HEDG
HEALTH, ECONOMETRICS AND DATA GROUP

THE UNIVERSITY of York

WP 11/24

Estimating the Impact of Health Programmes on the Anthropometric Indicators for Bangladeshi Women and Children Using Cross-Sectional Data

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July 2011

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Abstract

In this paper we investigate the impact of health related programmes on health outcomes of women and children by applying the method of difference-in-differences on repeated cross-sectional datasets. Health outcomes are measured using an anthropometric indicator: weight-for-height z-score. We find a positive impact, due to financial protection and social safety net programmes in a seasonally famine-affected area in Bangladesh, on the health outcome of children. We also find that the BRAC Healthcare Programme (BHP), a healthcare programme run by a reputable NGO, BRAC, has a positive impact on the health outcome of its members living in urban slums. We apply a simple decomposition approach to measuring the contributions of the programmes in lowering or increasing the inequalities in the distribution of outcomes and find that none of the programmes analysed has made the inequalities in health worse. Our key objective in this study is to show that, in developing countries, where programme-specific data are rare, using broad data like the Demographic and Health Surveys (DHS) and the Multiple Indicators Cluster Surveys (MICS) etc. it is possible to identify relevant groups and periods in order to assess the performances of several government and non-government programmes.

Keywords: Difference-in-differences; Weight-for-height z-scores; Decomposition.

1. Introduction

In this paper we generalise and adapt evaluation approaches to health related programmes in developing countries using repeated cross-sectional data. Programme-specific datasets are rare in many developing countries. Therefore, finding associations between health programmes and health outcomes using repeated cross-sectional datasets like the Demographic and Health Surveys (DHS) or the Multiple Indicator Cluster Surveys (MICS) etc. can be useful in identifying aspects of health in which the programmes are effective and those in which they are not. In this context our proposed methodology should have wider applications, especially in developing countries.

We generalise two specific evaluation approaches, namely the difference-in-differences and decomposition analysis, in the context of repeated cross-sectional datasets. If broad cross-sectional datasets for two or more successive periods are available where data are collected applying the same framework of data collection procedure, it is possible to find out groups and periods for several programmes to apply these evaluation approaches.

We analyse two health related programmes, both of which have targeted the health needs of disadvantaged groups. Firstly we analyse the impact of a comprehensive safety net programme that has been implemented on a wide scale since 2005 among poor households living in a seasonally famine-affected area in Bangladesh. The seasonal famine is known as Monga and has been affecting parts of the Rangpur Division in Bangladesh for three/four months every year. This seasonal famine has been arising mainly due to two reasons: a very limited food production during those months and a lack of employment opportunities for poor households to generate money in order to purchase foods. Accordingly, it has severe consequences on the health status of women and children living there. In order to overcome it, since 2005, the government of Bangladesh and several non-governmental organizations (NGOs) have been implementing safety net programmes in those months by offering poor households food-for-work and cash-for-work and by providing direct food and cash transfers to some groups. These steps have been thought to be influential in improving the nutritional status of people living those areas (Zug S 2006).

The second programme we analyse is a healthcare programme run by Bangladesh Rural Advancement Committee (BRAC). BRAC is one of the biggest non-governmental organisations offering microcredit and other financial and non-financial supports to a large number of poor households. It has been implementing a healthcare programme, BRAC Health Programme (BHP), since 2002, for all of its members, through its own healthcare facilities and providers, along with a referral mechanism to public hospitals for complicated cases (Nasreen, 2007). An important reason for choosing this programme is that the provision of healthcare through NGOs has been attracting the attention of policy makers and it is now widely believed that providing healthcare through NGOs is an effective method of targeting the health needs of poor households in developing countries.

We analyse the impact of these programmes on the health status of women and children. Both groups are very important for a sustained development of a nation (Bhargava 1997, Bhargava 1999, Strauss and Thomas 1998). We use an anthropometric measure as a health outcome: weight-for-height z-scores. Analysing anthropometric progress for mothers and children is important as it is evident that a large number of mothers and children in developing countries are still undernourished and that this situation has not improved much over the last decade (FAO 1992, FAO

1996, WHO 2007). The literature suggests that the poor anthropometry of a child adversely affects his/her activities over the entire life span (Bhargava 2000, Waterlow 1994, Mata 1978). In a recent report, the Bangladesh Bureau of Statistics has reported that more than one-third of the children in Bangladesh are still severely malnourished (BBS 2009).

The evaluation approaches we use are: (i) difference-in-differences to measure the average impact of health programmes; and (ii) the decomposition of inequality indices to evaluate the distributional consequences for those programmes. We decide to use these methods after considering two key features: (i) given the repeated cross-sectional nature of our data (and available datasets), we are able to distinguish between different groups, on the basis of the programme's objectives and on the basis of its period of intervention, and this places our study within the framework of difference-in-differences; (ii) the programmes we consider are broad in nature, therefore it is also important to account for their distributional consequences.

Several studies use difference-in-differences to evaluate the impact of programmes and policies on a targeted group by comparing outcomes with a corresponding comparison group (Card 1990, Card and Krueger 1994, Blundell, Duncan and Meghir 1998). This is often undertaken within a regression-based framework which estimates the parameter of interest together with its corresponding standard error (see Jones and Rice 2009).

In order to evaluate a programme on the basis of its distributional impact, one can decompose the concentration index of health outcomes to determine the programme's share in raising or lowering inequality. Wagstaff, van Doorslaer and Watanabe (2003) use data from Vietnam to decompose the concentration index for health for several factors where they propose the use of a regression-based approach for decomposition.

This approach can be generalised to compute a concentration index for a specific programme and a health outcome and to decompose this index using the same regression model used for the difference-in-differences. Applying this method we can estimate the contribution of the programme to that concentration index.

The data we use were collected by the Measures DHS in three waves: 1999-2000, 2004 and 2007-08 (BDHS 2008). The MEASURE Demographic and Health Surveys (DHS) Project is responsible for collecting high quality data on health and population in developing countries and is funded by the United States Agency for International Development (USAID), UNICEF, UNFPA, WHO, and UNAIDS. We merge the waves to prepare the data for this study.

The reminder of the paper is organised as follows. Section 2 explains how the regression-based difference-in-differences and the methods for decomposing the inequality indices apply to our data. Section 3 briefly describes the programmes and variables. Section 4 presents a descriptive analysis and results and section 5 offers conclusions.

2. Methods

2.1. Regression framework for the difference-in-differences analysis

In this paper we outline a framework to estimate (i) associations between health programmes and the measures of health outcomes and (ii) the impact of those programmes on the distribution of health, using repeated cross-sectional data, and by applying the methods of difference-in-differences and the decomposition of inequality indices. Indeed, if we have repeated cross-sectional datasets, and sufficient information about different groups based on the target of a programme,

$(g_l \in g, l = 0,1|P)$, where g stands for groups and P for the programme, we can apply the difference-in-differences and the decomposition methods. Here, if l=1 the subgroup is a study group and if l = 0, the subgroup is a comparison group.

We can constitute our study group, $(g_1|t_{l'}, l' = 0,1)$, where t stands for periods, by taking samples from those households where the programme has been implemented, and a comparison group $(g_0|t_{l'}, l' = 0,1)$ by taking samples from similar households not covered by the programme. We can further differentiate each group into two subgroups, in which one subgroup $(l' = 0)$ includes pre-programme observations, $(g_i|t_0)$, and another subgroup $(l' = 0)$ includes post-programme observations, $(g_i|t_1)$.

We need to take account of three key aspects in considering the difference-in-differences framework. First, a gap between the outcome of two groups prior to the programme is likely due to a number of observable and unobservable factors $\{z, u\}$. This can be dealt with in two ways. We can include a binary variable, *g*, to capture this group difference. Or along with the group variable *g*, we can include a vector of observable characteristics, *Z*, including relevant demographic, biological and socioeconomic factors that are likely to be associated with the health stock of a mother and/or her child. Second, it is important to rely on the assumption, that in the absence of the programme, groups would enjoy a common trend $\beta|t_1$ in health outcomes. And third, the implementation of the programme has an additional influence on the health status of study group, τ, in period t_1.

We can derive the key estimator $(\hat{\tau})$ and its standard error $(SE[\hat{\tau}])$ for measures of health using a regression-based difference-in-differences analysis (see Jones and Rice 2009):

$$h_i^j = \hat{\alpha} + \hat{\beta} t_i + \hat{\gamma} g_i + \hat{\tau} W_i + e_i \qquad i = 1,2,\ldots,n \qquad (1)$$

Where $\hat{\beta}$ is the estimator of the time trend and $\hat{\gamma}$ is the estimator of the group difference. Variable W_i is the interaction term between the group indicator variable (g_i) and period indicator variable(t_i) and the coefficient, $\hat{\tau}$, is the estimated difference-in-differences estimator in which we are interested. Equation (1) provides an unstandardised difference-in-differences estimator.

We can include the vector (Z) of demographic, biological and socioeconomic variables in the regression process, and in this way can derive the indirectly standardised difference-in-differences estimator. Suppose, to some extent, changes in these variables are responsible for the changes in health measures; indirect standardisation using the OLS could offset this effect from an unstandardised difference-in-differences estimator.

$$h_i^j = \hat{\alpha}^* + \hat{\lambda}^*[Z] + [\hat{\beta}^* t_i + \hat{\gamma}^* g_i + \hat{\tau}^* W_i] + e_i^* \qquad (2)$$

Here Z is the vector of k-covariates and (.*) represents the indirectly standardised coefficients.

2.2. A graphical presentation

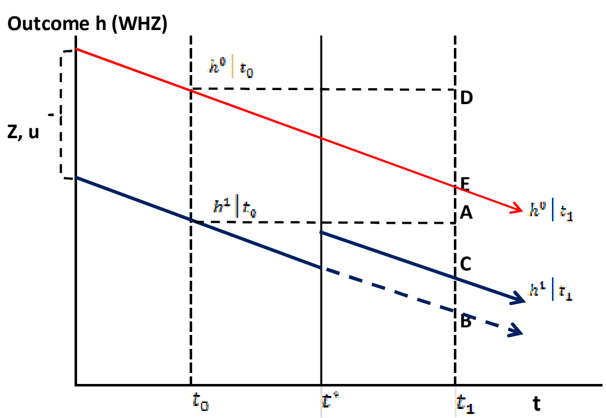

Figure 1: A simple example of potential outcomes

A graphical presentation can explain how our proposed model can derive the impact of a programme *P*. Suppose that the programme is implemented at time t^*. And suppose we have cross section data collected before treatment at time t_0 and after treatment at time t_1. Further, suppose there is an outcome gap between the groups, in favour of the comparison group. Given these assumptions, Figure 1 plots the potential outcomes for the treated (h^1) and control (h^0) groups plotted against time by further assuming a common trend in health outcomes between the groups in the absence of the programme. It should be noted that in this figure we assume that the health stock has a downward trend, in line with the findings of the World Health Organisation (WHO 2006).

Graphically, the difference-in-differences estimates the treatment effect by taking the difference between (i) the change over time for the treated (AC) and (ii) the change over time for the control (DE=AB). As long as the common trend assumption holds, the resulting difference-in-differences is the treatment effect of the programme, BC [=AC-DE=AC-AB]. We can estimate this effect using the regression models described earlier.

2.3. Checking the validity of the parallel time-trend assumption

Our estimation process relies heavily on the assumption that in the absence of the programme there is a common trend on the health outcomes of the two groups. To rely on the results that the difference-in-differences analysis provides, it is important to check the validity of this assumption. One potential way to check this is to run a difference-in-differences analysis using only the observations before implementing the programme, given that sufficient data is available. Suppose that the data allow us to undertake a difference-in-differences analysis using only the observations before implementing the programme and suppose that the time trend is not parallel. Then the difference-in-differences analysis would provide an estimator equals to $B'C'$ in Figure 2 and in the regression process this would be statistically significant. Now suppose that the difference-in-differences analysis comes up with a statistically insignificant difference-in-differences estimator; this can provide some justifications regarding the validity of a parallel time trend of health stocks between the groups in the absence of the programme.

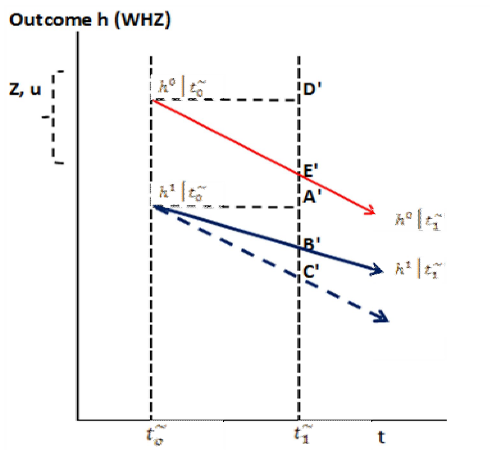

Figure 2: Examining the validity of parallel time-trend

Let us discuss this mathematically. Suppose we have information about two periods before implementing the programme, $t_o^{\sim}$ & $t_1^{\sim}$, and suppose both groups do not have a common trend.

Based on these assumptions the expected outcomes for different groups and periods are:

$$E\left(h^j \mid t_0^{\sim}, g_0^{\sim}\right) = \propto^{\sim} + \gamma^{\sim} \tag{3}$$

$$E\left(h^j \mid t_0^{\sim}, g_1^{\sim}\right) = \propto^{\sim} \tag{4}$$

$$E\left(h^j \mid t_1^{\sim}, g_0^{\sim}\right) = \propto^{\sim} + \gamma^{\sim} + \beta_0 \tag{5}$$

$$E\left(h^j \mid t_1^\sim, g_1^\sim\right) = \propto^\sim + \beta_1 \tag{6}$$

Here β_0 and β_1 stand for trends which are not common for both groups, $\beta_0 \neq \beta_1$. Now suppose $\beta_0 = \beta^\sim$ *and* $\beta_1 = \beta^\sim + \tau^\sim$. Equations (5) and (6), therefore, can be written as:

$$E\left(h^j \mid t_1^\sim, g_0^\sim\right) = \propto^\sim + \gamma^\sim + \beta^\sim \tag{7}$$

$$E\left(h^j \mid t_1^\sim, g_1^\sim\right) = \propto^\sim + \beta^\sim + \tau^\sim \tag{8}$$

Given these assumptions, the difference-in-differences analysis will provide an estimator, $\tau^\sim$, which will reflect that the trend is not common between the groups:

$$\left[E\left(h^j \mid t_1^\sim, g_1^\sim\right) - E\left(h^j \mid t_0^\sim, g_1^\sim\right)\right] - \left[E\left(h^j \mid t_1^\sim, g_0^\sim\right) - E\left(h^j \mid t_0^\sim, g_0^\sim\right)\right] = \tau^\sim \tag{9}$$

If this estimator, $\tau^\sim$, is not found to be statistically significant in the regression process, we can rely on the common trend assumption between the groups in the absence of the programme.

2.4 Distributional consequences of the programmes

Suppose within the study group, a subgroup has a greater access to the programme and receiving a greater share of benefits than other groups (which would lead to a positive impact of the programme as a whole). If this subgroup mainly includes observations that are from households having higher socioeconomic status, the average impact of the programme obtained using the difference-in-differences needs to be carefully interpreted. Accordingly, assessing the distributional consequences of a programme is also important to obtain a better understanding of its true impact. In this study we propose to check this by analysing the impact of each programme on the distribution of health.

We can use the concentration index to measure inequality in the distribution of health in each group. A concentration index provides information about global inequalities in health of the group under study. To estimate the contribution of the programme on the distribution of health we can decompose this index into contributing factors using the regression analysis of the relationships between the health outcome and its covariates.

We propose to apply a modified version of the decomposition method offered by Wagstaff, van Doorslaer and Watanabe (2003) in which they suggest to compute the contribution of each factor by multiplying the elasticity of health (η^k) with respect to factor k with the degree of socioeconomic inequality in k (CI^k). This relation can be captured using the regression model to decompose the concentration index. Recall our regression model:

$$h_i^j = \hat{\alpha}^* + \hat{\lambda}^*[Z] + \left[\hat{\beta}^* t_i + \hat{\gamma}^* G_i + \hat{\tau}^* W_i\right] + e_i^*$$

Following their approach the concentration index CI^j is:

$$CI^j = \sum_k (((\lambda^{j,k})\,\bar{z}^k)\frac{1}{\mu^j})CI^{j,k} + \frac{\beta^{*k}.\bar{t}_i}{\mu^j}\,CI^{j,t} + \frac{\gamma^{*k}.\overline{G}_i}{\mu^j}\,CI^{j,g} + \frac{\tau^{*k}.\overline{W}_i}{\mu^j}\,CI^{j,W} + \frac{GC_e}{\mu^j} \qquad (10)$$

Where μ^j is the mean of h^j, ($\bar{z}^k$) is the mean of z_k, $CI^{j,k}$ is the CI for z_k, and $\frac{GC_e}{\mu^j}$ is the generalized concentration index for the error term. Our main focus in this section is the term $\frac{\tau^{*k}.\overline{W}_i}{\mu^j}\,CI^{j,W}$, where $CI^{j,W}$ is the concentration index for variable W, and $\frac{\tau^{*k}.\overline{W}_i}{\mu^j}$ is the elasticity of h^j with respect to that variable. The interaction term, *W*, captures the difference-in-differences between the groups at the presence of the group variable and time variable, therefore, its contribution in the inequality index captures the contribution of the programme itself.

3. Programmes, groups and variables

3.1. Social safety net programmes in Monga-affected areas in Bangladesh

The first programme we assess is a comprehensive safety net programme operating in a seasonally famine-affected part in Bangladesh. The seasonal famine we consider is known as “Monga”. Sebastian Zug (2006) has defined Monga as follows: “Monga is a seasonal food insecurity in ecologically vulnerable and economically weak parts of north-western Bangladesh, primarily caused by an employment and income deficit before aman, a variety of rice, is harvested. It mainly affects those rural poor, who have an undiversified income that directly or indirectly based on agriculture”. Monga is also a synonym for seasonal food insecurity. Seasonal food insecurity is a problem for rural people everywhere in Bangladesh, but its severity is much higher in north-western Bangladesh.

Gaibandha, Lalmonirhut, Nilphamari, Kurigram and Rangpur districts, commonly known as Greater Rangpur, are mainly known as Monga-affected districts as consequences of food insecurity are much higher in these districts due to ecological and economical aspects. The rivers Jamuna and Teesta have a big influence on the livelihoods of a reasonable proportion of Greater Rangpur. Every year, preceding Monga, these rivers cause flooding for several months which results in a loss of assets as well as limiting employment opportunities. Many people living in these areas are also affected by river erosion every year during the Monga season. Economically, Greater Rangpur is one of the most disadvantaged regions of Bangladesh. There are insufficient and less diversified employment opportunities in Greater Rangpur. During the floods, employment opportunities become exceptionally limited. Access to government services is also restricted.

Given these deprived ecological and economical features of Rangpur, groups affected heavily by Monga are: households living in rural areas, agricultural workers, marginal farmers, unskilled labourers, transport workers, and households live on the generosity of others. These groups are unable to earn sufficient money during the Monga season to buy foods, cannot produce enough foods and lose assets because of floods and river erosion. About one-tenth of total population in Bangladesh are living in Greater Rangpur and almost 50 percent of them are affected by Monga either severely, moderately or at least marginally.

Seasonal migration presents an opportunity for affected individuals to earn money during Monga. The problem is that the employment opportunities are also very limited in other districts, so the migrated workers need to work for a very low wage. In the major cities they need to find a job for a very low wage and a very high rent. Alternatively they can remain in their areas and can borrow money from money lenders. The problem is that during Monga season interests payable to local money lenders are extremely high and near 100 percent (Zug S 2006). Another possibility is that families can sell or mortgage their assets during crises. This adversely affects their living capacity for the future (DER report 2004).

During Monga many families, therefore, minimise their expenses on clothing, crockery and foods. The lack of income reduces the foods necessary for their nutritional requirements. They take fewer meals, consume less milk, eggs and vegetables and buy unclear broken rice. They postpone repairing houses and tube wells. Repetition of Monga every year, consequently, affects their overall nutritional status, and the most vulnerable groups include women and children living in those areas, mobility and employment opportunities for whom are very limited. Accordingly, the physical capacity of these people decreases both in a short-run and in a long-run.

Pushed by the media, NGOs and development organisations, the Poverty Reduction Strategy Paper (PRSP) in Bangladesh has included Monga as one of the priority areas to reduce poverty. The government of Bangladesh has been implementing cash and food protection programmes in Monga-affected parts since 2005. NGOs, for example the Palli Karma-Sahayak Foundation (PKSF), Rangpur-Dinajpur Rural Services (RDRS) and Gana Unnayan Kendra (GUK) etc., and development organisations, for example the World Bank, have been collecting funds and implementing programmes to reduce the extent of Monga on the poor households. These organisations have been carrying out Food-for-Work and Cash-for-Work programmes during Monga season and also giving direct relief during Monga to people not fit for work.

Various NGOs have been working with isolated programmes during the lean season without regard to the issue of sustainability and withdrawn aid when the lean season is over Palli Karma-Sahayak Foundation has implemented a programme named “Programmed Initiatives for Monga Eradication”, PRIME, since 2006 in which it has incorporated several of those NGOs. The main objective of PRIME is to provide employment opportunities through involving them in infrastructure development activities during lean season.

These programmes by the government and NGOs in the lean season have been proved effective to prevent people from a severe starvation. We aim to assess the overall impact of these programmes overlooking the costs involved, whether the programmes are actually reaching everyone, and whether the programmes are affected by on-going corruption.

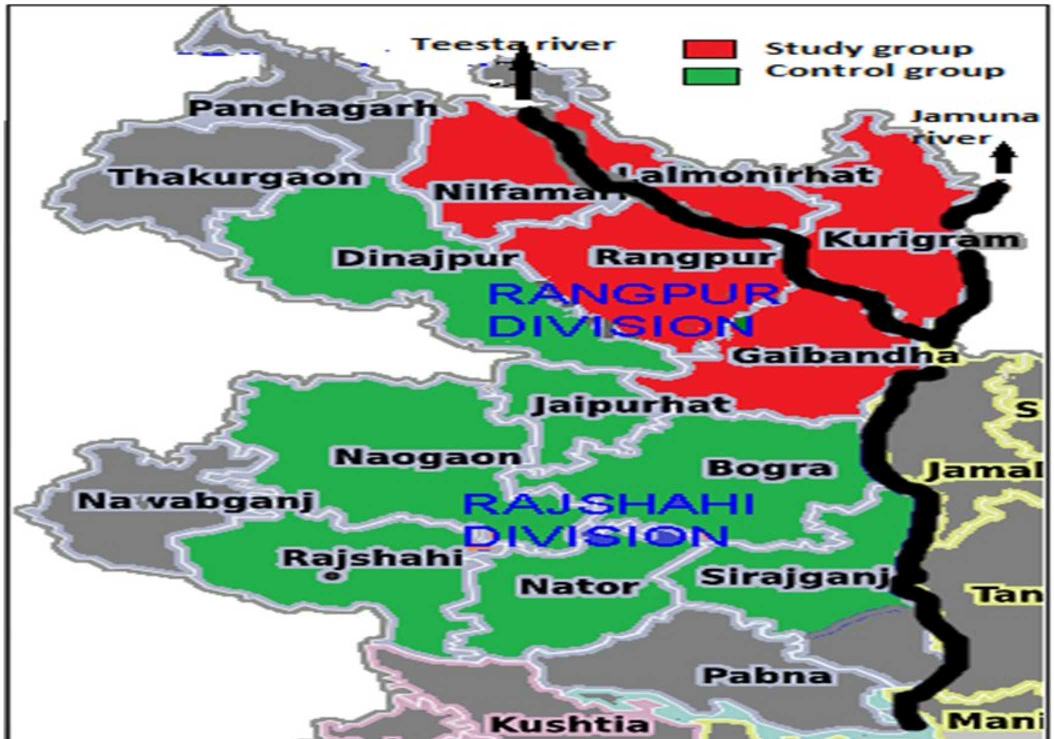

Figure 3: Safety net programmes: study & control areas

We use a method we term “geographical matching”, to locate areas where the government and NGOs have been implementing safety net programmes, using the Global Positioning System, and the nearest areas where safety net programmes have not been implemented. In our dataset, we have information about the global position of each cluster in terms of its latitude and longitude. We use a latitude-longitude finder to identify the location of each cluster on the country map. We then match this with the government's data in order to identify whether the households in that cluster are eligible for support from the social safety net programmes. In this way we identify all clusters receiving benefits from the social safety net programmes targeting Monga. Following this, we identify the nearest areas that are not affected by the severity of Monga, which means that households living there are not eligible to receive benefits from social safety net programmes we are considering. From these households we identify similar households to our treatment group in terms of their asset ownership. After deriving treatment and control households using the latitude-longitude finder and matching with the government data, we differentiate these groups into two sub-groups. As social safety net programmes in Monga areas have started rigorously from 2005, observations prior 2005 form our pre-programme groups, and observations post 2005 form our post-programme groups.

3.2. BRAC Health Programme (BHP)

Bangladesh Rural Advancement Committee (BRAC), which was initiated in 1972, has been provided microcredit and other supports to the poor since 1974. Its target groups include those who are poorest of the poor, those who are marginal farmer, and those who provide manual labour. BRAC tackles poverty from a holistic standpoint. It aims to make those empowered citizens who receive supports and loans from its funds. Majority of its members are women living either in rural areas or in urban slums.

Health is a central component of BRAC's development intervention since 1980s. Beginning with a small scale curative care to a large scale Oral Therapy Extension Programme (OTEP) to fight massive diarrhoeal deaths in the 1980s, it extended its programmes to Reproductive Health and Diseases Control (RHDC) Programme and National Nutrition Programme (NNP) in the 1990s. After 2000 it has become an active partner of the Government of Bangladesh in executing its ‘Health, Nutrition and Population Sector Programme’ (HNPSP) and is working closely with the government to attain Millennium Development Goals (MDGs). From 2002, all BRAC’s health interventions have been integrated under a programme named BRAC Health Programme (BHP). Since then, BRAC has been implementing health care programmes for all BRAC members using its own staff members and community health volunteers. Under the BHP it has been prioritised in providing quality basic healthcare to mothers and babies and for complicated cases it has collaboration with government facilities as a partner of the Government. Currently BRAC has more than 18000 staff and 60000 women volunteers who are working in providing healthcare. Under this programme, BRAC has a target of 8 million urban slum dwellers and 11 million rural people to provide maternal, neonatal, and child health programmes.

We aim to assess the performance of BHP in improving the health of BRAC members. In our data, we have information regarding the members of BRAC both before and after the implementation of BHP programme. To create a comparison group we identify households that are members of other NGOs. It is worth mentioning that all these NGOs, including BRAC, had been running some basic healthcare programmes for their members since the 1980s. However, BRAC has made the programme rigorous and comprehensive and set up a referral mechanism in collaboration with the public healthcare system from 2002 onwards. This has differentiated BRAC from other NGOs in terms of providing healthcare from that point of time. Finally, for evaluating the BHP programme, observations from the

BDHS 2000 constitute pre-programme groups and observations from the BDHS 2004 and BDHS 2007 constitute post-programme groups.

3.3. Health outcome

We use an anthropometric measure as the dependent variable: weight-for-height z-scores. This measure of anthropometry can capture short-term changes in nutritional status and the consequences of severe diseases and chronic conditions (O'Donnell et al. 2007). We compute these scores by comparing them with a healthy reference population taken from the United States National Centre for Health Statistics (NCHS) data. We first compute the difference between the value for an individual and the median value of the NCHS population for same sex and height for the corresponding age group. We then divide this score by the standard deviation in health of the reference population to obtain the z-score we are looking for.

3.4. A summary of the programmes

Table 1 summarises the programmes, groups and periods and lists the variables we use in this study.

Table 1: Summary of the programmes

	Safety Net Programme	BHP
Year of implementation	2005	2002
Treatment group	Children	Women
Comparison group	Children from nearby locations	Women from other NGOs
Selection of comparison group	Geographical matching using the GPS	Matching by NGO membership
Period 0	Before 2005 (BDHS 2004 and BDHS 2000)	Before 2002 (BDHS 2000)
Period 1	After 2004 (BDHS 2007)	After 2002 (BDHS 2004 and 2007)
Health outcomes used	WHZ	WHZ
Standardising variables	Age, sex, HAZ of mother, asset, disease, pregnancy and household members	
Regression method	OLS, Decomposition	OLS, Decomposition

4. Findings

We use weight-for-height z-scores as our dependent variable in a number of models. Given its specification, and the specifications of the regressors, a positive coefficient is preferred to a negative coefficient in our regression results. A positive difference-in-differences estimator along with a small standard error, hence, is an indication regarding the effectiveness of the programme. On the other hand, in the decomposition of concentration index, any negative contribution by a factor is preferred to a positive contribution. A positive concentration index implies the presence of socioeconomic inequalities favouring the better-off. Further, suppose for a programme we find that the contribution of the programme in that concentration index is negative. This implies that the programme does not contribute to the existing socioeconomic inequality in health.

4.1. The impact of social safety net programmes on children's health

In the sample, that we use to analyse the impact of safety net programmes during Monga, the mean weight-for-height z-scores are -1.17 and –1.09 for the treatment group and comparison group respectively. About 52 percent of the babies are male in our treatment group whereas in the comparison group 51 percent of the babies are male. All households are chosen from middle, lower middle and poor households in terms of assets ownership.

Table 2 and Table 3 summarise the estimates from regression-based difference-in-differences analysis which are used to evaluate the impact of social safety net programmes targeting Monga. Table 2 presents unstandardised coefficients derived using the ordinary least squares method and Table 3 presents standardised coefficients.

In Table 2, the variable reflecting periods is negative and significant which indicates that the health status of children has deteriorated over time. This is not surprising as it is in line with the findings of World Health Organisation that in Bangladesh, and many other developing countries, on average, the anthropometry of babies in terms of their weights has been deteriorating (WHO 2006). Yet, the indicator variable for the difference-in-differences analysis is estimated with a positive coefficient of 0.2055, and a standard error of 0.0987. This indicates that, since implementing the programmes, the weight-for-height z-scores of children living in famine-affected areas have deteriorated less than the health status of children belonging to the comparison group. On average, in comparison with the control group, the gap in weight-for-height z-score between a child living in a Monga-affected part and a child from the NCHS, for the same sex and height, reduced by a score of 0.2055, after implementing social safety net programmes there. This is because the safety net programmes have ensured a greater access to basic foods and amenities for those households either through a direct food subsidy, or a cash transfer which has increased the purchasing power of households, or both. Consequently, the average health stock of children living in that region has deteriorated less than the average health stock of comparison group of children.

Table 2: Impact of the Safety net programmes on the WHZ for children
'Unstandardized coefficients'
Bangladesh 2000-2007 Bangladesh 2000-2007

WHZ	Coef.	Std. Err.	t	P>t
Period 2	-0.2539336	0.0726342	-3.5	0
Location: Monga	-0.1242838	0.0520972	-2.39	0.017
τ (Did estimator)	0.2055348	0.098738	2.08	0.038
_cons	-1.026519	0.0386793	-26.54	0
n	1741			

In Table 3 we standardise these coefficients for other variables relevant to a child's health. An important variable associated with anthropometric measures is a household's socioeconomic position. On average a baby living in a household with a higher socioeconomic status has a higher level of health stock than a counterpart living in a household with a lower socioeconomic status. A common disease like diarrhoea has a significant association with weight-for-height z-scores. In the presence of these significant factors, the difference-in-differences estimator is still statistically significant and positive in magnitude, 0.2237 (S.E. 0.0966), and fairly close to the unstandardised difference-in-differences coefficient presented earlier. Therefore, standardising confirms that the programme is effective in improving the health stock of the children-affected.

Table 3: Impact of the Safety net programmes on the WHZ for children
'Standardised coefficients'
Bangladesh 2000-2007

WHZ	Coef.	Std. Err.	t	P>t
Age	-0.0873527	0.0161672	-5.4	0
HAZ of mother	0.0338851	0.0221985	1.53	0.127
Sex: male	0.0384298	0.044021	0.87	0.383
Asset index	0.0644233	0.0272677	2.36	0.018
Disease recently: yes	-0.2655114	0.0799964	-3.32	0.001
Period 2	-0.2514966	0.0709739	-3.54	0
Location: Monga	-0.1126835	0.0519544	-2.17	0.03
τ (Did estimator)	0.2237064	0.096684	2.31	0.021
_cons	-0.9070473	0.093546	-9.7	0
Number of observations	1733			

Checking the validity of the parallel time-trend assumption

To check the validity of the crucial parallel trend assumption, in the absence of the programme, we run a difference-in-differences analysis using only pre-programme observations; the findings are in Table 4. The difference-in-differences estimator, in this analysis, is small and not statistically significant whereas if the trend was not parallel, the difference-in-differences estimator should be large and statistically significant. This justifies our interpretation regarding the difference-in-differences estimators in Table 2 & 3.

Table 4: Impact of the Safety net programmes on the WHZ for children
Assessing the validity of the parallel time trend
Bangladesh 2000-2004

WHZ	Coef.	Std. Err.	t	P>t
Year 2004	-0.1631116	0.0766957	-2.13	0.034
Location: Monga	-0.1798621	0.0718608	-2.5	0.012
τ (Did estimator)	0.0972734	0.1037218	0.94	0.349
_cons	-0.9388732	0.0531526	-17.66	0

Decomposition of the inequality index

In the sample we use to evaluate safety net programmes, we observe inequalities in health, in favour of households with more assets. Keeping the same regression model used for the standardised regression analysis, we estimate a global inequality index for the distribution of health, 0.012, and then decompose it for the factors that used in the regression model. Using this decomposition approach we find that the contribution of the programme, in the global inequality index, is negative, -8.05%, which is clearly in favour of the programme. It implies that the programme has not contributed to the socioeconomic inequality in health outcome. It should be mentioned here that the foremost share of the socioeconomic inequalities in health outcome is originated from the socioeconomic and biological variables which indicates the model is well-specified.

Table 5: Decomposition of the concentration indices for the WHZ

Contribution of the safety net programmes

	Contribution	% Contribution
Contribution of the socioeconomic and biological variables	0.01135644	92.40841701
Contribution of the period and the group variables	0.00249696	20.31799762
Contribution of the programme	-0.00098915	-8.048806288
Residual	-0.00057485	-4.677608345
Total (CI and contributions	0.0122894	100

4.2 BRAC Healthcare Program (BHP)

Women, who are members of NGOs, on average has a lower health status than the average health of reference women from the NCHS data. The mean weight-for-height z-score for BRAC members, in our data, is -1.48 whereas the mean weight-for-height z-score for the members of other NGOs is slightly better, -1.34. In each case, the deviation of health from the health stock of reference women is quite large.

In Table 6 we summarise the estimates from regression-based difference-in-differences analysis for the BRAC Healthcare Programme, BHP, for weight-for-height z-scores for women. This Table contains three models: Model A and Model B present the estimates from unstandardised difference-in-differences analysis, for rural and urban areas, respectively; and Model C presents the results of standardised regression analysis, only for urban members.

Model A shows that the difference-in-differences estimator, estimated using the unstandardised approach, is positive in line with the hypothesis, but not statistically significant. This leads to a conclusion that the BHP is yet to be effective in rural areas.

Now turn to the findings that are obtained for urban areas. Both difference-in-differences estimators, 0.4208 (S.E. 0.1816) and 0.5185 (S.E. 0.1766), estimated using the unstandardised and standardised approaches respectively, are strongly significant and in favour of the programme. When we use the standardising factors, we find that the standardising variables have strong associations with the level of health, and are all in line with the standard hypothesis. In the presence of these variables, the difference-in-differences estimator is still significant giving an impression that the BHP has effectively improved the health status of its members living in urban slums.

Table 6: 'Impact of the BRAC Healthcare Programme on the WHZ'
'Unstandardised' and 'after standardising'
Bangladesh 2000-2007

6 A. Unstandardised difference-in-differences analysis (Rural area)

	Coef.	Std. Err.	t	P>t
year2004	0.1037235	0.0650067	1.6	0.111
year2007	0.2031381	0.0560379	3.63	0
Member of BRAC	-0.0429315	0.0647022	-0.66	0.507
τ (Did estimator)	0.0080715	0.0793143	0.1	0.919
_cons	-1.652675	0.0448567	-36.84	0
n	3279			
6 B. Unstandardised difference-in-differences analysis (Urban area)				
year2004	-0.3140006	0.11225	-2.8	0.005
year2007	-0.0456192	0.1044439	-0.44	0.662
Member of BRAC	-0.5417789	0.1661529	-3.26	0.001
τ (Did estimator)	0.4208405	0.1815717	2.32	0.021
_cons	-0.9166316	0.0945093	-9.7	0
n	1881			
6 C. Standardised difference-in-differences analysis (Urban area)				
Age of women	-0.0181652	0.0033031	-5.5	0
Birth in past year	0.0756125	0.1020853	0.74	0.459
Currently pregnant	-0.2806974	0.1376499	-2.04	0.042
No. of household member	-0.0265612	0.0109422	-2.43	0.015
Asset	0.4742002	0.0323838	14.64	0
year 2004	-0.4160602	0.1079393	-3.85	0
year 2007	-0.156381	0.1030064	-1.52	0.129
Member of BRAC	-0.5513413	0.1631769	-3.38	0.001
τ (Did estimator)	0.5184569	0.1765805	2.94	0.003
_cons	-0.2846669	0.147724	-1.93	0.054
n	1881			

Although the reasons behind this difference in effectiveness between rural areas and urban slums are not reflected in our regression analysis and data, it can be noted that the referral mechanism that the BHP has been following is more effective in urban areas because of the presence of an extensive public healthcare system there. Therefore, it looks like that, in countries like Bangladesh, an NGO can improve the health status of its members to a certain extent through its healthcare facilities, but for dramatic improvement, collaboration with the public system is also important.

Checking the validity of parallel trend assumption

For the BRAC Healthcare programme we do not have information for two successive periods prior the programme. However, we have information for two successive periods after the programme. We run the difference-in-differences analysis using only the observations after implementing the programme. As, in this analysis, we use only post-programme observations, the impact of the programme should be merged within the group variable. Given this, an unparalleled trend should be reflected in a large and statistically significant difference-in-differences estimator. We observe that (Table 7) the group difference in this sample is not significant; this is because the impact of BHP is now merged in the group variable making the group difference a numerically smaller and statistically insignificant one. We also observe that the difference-in-differences estimator in this analysis is not significant. Given the specification of this regression model, if the trend is not parallel between the groups, we should observe a strong and significant difference-in-differences estimator in the regression process. Looking at the size and significance level of the difference-in-differences estimator we can rely on the assumption that the trend in health is parallel between the groups after implementing the programme and we can assume with more confidence that it was parallel in the absence of the programme as well.

Table 7: Impact of the BRAC Healthcare programme on the WHZ for women
Assessing the validity of the parallel time trend
Bangladesh 2004-2007

WHZ	Coef.	Std. Err.	t	P>t
Year 2007	0.2889427	0.0829276	3.48	0.001
Member of BRAC	-0.0844029	0.1090277	-0.77	0.439
τ (Did estimator)	-0.065352	0.1470681	-0.44	0.657
_cons	-1.244463	0.0683993	-18.19	0

Table 8: Decomposition of concentration indices for WHZ*(-1) for women
Distributional impact of the BRAC Healthcare Programme

WHZ*(-1)	Contribution	% Contribution
Contribution of socioeconomic and biological variables	0.0872	101.5759
Contribution of period and group variables	0.0034	3.9090
Contribution of the programme	-0.0033	-3.8388
Residual	-0.0014	-1.6461
Total CI and contributions	0.0859	100

Decomposition of the inequality index

We calculate the health inequality index for the NGO members living in urban areas and observe a very high level of socioeconomic inequality in health among them, evident from a very high concentration index, 0.0859. After decomposing the concentration index we find that the contribution of the programme in this index is small and negative. On the basis of this finding, we do not have enough evidence to conclude that the BRAC Healthcare programme has made the inequalities in the distribution of health worse among its members.

4.3. Impact of the programmes on other groups

In Section 4.1 & 4.2 we only discuss the programmes for groups where we find the programmes have some success, at least to a certain extent. For other groups, but for the same programmes, we find that the difference-in-differences estimators are positive in magnitude, in line with the hypothesis, but not statistically significant. For example, when we analyse the impact of the safety net programmes on women's health, we find that the difference-in-differences estimator is positive but not statistically significant. We summarise these findings in Table 9.

These findings suggest that the programmes we analyse are partially successful but yet to achieve a universal success for all groups. However, the positive difference-in-differences estimators suggest that continuation of the programmes might bring success to other groups over time.

Table 9: Summary of the statistical significance of difference-in-differences* estimators for different groups and programmes

			BRAC Healthcare	
Health outcomes	Group	Safety net	Rural area	Urban Area
WHZ	Children	Significant	Not significant	Not significant
WHZ	Women	Not significant	Not Significant	Significant

* All difference-in-differences estimators are positive, in line with the hypothesis

5. Conclusion

In this paper we aim to evaluate two programmes that are related to the health development of women and children. Using difference-in-differences analysis we find that the programmes are successful in improving the health of some of these groups. The limitation of this approach is that it does not tell us about the programme effects on the distribution of outcome. Therefore, we apply a simple decomposition approach using the health inequality indices. Using this approach, we find that the programmes have not made the inequalities in the distribution of health of the target groups worse than during the previous periods.

One of the strengths of this study is that we propose to use cross-sectional datasets that are broad in nature in order to evaluate specific programmes. In developing countries this is particularly important in evaluating past and on-going programmes where programme-specific data are rare. We show one way of specifying the groups and periods using repeated cross-sectional waves and how one can apply the evaluative approaches. This is not applicable for all programmes, but there are several programmes which can be evaluated in this way, and this can be extremely helpful for policy makers. We also propose to assess the distributional consequences if necessary and one simple approach for doing so is to decompose the inequality index to discover the contribution of the programme.

The results we obtain suggest clear policy implications. For disadvantaged groups in society, such as those living in famine-affected areas, safety net programmes are beneficial for their health development. Also, non-governmental organisations can play a key role in improving the health status of women and children in collaboration with the public system. Therefore, an NGO-public mix can be a useful mechanism for improving the health of treatment groups.

Finally, broad datasets can provide an estimate and overview of the impact of a programme. The programmes we analyse are very important in improving the health of disadvantaged groups in developing countries. Besides, there are several issues that are not reflected in broad datasets. For example, cost of the programmes, responsiveness, and constraints during implementation process etc. are not reflected in these broad datasets. Therefore, for the evaluation purpose, we suggest collecting data at micro levels for these programmes in addition to using the broad datasets.

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