004)
Constant	2312.33*** (7.57)	2142.80*** (33.73)	2132.87*** (31.91
R^2		0.10	0.10
No of Obs.	12240	12240	12240
First Stage F-Statistics			12.65 (0.000)
Over-identifying Restriction J-Test and P-Value			58.68 (0.000)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7 presents the results of our baseline model. Column 1 shows that the sole effect of SSN programs on calorie consumption is small but positive. Households under SSN coverage on an average consume 6 calories more than non-treated households, although the effect is statistically insignificant. However, the estimated coefficients for the intercept are positive and highly significant in all three models. It suggests that regardless of whether households are under SSN coverage or not, on an average a household member will consume more than 2100 calorie.

Column 2 shows the impact of the SSN dummy on daily calorie consumption after controlling for important household characteristics such as income and education. In this case, the impact of SSN on calorie consumption produces a negative value suggesting that households who are under SSN coverage experience a lower calorie intake than non-benefitted group. It is possible that the non-benefitted (control) group include households who are not eligible for SSN coverage but receive benefits anyway. We explore this possibility in detain the next section.

The estimated coefficient on age of household head is positive and statistically significant at the 1% level. This indicates that as the household head gets older, a household consumes 10 calories more. As such, the more experienced a household head is, it is more likely that her family would consume more healthy food. Education has a similar effect on calorie consumption. The results suggest that an additional year of schooling leads to an additional 10 calorie intake by households. Household size has the expected negative impact on calorie consumption. The impact of an additional family member is associated with a 100 calories reduction in consumption. Household's income has negligible impact on daily calorie consumption. According to the results, if income increases by Tk.1,000, calorie consumption increases by 16 calories.

An interesting finding is that households living in rural areas consume 150 calories higher than those living in urban or municipality areas. This is mainly because most SSN programs such as disaster relief and income-generation activities have a build-in rural focus.

We suspect endogeneity in SSN dummy as explain in section 4.2 and this section provide result of our estimates where we control the problem of endogeneity. The IV regression is a more appropriate method to estimate our empirical model. As already stated, we use the divisional dummy as instruments to address the potential endogeneity bias in our regression. The results are presented in the third column of Table 7. The first stage of IV regression has a F-value of 12.65 with an associated p-value is 0.000, implying that instruments are jointly significant and that the instruments are relevant. The Hansen J-statistic shows that the instruments are not over identified. The IV regression results are obtained using the Generalized Methods of Moment (GMM) estimator. On the full sample we see that SSN dummy produce insignificant negative result. The estimated coefficient on SSN dummy suggests that on a person with SSN coverage consumes 147 calories less than those who are not covered. This is from the fact that those who are under the cover of SSN programs have lower calorie intake before the programs. This conclusion lead us to run matching estimator on reduced sample and we do son in section 6.2.

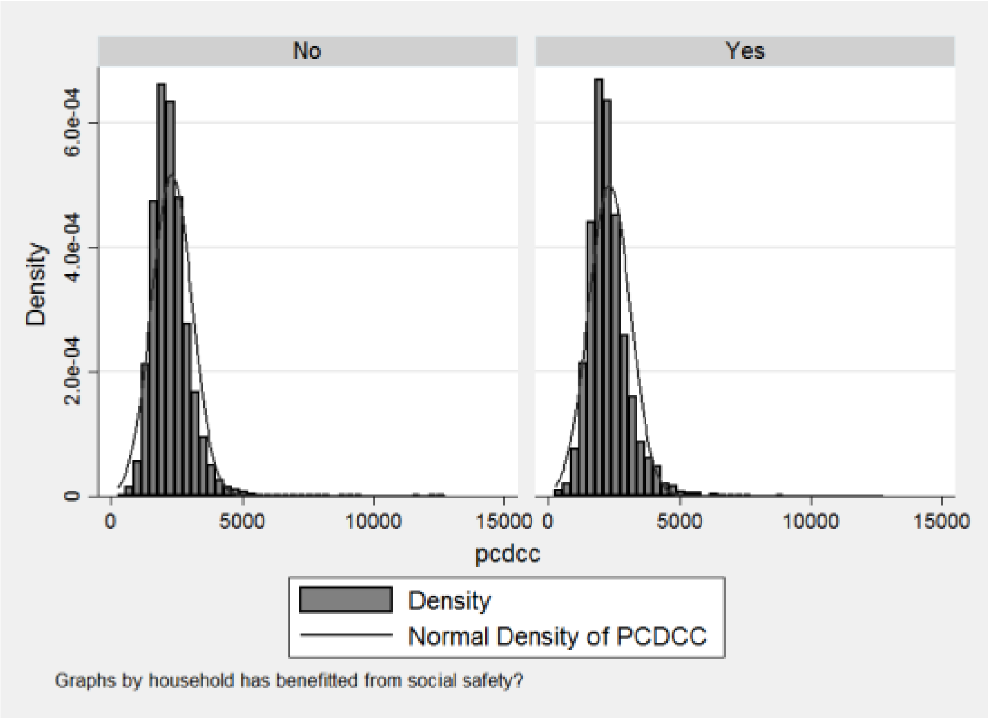


Figure 5: Histogram of Per Capita Daily Calorie Consumption

We introduce figure 5 to see the distribution of data, possible outlier that affect our estimates and ways we can modify our dependent variable to make our estimates more robust. We see that both groups calorie consumption has right skewness and have outlier. Our dealings with such case describe in section 6.2 in more detail.

6.2 Matching Estimator

One of the pitfalls of the mean difference model presented in Table 7 is that households that are not eligible to receive SSN are nonetheless included in the welfare programs. This happens because identifying SSN households is extremely difficult due to large exclusion (poor non-beneficiary households) and inclusion (non-poor beneficiary households) errors. Although Bangladesh's targeting criteria is relatively good at targeting the poorest, many SSN programs have significant administrative leakages (World Bank, 2006). The empirical analysis so far has focused on comparing the effect of SSN programs between households who are under SSN programs and households who are not. But, an appropriate comparison should be between i) households who are eligible for SSN programs and have been benefitted from these programs and ii) households who are eligible for SSN programs but do not get any benefit from these programs. This distinction is not captured by the mean difference model presented above and the primary motivation for using a matching estimator model.

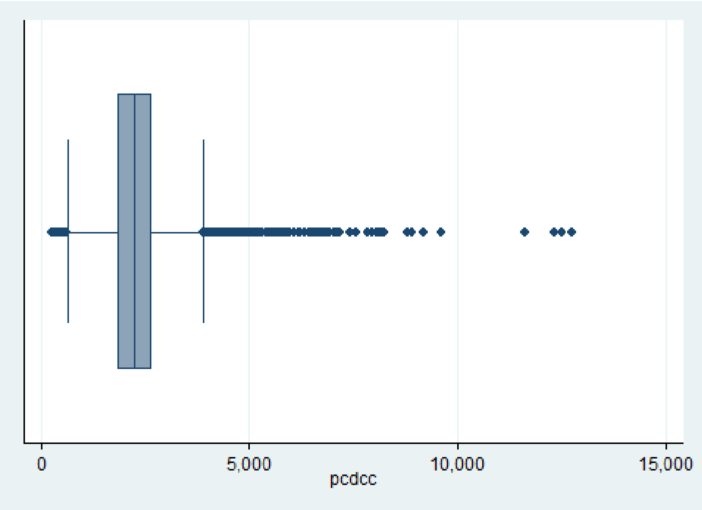


Figure 6: Box Plot of Per Capita Calorie Consumption

The identification behind the matching estimators follows several steps. First, we dropped observations that show a daily calorie consumption of 4500 grams. Figure 6 presents the boxplot of daily calorie consumption. As can be seen, a good number of households consume more than 4500 grams of goods each day, which are clearly outliers relative to the median calorie consumption by SSN households. After dropping the outlier, we see that both group's distribution of per day calorie consumption have similar pattern and follow normal distribution.

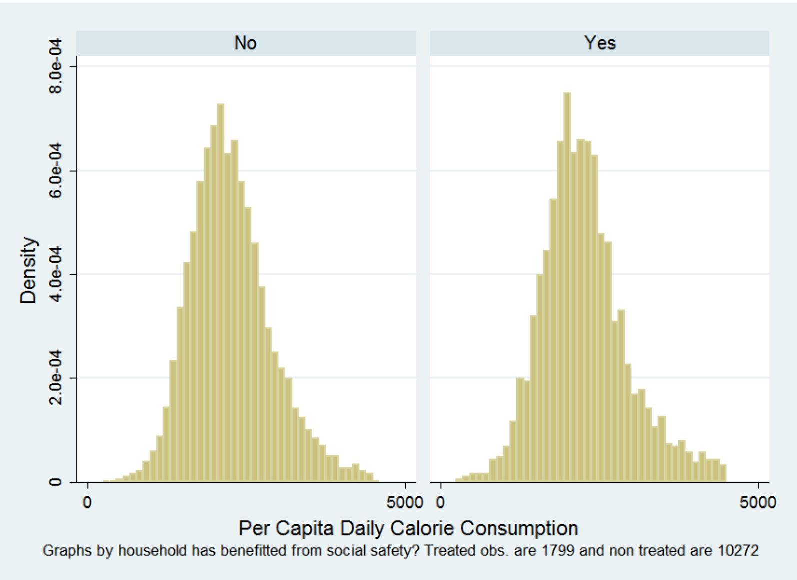


Figure 7: Calorie Consumption Distribution after dropping some outlier observations

Second, following Rahman (2012), we exclude observations with negative net income and monthly income exceeding Tk. 2,400. The main reason for using Tk. 2,400 as a threshold is because it is equivalent to a daily income of US$1 (Tk. 2,400/30 day = Tk. 80, which is approximately equal to US$ according to current exchange rate). Moreover, the Tk. 2,400 thresholds is roughly equal to the average income of the households in our sample (i.e., Tk. 2,462, see Table 1). As we can see from figure 8 that after dropping the observation with more than one dollar's income a day, there is a high similarity in income distribution and both group's data follows approximately normal distribution.

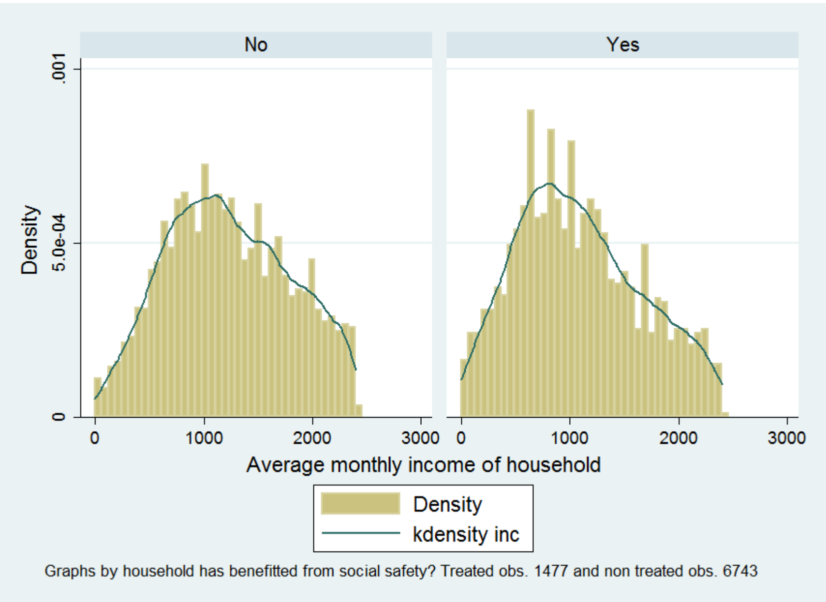


Figure 8: Histogram and density of Income

Third, we also exclude observations that show zero year of schooling as well as households with more than 12 years of education. This distribution of education is given in figure 9.

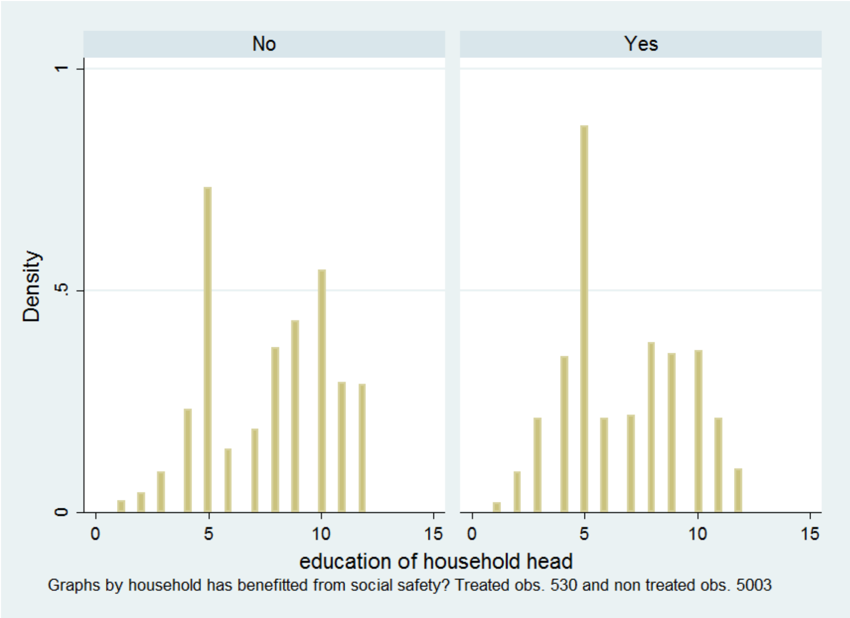


Figure 9: Histogram of Education of Household Head

Considering all the adjustments just discussed above, Table 8 presents the results off the matching estimator using two different algorithms: the propensity score match (PSM) and the nearest neighborhood (NN).

Table 7: Estimates of the average treatment effect

Dependent variable: Daily per capita calorie consumption		
	(Matching: PSM)	(Matching: NN)
SSN Dummy	76.29* (35.45)	80.74* (37.47)
Other controls	Yes	Yes
No of Obs.	3180	3180
We used robust standard error (SE), SE in the parenthesis, * p<0.05, ** p<0.01, *** p<0.001		
Note: In this regression number of treated observations are 421 and number of non-treated observations are 2759.		

The PSM estimator shows that the treated households consume 76.29 calorie more than the non-treated households and is statistically significant at the 5% level. The NN matching estimator produces a similar result. Abadie and Imbens (2011) argue that nearest neighbor matching estimator is not consistent when matching among two or more continuous outcome covariates. They recommended to use the biased adjusted estimator to overcome this problem. Households are matched by household head's sex, age, education, income, and living area. Moreover, we ensure exact matching by sex of household head and our matching criteria included minimum one household characteristic. It is clear from the table 7 that SSN programs increase calorie consumption, though small but statistically significant.

6.4 Quantile Regression Result

As pointed out earlier, it is important to estimate quantile regression for different quartile to determine the effectiveness of SSN programs especially at the bottom quartile. As can be seen from Table 9, the bottom quartile people consume less than 1850 calorie a day. We also see that 50% of the people consume more than 2211 calorie a day. The condition is worse at the bottom 1% percentile, where they consume less than 975 calorie a day, well short of the daily recommended calorie intake.

Table 9: Percentile Distribution of Dependent Variable

	Percentile	Smallest		
1%	973.89	248.16		
5%	1345.55	289.26		
10%	1519.40	325.99	Obs.	12,240
25%	1833.04	375.20	Sum of Wgt.	12,240
50%	2211.44		Mean	2313.28
		Largest	Std. Dev.	776.60
75%	2649.43	11624.71		
90%	3182.24	12341.83	Variance	603113.6
95%	3596.78	12514.57	Skewness	2.33
99%	4861.83	12714	Kurtosis	19.11

Source: Author Calculation Using HIES 2010 data

From Table 9 we see that the coefficient of skewness is 2.33, indicating that the data has considerable right skewness. Figure 6 confirms the result of right skewness of calorie consumption.

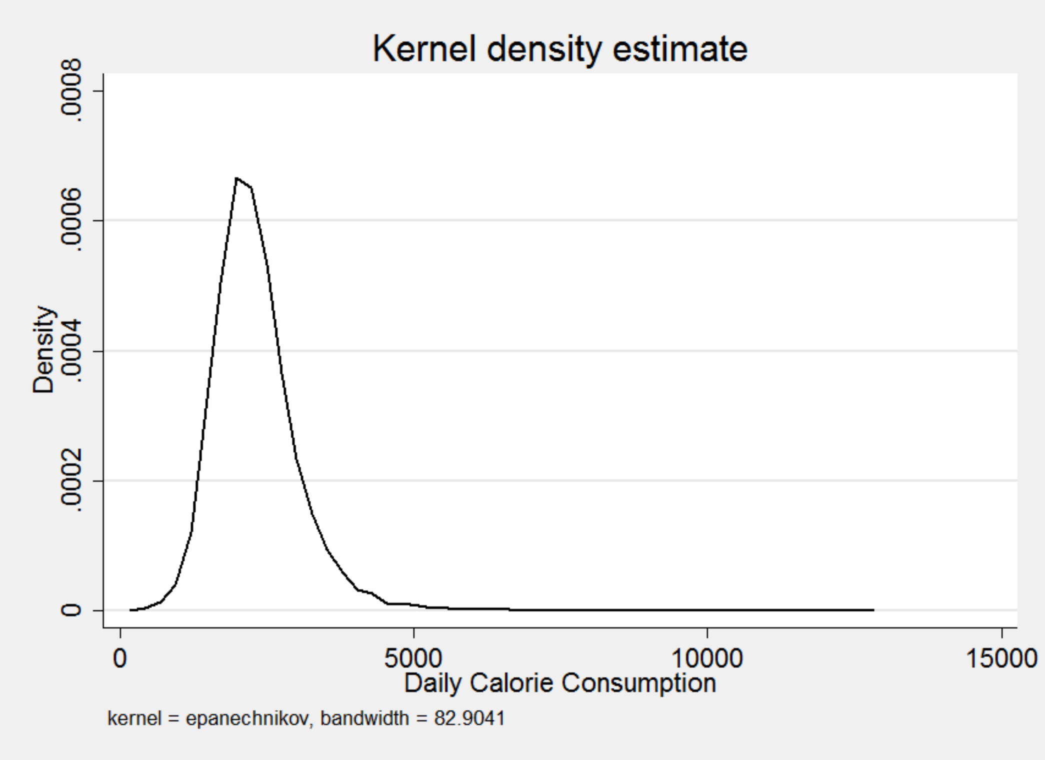


Figure 6: Distribution Plot of Daily Calorie Consumption

According to Angrist and Pischke (2009), 95 percent of economists are concerned with avarage effect, which hardly provide a relaiable picture of the casual effect.

Table 8: Estimates of the Effect of SSN Using Quantile Regression

Dependent Variable: Daily per capita Calorie Consumption		
	Q = 0.25	Q = 0.25
SSN Dummy	-3.38 (-0.19)	-43.22* (-2.16)
Other Controls	No	Yes
No of Obs.	12240	12240
We have used robust SE, t-statistics in the parenthesis, * p<0.05, ** p<0.01, *** p<0.001		

Table 10 shows the results of the quantile regression for bottom quartile. As can be seen, the impact of SSN dummy is negative on calorie consumption, suggesting that the SSN programs fail to increase the calorie consumption of the bottom quartile people. The positive impact of SSN programs produced by the average treatment effect model is due to the nature of computation, which emphasizes on the average of a distribution. The results based on average effect such as ATE and IV regressions are highly affected by large values from the top quartile which fail to depict the actual scenario of the bottom quartile people. Our quantile estimates show that SSN programs are not performing satisfactorily in increasing calorie consumption of the bottom quartile people.

7. Compersion of HIES 2005 Result and HIES 2010 Result

Rahman (2012) uses HIES 2005 data and used some of the variables that are also used here. Therefore, we compare our estimaets with that of Rahman (2012). In this compersion we will focus mostly on the beneficiary households and income in 2010 was converted in 2005's taka.

In 2005, the beneficiary households member per capita average income was BDT 843.54 and non beneficiary households average income was BDT 1459. The non treated households had Tk. 648 (76.9 percent) more income than the beneficiary households. Using the HIES 2010 data we find that the beneficiary households per capita average income is BDT 1027 and non beneficiary households average income is BDT 1872. The non beneficiary households have BDT 845 more income than the beneficiary households. The beneficiary households average income in 2010 is BDT 184 higher than those in 2005, reflecting a 21.83 percent more income. It is clear from table 10 that income of both groups increases from 2005 to 2010.

Using the HIES 2005 data, Rahman (2012) estimates that the beneficiary households per capita daily average calorie consumtion was 2193.27 and non-beneficiary households average daily calorie consumption was 2261.78. The non beneficiary households on an average had consumed 68.51 calorie more than the beneficiary households. Using the HIES 2010 data, we estimate that the beneficiary households per capita daily average calorie consumption is 2318.66 and non-beneficiary households daily average calorie consumption is 2312.3. Both beneficiary households and non beneficiary households consume almost same amount of calorie in 2010. The beneficiary households average calorie consumption in 2010 sample is 147 calorie higher than 2005 beneficiary households. This small difference in calorie consumpotion begs three explanations: 1) households real income reamin unchanged in both periods, 2) average calorie consumption in both periods is sufficient for both groups to live a healthy life, and 3) people do not spend money to buy good and services even when their income goes up. However, macro variables confirm that the real income of Bangladeshi nationals increased between 2005 and 2010. Banerjee and Duflo (2007) use household level data from 13 countries and find that, among others, in India a person living under $1 a day does not spend much on calorie consumption. In fact, poorer households spend a sizable portion of their income for festivals. Hence, even if the income of the beneficiary households goes up, the consumption of calorie doesn't necessesarily increase. Even eating more and healthy food are not practised by poor households. Banerjee and Duflo (2007) explain this puzzle as follows: eating more would not help them that much, or not for long, because they would become weak again at the first attack of disease. Indeed, poor people spend a large amount of their money on entertainment.

The HIES 2005 survey show that the average education of beneficiary households head is 1.65 year and the non beneficiary households head average education is 4.34 year. In 2005 non beneficiary households had about 2 year more schooling. In the HIES 2010 survey average education of beneficiary households head is 2.11 year and the non beneficiary households household head average education is 4.16 year.

Table 9: Summary Statistics of HIES 2005 and 2010 key variables

Variable	2010		2005	
	Treatment	Control	Treatment	Control
Calorie Consumption	2318.66	2312.33	2193.27	2261.78
	(798.45)	(772.74)	(514.32)	(562.24)
Income	1027.43	1872.46	843.54	1459.35
	(1189.63)	(3782.54)	(810.38)	(1315)
Education	2.11	4.16	1.65	4.34
	(3.51)	(4.58)	(3.19)	(5.1)
Household Size	4.30	4.58	4.59	4.9
	(1.88)	(1.88)	(2.01)	(2.08)
Age of Household Head	50.46	45.22	--	--
	(14.94)	(13.54)		
No of Obs.	1828	10412	1226	8844

Note: Result of 2005 HIES data we directly put from Rahman (2012) article. We present standard deviation in parenthesis. Age of household was not reported in Rahman (2012) article. We present real income of 2010 based on 2005 CPI = 100

World Bank (2014) studies the relationship between SSN and eliminating gender dispairity. They show that cash transfer can empower women and increase their bergaining power. Ahmed et al. (2009) examin the efficacy of food and cash transfers in enhancing the food security and livelihoods of the ultra poor in rural Bangladesh. In particular, they examine four programs: (1) income-generating VGD, (2) food security VGD, (3) food for asset creation program, and (4) rural maintenance program. They conclude that these programs have an important role in helping ultra-poor households but these programs are not the sole mechanisms for sustainable poverty reduction.

8. Why SSN Does not Significantly Affect Calorie Consumption?

There is a noticeable difference between rural and urban SSN coverage, with substantially lower coverage in the latter group area. This is partly because, currently, more poor people in Bangladesh live in rural areas than in urban centers. Moreover, most of the existing programs such as disaster relief and income-generation activities have an in-built rural focus. But, day-by-day the number of urban poor is increasing so the authority should come forward with programs for urban poor.

According to the Ministry of Planning (2015) the safety net programs have mainly emerged in a somewhat ad hoc fashion to meet the needs of an ongoing economic or social crisis resulting from an exogenous shock (e.g. natural catastrophe). As a result, there are many programs for same type of benefit, budget allocations for individual programs are limited, and involve many execution agencies. The monitoring and evaluation characteristics of these programs are inadequate and implementation progress is mainly measured in terms of amount of money spent rather than results achieved.

Being reactive to the existing needs, these programs are not well-entrenched in a strategic framework, such as the commonly used life-cycle framework, and in particular do not reflect future needs resulting from demographic changes (Ministry of Planning, 2015). Additionally, as Bangladesh moves away from a primarily agrarian economy towards a more urban-based manufacturing and modern service economy, the underlying social and economic risks faced by the poor and near-poor will also change. Indeed, on counts of both demographic and economic structural changes, a number of important gaps in the structure of SSN are already emerging. These changes require a broadening of the safety net strategy to a more inclusive concept of a Social Security strategy that also supports recipients of schemes to engage in the labor market as well as social insurance schemes. This vision of Social Security fits much more cogently with the needs of a modern urban-based economy and in the context of a life cycle framework.

The underlying reasons for this ineffectiveness are numerous. One possibility is that cash is very much transferable than any other forms of aid. So cash may go from one hand to another and treated households may not use his/her money for consuming calorie. Another possible cause is the identification bias, i.e. those who live in bottom quartile or bottom decile in calorie consumption distribution may be excluded from programs due to corruption in selection. Personal heterogeniety always exists in human being so a homogenous programs may not help much in general. High fragmentation of SSN programs put additional burden on implementation agency and create complexity in targeting individual who is likely to get benefit from the programs.

9. Conclusion

The purpose of this thesis has been to empirically examine the effect of SSN on calorie consumption among rural households in Bangladesh. Our results can be summarized as follows. First, empirical results show that the SSN programs do not have a significant impact on calorie consumption but to some extent it increases the calorie consumption. But focusing on average is misleading and do not give the complete picture of effectiveness of SSN programs for bottom quartile people. The quantile regression on bottom quartile result produces insignificant negative impact. It is important in this context to also examine the inclusion of floating people in SSN programs. In battling against hunger, malnutrition and poverty, we also have to take note of the fact that policy problems can take place in forms of identifying the deprived individual and formulate optimal SSN for her/him.

Finally, in addition to the provision of SSN programs, it is necessary to consider the coverage of SSN programs. Focusing on the effectiveness instead of number of programs may improve the SSN system in Bangladesh. SSN programs predominantly rural based but with a rapid urbanization and an increasing proportion of the urban poor living in informal settlements, some programs should focus on helping urban poor too.

9. References

Abadie, A., & Imbens, G. W. (2011). Simple and Bias-corrected Matching Estimators for Average Treatment Effects. *Journal of Business and Economic Statistics*, 1-11.

Ahmed, A. U., & Ninno, C. D. (2002). *The Food for Education Program in Bangladesh: An Evaluation of its Impact on Educational Attainment and Food Security.* Washington, D.C.: International Food Policy Research Institute.

Ahmed, A. U., Quisumbing, A. R., Nasreen, M., Hoddinott, J. F., & Bryan, E. (2009). *Comparing Food and Cash Transfers to the Ultra Poor in Bangladesh.* Washington, D.C.: International Food Policy Research Institute.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton, NJ: Princeton University Press.

Banerjee, V. B., & Duflo, E. (2007). The Economic Lives of the Poor. *Journal of Economic Prespectives, 21*, 141-167.

Bangladesh. (1972). *Constitution of the People's Republic of Bangladesh.*

Bangladesh Bureau of Statistics (BBS). (2010). *Report on Bangladesh Household Income and Expenditure Survey.* Dhaka: Bangladesh Bureau of Statistics.

Barrett, C. (1999). *Food Security and Food Assistance Programs.* (B. Gardner, & G. Rausser, Eds.) Amsterdam: Elsevier Science.

Bouis, H., & Haddad, L. (1992). Are Estimates of Calorie Income Elasticities too High?: A Recalibration of the Plausible Range. *Journal of Development Economics*.

Dehejia, R., & Wahba, S. (1999). Causal Effects in Non-experimental Studies: Re-evaluating the Evaluation of Training Programs. *Journal of the American Statistical Association*.

Federal Safety Nets. (n.d.). Retrieved 02 23, 2017, from http://federalsafetynet.com/social-safety-net.html

Gibson, J., & Rozelle, S. (2002). How Elastic is Calorie Demand? Parametric, Non-Parametric, and Semiparametric Results for Urban Papua New Guinea. *Journal of Development Studies*.

Hayashi, F. (2000). *Econometrics.* Princeton, New Jersey: Princeton University Press.

Heckman, J., & Hotz, J. (1989). Alternative methods for evaluating the impact of training programs. *Journal of the American Statistical Association*.

Heckman, J., Ichimura, H., & Todd, P. (1998). Matching as an Econometric Evaluation Estimator. *Review of Economic Studies*.

Khandker, S. R., Koowal, G. B., & Samad, H. A. (2010). *Handbook on Impact Evaluation: Quantative Methods and Practices.* Washington, D.C.: The World Bank.

Khanum, S. (2000). Knocking at the Doors: “The Impact of RMP on the Womenfolk in the Project Aadjacent Areas. *Journal of the Institute of Bangladesh Studies*.

Khuda, B. E. (2011). Social Safety Net Programmes in Bangladesh: A Review. *The Bangladesh Development Studies*, 87-108.

Koenker, R., & Gilbert Bassett, J. (1978). Regression Quantiles. *Econometrica*, 33-50.

Martin, I., & Hulme, D. (2003). Programs for the Poorest: Learning from the IGVGD Program in Bangladesh. *World Development*.

Ministry of Finance. (2016, 06). *Ministry of Finance*. Retrieved 02 22, 2017, from http://mof.gov.bd

Ministry of Planning. (2015). *National Social Security Strategy (NSSS) of Bangladesh.* Dhaka: Ministry of Planning, Bangladesh.

National Service Program. (n.d.). Retrieved 03 14, 2017, from http://oldsite.dyd.gov.bd/nsp.php

Ninno, C. D., & Dorosh, P. A. (2001). Averting a food crisis: private imports and public targeted distribution in Bangladesh after the 1998 flood. *Agricultural Economics*, 337-346.

Pitt, M., Rosenzweig, M., & Hassan, M. (1990). Productivity, Health and Inequality in the Intra-household Distribution of Food in Low-income C ountries. *American Economic Review*, Pitt, M. M., M. R. Rosenzweig and M. N. Hassan.

Quade, D. (1982). Nonparametric Analysis of Covariance by Matching. *Biometrics*.

Quisumbing, A. (2003). Food Aid and Child Nutrition in Rural Ethiopia. *World Development*.

Rahman, M. M. (2012). Estimating the Effect of the Social Safety Net Programmes in Bangladesh on Calorie Consumption of Poor Households. *Bangladesh Development Studies*.

Ravallion, M. (1990). *Markets and Famines.* Dhaka, Bangladesh: University Press Limited.

Roger, K., & Kevin, H. (2001). Quantile Regression: An Introduction. *Journal of Economic Perspectives*, 43-56.

Rubin, D. (1973). The Use of Matching And Regression Adjustment To Remove Bias In Observational Studies. *Biometrics*.

Sen, A. (1982). *Poverty and Famines.* Oxford: Clarendon Press.

Sinha, K. (2005). *Household Cheracteristics and Calorie Intake in Rural India: A Quantile Regression Approach.* The Australian National University.

Smith, A. (1776). *An Inquiry into the Nature and Causes of the Wealth of Nations.* London: W. Strahan and T. Cadell, London.

Stiglitz, J. E. (2000). *Economics of the Public Sector.* (T. Edition, Ed.) New York: W.W. Norton & Company.

Stock, J. H., & Watson, M. W. (2011). *Introduction to Econometrics.* Pearson Education Inc.

Subramanian, S., & Deaton, A. (1996). The Demand for Food and Calories. *Journal of Political Economy*.

The Daily Star. (2016, 12 06). *The Daily Star*. Retrieved 03 12, 2017, from http://www.thedailystar.net/country/corruption-tk-10-rice-poor-1325677

The World Bank. (2014). *Social Safety Nets and Gender Learning from Impact Evaluations and World Bank Projects.* Washington, DC: The World Bank.

Tiffin, R., & Dawson, P. (2002). The Demand for Calorie: Some Further Estimates in Zimbabwe. *Journal of Agriculture Economics*, 331-350.

UNDP Bangladesh. (2016). *UNDP Country Program for Bangladesh.* Dhaka: UNDP Bangladesh.

Varian, H. R. (2010). *Intermediate Microeconomics A Modern Approach.* New York: W. W. Norton & Company, Inc.

Wooldridge, J. M. (2013). *Introductory Econometrics: A Modern Approach.* Boston: South-Western, Cengage Learning.

World Bank. (2006). *Social Safety Nets in Bangladesh: An Assessment.* Dhaka: The World Bank Office.