Ex ante decomposition of changes in the distribution of child nutritional status from a Conditional Cash Transfer Program in Nicaragua

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Abstract

This paper uses data from Nicaragua's social protection program Red de Protección Social to decompose from a pre-program scenario the contribution of one year of the cash transfer component to the total change in the weight-for-age Z score (WAZ) distribution for children aged below 5 years. The estimation compares two semiparametric approaches - a quantile regression approach and a distributional regressions based approach with a nonparametric approach to estimate the unobserved unconditional counterfactual distribution under the cash transfer. The overall program has the largest effect at the lower part of the WAZ distribution; in contrast, the estimates explain the contribution of the cash transfer to be increasing across the distribution highlighting the importance of the health related conditionalities in improving child health for the most malnourished. In addition, two alternate policy scenarios are simulated. Providing just a food security transfer shows no improvement in the WAZ distribution while providing an unconditional transfer equal to twice the original program does not result in a major change from the original specification.

Keywords: decomposition, conditional cash transfers, distributional regression, malnutrition, quantile regression, nonparametric estimation

JEL classification:I13, O12

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1 Introduction

The impact of conditional cash transfer programs on child health is well documented in the literature (Gertler 2004, Fernald et al. 2008, Maluccio & Flores 2005). However these studies restrict themselves to the average impact of the programs and do not highlight distributional consequences. Even in cases where limited impact is found Heckman, Smith and Clements (1997) emphasize the importance of extending program evaluations to explore beyond average impacts. The heterogeneity can exist either across different observed covariates such as gender and age or the treatment effect itself may not be the same across all individuals. Following the paper by Djebbari and Smith (2008) in which the authors provide a formal analysis of heterogeneity in treatment effects, using data from Mexico's social protection program Progresa, there has been a small but growing literature on estimating distributional impacts in evaluating social programs in developing countries, particularly conditional cash transfer programs. This paper adds to the literature on distributional effects of conditional cash transfer (CCT) programs by analysing across quantiles the total change in the child health distribution from Nicaragua's CCT program Red de Protección Social (RPS). It then decomposes the total change in the child health distribution to explain the extent to which one year of the cash transfer component contributes to this change. But it is unique in that it attempts to forecast this contribution to the total change from a pre-program scenario and by doing so makes an important addition to the limited literature on ex ante analyses of social programs.

Ex ante evaluations of social programs attempt to forecast the outcome of a program before it is implemented (Todd & Wolpin 2006, Attanasio et al. 2005, Todd & Wolpin 2008). These papers rely on household behavioural models to forecast school education outcomes for the Progresa program in Mexico. But while the first two rely on dynamic structural estimation procedures the last paper proposes the use of simple non-parametric estimation of reduced forms derived from an underlying behavioural model. The current paper is also based on a cross-sectional approach like Todd & Wolpin (2008) but instead of the mean impact this study analyses changes in the entire distribution of weight-for-age z scores (WAZ) of children below 5 years. The contribution of the cash transfer component in explaining this total change is then studied across quantiles. Finally, two alternate policy scenarios are simulated i.e changes in the size of the cash transfer. The data comes from the randomized experiment of RPS and uses information for just the control group.

This paper also adds to the existing literature by applying recently developed estimators to forecast unobserved distributions. It draws on three different estimators - two semiparametric estimators, the first based on linear quantile regression (Melly 2005) and the second using distributional regressions (Chernozhukov et al. 2009); while the third uses a completely nonparametric specification to estimate the unobserved distribution (Rothe 2010). In all three cases changes in different quantiles of the WAZ distribution under the cash transfer are estimated. Each of the estimators is a two stage process involving first-step estimation of the observed conditional distribution function of WAZ given a set of covariates. The second stage of estimating the unobserved unconditional (marginal) distribution of WAZ under the program involves integrating over the set of covariates in the post-treatment scenario. The main difference in the estimators lies in the first stage, each of the estimators uses one of the three methods mentioned above to estimate the conditional distribution function. In addition, tests for stochastic dominance are carried out to compare the estimated counterfactual distribution with the observed untreated distribution.

Section 2 of the paper provides the background to child health and CCT programs and an overview of earlier work forecasting the contribution of economic growth to changes in child health. This section also provides a description of the RPS program. Section 3 outlines the behavioural model and empirical framework. Section 4 presents the data and specifications. Section 5 discusses the results and simulations. Section 6 summarizes conclusions.

2 Background

2.1 Malnutrition and CCTs

Undernutrition of children is still widely prevalent in many parts and is associated with about half of child deaths around the world. Malnourishment makes children more susceptible to infections and less likely to survive other childhood illnesses such as diarrhoea and malaria. In 2007, UNICEF estimated that one out of four children in developing countries is under-weight. It also has severe long-term consequences on growth and development. Malnutrition at an early age results in reduced mental and physical development and these children lose more days to illness than children not faced by this risk, resulting in poor school enrolment rates and education outcomes culminating in poor productivity and earnings in adulthood (Glewwe et al. (2001),Grantham-McGregor et al. (2007), Mendez & Adair (1999)).

Nutrition levels in children are largely determined by the food consumed, exposure to illnesses, availability and access to medical treatment and household and community factors. Cash transfer programs aim at reducing financial barriers to improving food intake, accessing education and health care while simultaneously investing in some household factors such as education of mothers to invest in better nutrition levels for the family. The objective is to reduce poverty while improving investment in human capital.

The positive relationship between income and child nutritional status is well documented in the literature. Typically the literature explores a longer term outcome - height-for-age(HAZ) Z score. In this paper the interest is in the short term change in child nutrition and hence the outcome weight-for-age Z score (WAZ) is used as a measure of nutritional status. In the literature the income effect of a cash transfer is expected to operate through food availability, women's education and access to clean water and sanitation facilities. Analyses range from cross country surveys to forecasting reductions in child malnutrition based on income growth. Haddad et al.

(2003) use household survey data from 12 countries and malnutrition rates from a cross-section of countries to examine the relationship between income and nutrition status. The authors find that raising income growth to beyond historical income growth rates will not reduce malnutrition sufficiently to achieve the 2015 Millennium Development Goals on child malnutrition and conclude that income growth must be accompanied by nutrition policies. Other studies looking to forecast reductions in child malnutrition include Glewwe et al. (2004) and Edmonds (2004), both of which use data from 1993 and 1998 Vietnam Living Standards Measurement Survey to measure income contribution to reduction in child malnutrition in this period. However, both these papers conclude that income growth accounts for only a small fraction of the improvement in child health status. A study that takes the analysis of these two papers further and is closest in method to the ones applied in the current paper is O'Donnell et al. (2009). This study estimates the full marginal distribution (counterfactual) from a change in covariates (over time) and decomposes the observed difference in child height into the contribution of an income change and a shift in the returns to an improvement in nutrition ie. "nutrition function". The similarity lies in the approach used to estimate the counterfactual distribution, the objective here is to forecast the counterfactual(treated) distribution resulting from the one year cash transfer component of the CCT program and compare the counterfactual with the experimental results to identify the partial contribution of the cash transfer separate from other aspects of the program and any change in the nutrition function.

2.2 The RPS Program

The data for this paper is taken from the RPS conditional cash transfer program introduced in 2000 by the Government of Nicaragua and was implemented as a two year randomized social experiment. Like all cash transfer programs RPS is a demand side social protection initiative that aims at reducing financial and informational barriers to accessing education and health care. It aims at reducing poverty across generations by encouraging investment in human capital. Two rural districts of Central Nicaragua - Madriz and Matagalpa were selected as pilot areas based on their poverty levels and capacity to implement the program. According to the 1998 Living Standards Measurement Survey 48% of Nicaraguans were classified as poor. The randomized experiment was implemented in 42 *Comarcas* (administrative units within municipalities) within the two districts chosen based on a marginality index.

The program had two components - education and food security/health. Under each component families received cash transfers conditional on their fulfilling certain requirements. In the education component families with children between the ages of 7-13 years who had not completed grade 4 of primary school were eligible for the transfers conditional on the eligible children enrolling and maintaining 85% attendance. Families received two transfers (Maluccio & Flores 2005) - a 'school attendance transfer' provided as a fixed sum for all families equalling the Córdoba 2000 equivalent of US$112 per year; and a per child 'school supplies transfer' of US$5. If any of the children did not meet the conditionality the family failed to receive the lump sum transfer.

The food security/ health component of the program also involved a per family cash transfer of US$224. To receive this transfer two main conditionalities had to be met - mother's of children under age 5 years had to attend in alternative months health education workshops, and the children aged below 5 years had to be taken to scheduled preventive health care appointments. Services at the appointments were offered free of charge and included growth and development monitoring, vaccinations, provisions of anti-parasites, vitamins and supplements. Program implementers found that there were frequent delays in the delivery of vaccines during these health checks and consequently a sub-conditionality of maintaining up-to-date vaccination schedules for the children was removed from the program design. While these supply-side issues were being dealt with, for the first 8 months of the program none of the health related conditionalities were imposed.

3 Model and Empirical Specification

3.1 Model

This paper applies three different approaches to recover the unobserved WAZ distribution under the cash transfer. In an *ex ante* exercise data is available on the untreated population. Then the unobserved distribution to be estimated is the outcome for the untreated group if they had been treated. In this case, the dependent variable H and a vector of covariates X are observed for the control group. Each of these has marginal distributions F_H and F_X. The relationship between H and the covariates is assumed to to be generated through the equation:

$$H^* = f(X, \epsilon) \tag{1}$$

To specify the relationship between H and X a simple behavioural model based on Thomas (2010) is applied. A household's preference ordering is characterized by

$$U(C, H_i, S_i) \tag{2}$$

with non-medical consumption represented by C, each child's health status is represented by H_i and school enrolment by S_i and multiple eligible children $i = 1...n$.

The production of child health is described by the production function:

$$H_i = h(L.E^m, E^m, M; D_h) \tag{3}$$

M represents health inputs that do not affect utility but improve child health such as medical care. L represents additional health inputs/ investments in nutritious food etc that is consumed if the food security/nutrition transfer is received, conditional on mothers attending health education workshops and children attending health checks, E^m (a binary indicator which equals zero in the pre-program scenario). D_h represents a vector of household characteristics.

The household budget constraint for the purchased goods in the pre-program scenario is:

$$C + \sum_{i=1}^{n} p_{si}.S_i + p_m.M = Y + \sum_{i=1}^{n} w_i.(1 - S_i) = F \tag{4}$$

Where p_{si} represents the direct cost of schooling for each child, p_m is the cost per unit of medical care consumed and Y is household income net of the earnings of the program eligible children and w_i is the wage each child receives if employed and not enrolled in school. Full income of the household is represented by F. The total price of schooling for all eligible children in the family is $(\theta = \sum_{i=1}^{n}[p_{si} + w_i])$. The pre-treatment model of child health is:$H^* = \Omega(F, \theta, p_m; D_h)$

In this paper F_H represents the marginal distribution of WAZ for the control group in the year 2002 and F_X the distribution of the covariate vector, which includes a measure of consumption -F_{02} and school costs -S_{02} for the program eligible children. The pre-treatment model for the control group can then be represented as:

$$H^* = f(F_{02}, S_{02}, Z, \epsilon) \tag{5}$$

where Z includes all other covariates.

The two cash transfer components of the RPS program are introduced into the budget constraint by (e_{s1}, e_{s2}) and $e_f.E^m$. The school transfer (e_{s1}, e_{s2}) changes the price of schooling and is meant to substitute for any wages earned by the child. The first component e_{s1} is provided for each eligible child in the family while e_{s2} is a lump sum transfer irrespective of the number of eligible children. Both transfers are conditional on all eligible children enrolling in school. The food security/health transfer $(e_f.E^m)$ is modelled as increasing household income without adjustment of any specific costs.

With the introduction of the subsidies $e_f.E^m$, $e_{s1}.\sum_{i=1}^{n} S_i.S_p$ and $e_{s2}.S_p$, where $S_p = 1$ if $\sum_{i=1}^{n} S_i = n$ ie. all eligible children enrol in school and $S_p = 0$ otherwise and assuming full compliance ie $E^m = 1$, the budget constraint for a beneficiary family is:

$$C + L.E^m - e_{s2}.S_p - e_f.E^m + \sum_{i=1}^{n} (p_{si} + w_i - e_{s1}.S_p) S_i + p_m.M = Y + \sum_{i=1}^{n} w_i = \tilde{F} \tag{6}$$

The new price of schooling under the subsidy program is $\tilde{\theta} = (\sum_{i=1}^{n}[p_{si} + w_i - \tau.S_p])$ and the new level of full income is $\widetilde{F}$. The model under the subsidies is $H^{**} = \Omega(\tilde{F}, \tilde{\theta}, p_m; D_h)$

Under the program the values of F_{02} and S_{02} are influenced by the policy-maker and shift with the exogenous cash transfer and, together with the other variables, form a new covariate vector $\hat{X}$

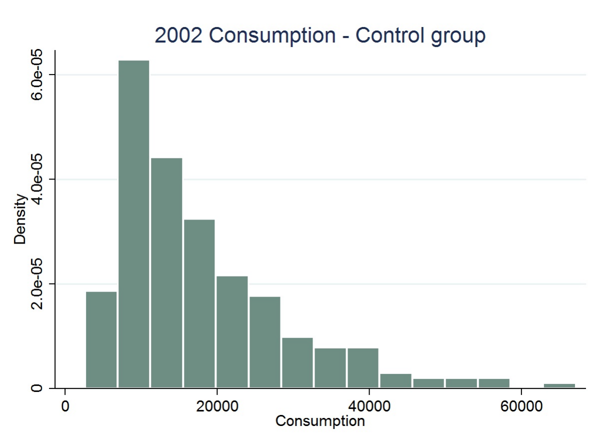
with a distribution $F_{\hat{X}}$. Under this new distribution of covariates ie. the distribution under the cash transfers for the control group, the unobserved counterfactual is:

$$H^{**} = f(\hat{X}, \epsilon) \tag{7}$$

H^{**} is assumed to have a distribution function F_H^{**}. The objective is to estimate this unobserved distribution and compare different quantiles with the observed distribution of H, F_H. The model under the program for the year 2002 is then:

$$H^{**} = f(\hat{F}_{02}, \hat{S}_{02}, Z, \epsilon) \tag{8}$$

Rothe (2010) refers to the above set up as a "dependent policy scenario" with a data structure $(\mathrm{H}_i, X_i, \hat{X}_i)_{i=1}^n$. The policy causes changes in the marginal distribution of the covariate vector that determines the WAZ score while maintaining the same conditional distribution of WAZ given X.



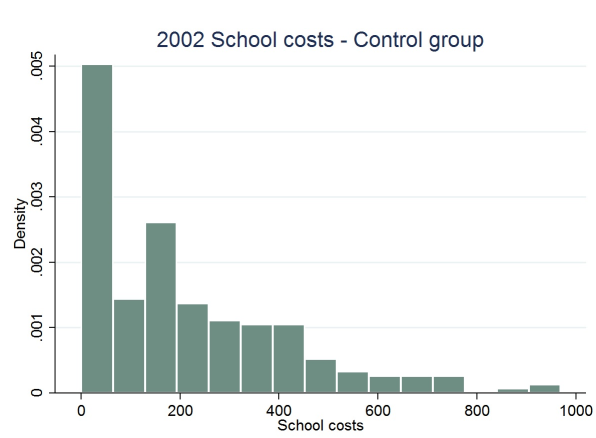


Figure 1: Data Variation

The two sources of variation in the data to estimate the counterfactual distribution are school costs and full income of the households. Income is not observed in the dataset but a measure of household consumption is available and is used as a proxy for full income. Figure 1(a) shows a histogram of consumption of families, with values ranging from c2618 to c67130.39; Figure 1(b) shows school costs which range from c0 to c969.

The underlying idea in the methods applied here is similar to other non-experimental methods such as matching which rely on 'selection on observables' (Heckman et al. 1998). The identification assumption in the methods used to estimate the equations is that conditional on these covariates unobserved factors are independent of the policy variables. In this paper, both components of the program are included. Under the assumption of full compliance, i.e. all mothers attending the compulsory health education workshops and all children being taken to scheduled health checks, the food security transfer is added to 'full income' of the household along with the lump sum school transfer. The per child school supplies transfer is adjusted against school costs. By relaying the impact of the program through the budget constraint this approach models the influence of the cash transfer component of the policy. It does not allow for the impact of the different health related conditionalities on health outcomes. Explaining the contribution of the cash transfers is in itself useful as it addresses a criticism of randomized experiments - in that they operate as a 'black box' (Deaton 2010) and it is impossible to see which components produce the change. In a program such as this, with conditionalities that are likely to influence health outcomes, it then provides an *ex ante* decomposition of the contribution of the first year's cash transfer to the distribution of WAZ for the year 2002. The nature of the estimation techniques used in this paper are all built around cross-sectional approaches and hence do not account for unobserved heterogeneity that could be caused by correlated unobservables. Particularly in this paper, the use of consumption as a measure of socio-economic status could be correlated with the unobservables that jointly determine nutrition status. Hence the effects detected here do not necessarily provide a causal effect of the cash transfers. The identified contribution is however useful in determining the extent to which the total change can be traced to the cash transfer. Following O'Donnell et al. (2009) the interpretation applied here is a partial contribution of the cash transfer to the total change in the WAZ distribution.

This paper looks at changes in different points of the WAZ distribution rather than just the mean. It also uses different estimation approaches that allow recovery of the differences in quantiles. The parameters of interest in this paper are the "quantile policy changes":

$$\Delta_Q(\tau) = Q_H^{**}(\tau) - Q_H(\tau) \tag{9}$$

The following section describes the different estimators used. In addition, linear quantile regression is also used to estimate the results from the *ex post* randomized experiment to provide the total change in the WAZ distribution after 2 years of the RPS program.

3.2 Empirical framework

3.2.1 Estimating School Costs - Two part model

The identification of the change in WAZ due to RPS relies on two policy variables - consumption and school costs for the households. School costs are however observed in the survey only for those enrolled in school at the time of the survey and must be estimated for those not enrolled. Estimating unobserved costs typically involves using models with two components - one that determines participation ie. enrolment in school and one that involves the determinants of the cost component that is used to extrapolate the costs for the unobserved individuals in the sample. The *two-part model*[1] assumes that the participation decision $Pr(y > 0|x)$ is determined by a parametric binary regression model either a logit or a probit, while the second part is a linear specification of x. Various specifications for the second part have been applied. Typically to deal with skewed cost data log transformations are applied. In this paper although costs are skewed a log transformation is not applicable since the observed school costs also include zeros. To deal with these issues a common specification of the second part is the *generalized linear model* which allows different distributional specifications from the exponential family to link the random with the stochastic components of the model. This however requires *a priori* specification of both the link and variance functions, in the latter case assuming certain forms of heteroskedasticity. Incorrect specifications can lead to bias and inefficiency in the estimates. An alternative is to use an approach that does not require prior assumptions about the link and variance functions. In this paper the second-part is estimated using a semi-parametric *extended generalized linear model* (Basu & Rathouz 2005) which allows for a flexible link function and variance parameter, both of which as estimated from the data. The approach allows for a family of link functions represented by λ:

$$g(\mu_i;\lambda) = \begin{array}{lll} \frac{\mu_i^{\lambda}-1}{\lambda} & if & \lambda \neq 0 \\ \log(\mu_i) & if & \lambda = 0 \end{array}$$

where g is a function that links μ to the linear predictor $X_i^T\beta$ and $\mu_i = \mu(X)$. The variance is characterized by family of functions represented by a power variance which allows for common distributions such as Poisson, Gaussian and Gamma:

$$h(\mu_i;\theta_1,\theta_2) = \theta_1\mu_i^{\theta_2}$$

[1]A selection model is difficult to apply here due to the difficulty of finding an exclusion restriction that influences school enrolment but not school costs. Also, school costs are not normally distributed but a log transformation is not feasible due to the zeros. To overcome these problem a two-part model is used.

3.2.2 Ex post outcomes - Linear quantile regression

Results from the randomized social experiment can be used to estimate the total change in the WAZ distribution from the RPS program. Linear quantile regression goes beyond the mean and provides information on the change at different points of the distribution. Heckman et al. (1997) highlight various parameters of interest that require more than the mean, including the proportion that benefit from the program and impacts at quantiles. Of particular interest in social programs such as CCTs is the impact at the lowest end of the distribution. In the case of WAZ children with scores less than -2 are considered malnourished. Then it is important to see if the program had any impact on the weakest sections of the population by exploring heterogeneity. Focusing on the average impact could disguise potentially important benefits to those most likely to need it. The impact at a given quantile of the WAZ distribution is the vertical distance between the quantile functions in the treatment and control groups. Figure 2 shows the quantile plots of WAZ for the two groups in the year 2002. The graph shows that the distribution of WAZ in the treatment group is marginally higher than in the control group in the lower quantiles but they converge at the upper quantiles of the distribution. The vertical distance between the two plots at each quantile is the quantile policy effect.

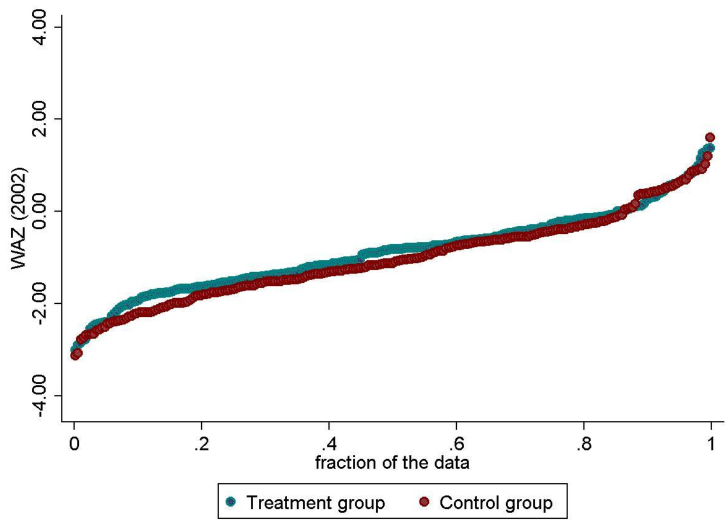


Figure 2: 2002 Quantile functions

Empirically, the required impact at a particular quantile (τ) is the coefficient on the dummy variable representing participation in the program (Koenker & Basset 1978) :

$$Q_\tau(h|T) = \alpha(\tau) + \beta(\tau)T \tag{10}$$

The above equation represents the change in the distribution of WAZ in 2002 due to participation in RPS. Interpreting these results as the treatment effect for individuals requires a further assumption of "rank preservation". This requires that the rank of the potential outcome for a specific individual remains the same with and without the treatment. This however is a strong assumption and can only be tested in terms of the observables. Since this assumption does not extend to the *ex ante* methods used here, the interpretation is a general change in the quantiles of the WAZ distribution in the treatment and control groups and no inference is made about individuals at specific quantiles of the distribution. From a policy perspective knowing the change in distribution of WAZ due to RPS is in itself informative. An upward shift would indicate an overall improvement in the WAZ score.

3.2.3 Quantile regression based approach

The first of the two semiparametric approaches applied in this paper is based on linear quantile regression. Proposed by Melly (2005) it involves a two step procedure to estimate the unobserved F_H^{**}. In the first step the conditional distribution of WAZ, given X, is estimated using linear quantile regression:

$$F_{h|x}^{-1}(\tau|x) = x'\beta(\tau) \tag{11}$$

where $F_{h|x}^{-1}(\tau|x)$ is the τth quantile of WAZ conditional on the covariates. The semiparametric nature of this estimator comes from maintaining the assumption of a linear functional form for the conditional distribution but relaxing the requirement of assuming a specific distribution. The second step involves integrating the estimated conditional distribution over the vector of covariates under the policy ie $\hat{X}$ to recover the unconditional distribution of WAZ after the cash transfer:

$$F_H^{**}(h) = \int_X F_H(h|x)dF_{\hat{X}}(x) \tag{12}$$

where from equation (11):

$$F_H(h|x) = \int_0^1 1[F_{h|x}^{-1}(\tau|x) \leq h]d\tau \tag{13}$$

Then for particular quantiles of WAZ the sample equivalent of the "quantile policy change" is estimated by replacing $F_{h|x}^{-1}(\tau|x)$ by its consistent estimate $x'\beta(\tau)$ in equation (12) and averaging over all the covariates in $\hat{X}$. Thus the difference between the observed and the estimated counterfactual is explained by changes in characteristics, in this case the cash transfers. This estimator is similar to the one proposed by Machado & Mata (2005). Both estimators use linear quantile regression regression to estimate the conditional distribution in the first step. The Machado & Mata (2005) approach differs in the second step by using a process of random sampling from the covariate vector under the policy $\hat{X}$ and weighting (combining) these with the vector of coefficients from the first step. Both methods have been shown to give similar results in large samples (Albrecht et al. 2009). In this paper the Melly (2005) approach is used as the sample is quite small and the repeated random sampling from different quantiles for the Machado & Mata (2005) approach does not work well.

3.2.4 Distributional Regression

The second approach used in this paper relies on a method applied initially by Han & Hausman (1990) and Foresi & Peracchi (1995) to allow for flexible estimation of conditional distribution functions. In this approach families of binary response models of varying 'cutoffs' are used to estimate a binary response, modeling the conditional distribution function separately at a set of thresholds. Chernozhukov et al. (2009) replace the linear quantile regression of Melly (2005) by applying this idea to the first step of the estimator to estimate the conditional distribution function of the outcome pre-policy:

$$F_H(h|x) = \Lambda(m(h, x)) \tag{14}$$

where a separate binary response model is estimated for each threshold h, Λ is a known link function such as a probit or logit and $m(h, x) = (x'\beta(h))$. Each $\beta(h)$ is estimated by maximum likelihood using a set of indicator variables $1\,[H \leq h] : h \in H$. The second step of this estimator follows the same process as Melly (2005) and integrates over the new covariate vector to recover the marginal distribution:

$$F_H^{**}(h) = \int_X \widehat{F}_H(h|x) dF_{\hat{X}}(x) \tag{15}$$

Similar to the linear quantile regression approach, the Chernozhukov et al. (2009) method also provides the marginal quantile function which can be used to estimate the quantile policy change in equation (9):

$$Q_{\hat{H}}(\tau) = \inf[h : F_H^{**}(h) \geq \tau] = Q_H^{**}(\tau) \tag{16}$$

3.2.5 Nonparametric Approach

The two approaches described above are both different forms of semiparametric estimators, while the first makes no assumptions about a distribution, it still assumes a linear functional form for the conditional quantiles. The second makes clear assumptions about a particular link function but is more flexible in that it allows for a series of binary response models that approximate the unknown distribution by a step function. The last approach applied in this paper is a nonparametric estimator (Rothe 2010) which makes no assumptions about either the distribution or functional form in estimating equation (8). Like the others, this estimator is also a two step process. The conditional distribution function is first estimated using kernel regression:

$$\hat{F}_{h|x}(h, x) = \frac{\hat{g}_{HX}(h, z)}{\hat{f}_X(x)} \tag{17}$$

where

$$\hat{g}_{HX}(h,x) = \frac{1}{n}\sum_j \{I(H_j \leq h\} K_{x,h}(X_j - x)$$

$$\hat{f}_x(x) = \frac{1}{n}\sum_j K_{x,h}(X_j - x)$$

In the above equations K is a kernel function, h represents the bandwidth. The above specification is similar to the Nadarya-Watson estimator for kernel regression commonly available in statistical software. The second step estimates the marginal distribution using sample counterparts:

$$F_H^{**}(h) = \frac{1}{n}\sum_{i=1}^{n} \hat{F}_{h|x}(h, \hat{X}_i) \tag{18}$$

As this is a nonparametric estimator extrapolation is valid only in regions of support in the data: the estimated policy changes are only valid in regions of $\hat{X}$ that are in the support of X. Rothe (2010) shows that despite the estimator being nonparametric it is not affected by the "curse of dimensionality" problem that frequently limits the application of such estimators. The estimates of the parameters of interest are shown to converge at the usual parametric rate of $\sqrt{n}$ irrespective of the dimension of the covariate vector X.

4 Data and Variables

The dataset used in this paper was collected as a panel survey for the randomized experimental evaluation. Three rounds of data were collected - baseline (2000) and two years of follow-up (2001, 2002). In total 1581 families were included in the experiment across both treatment and control groups. The randomization was at the locality level to avoid spill overs between treated and untreated individuals. Randomization at this level ensures that observable and unobservable characteristics are balanced across the treatment and control arms. Table 1 presents *t-tests* of the equality of means for some household level characteristics. The results show no major difference between the two groups except for number of children under 5 years which is slightly higher in the control group. Maluccio & Flores (2005) test a wider range of indicators and also find small differences only in household size and number of children under 5 years. In addition to the main survey, in the years 2000 and 2002 an additional module was included that captured information on the health of children aged under 5 years. The outcome used in this paper - weight-for-age (WAZ) Z score was collected in this module.

The analysis in this paper uses data from the 2002 follow-up survey and pre-program census survey. The analysis includes individuals from only the randomized out control group. In total the estimation sample consists of 358 households with children under the age of 5 years who are eligible for the food security and health component of the program and have been in the program for at least 2 years (i.e the length of the program); of these 236 families also have children between

Table 1: RPS summary statistics: Baseline 2000

	Treatment	Control	Difference
Household consumption	20657.68	20416.47	241.20
	(452.51)	(494.56)	(669.10)
Household head:			
Age	44.48	43.75	0.73
	(0.596)	(0.591)	(0.840)
Male	1.13	1.15	-0.19
	(0.013)	(0.014)	(0.019)
Highest qualification	1.49	1.46	0.03
	(0.057)	(0.060)	(0.083)
Household composition:			
Number of children under 5 years	0.907	0.988	-0.081
	(0.037)	(0.035)	(0.051)
Number of adults	3.354	3.44	-0.085
	(0.066)	(0.069)	(0.096)
Number of children 7-13 years	1.31	1.29	0.024
	(0.048)	(0.048)	(0.068)
N	722	675	1397

Standard errors in parentheses; includes households present in the baseline and 2002 surveys

the ages of 7-13 who have not completed grade 4 of primary school and hence were eligible for the school transfers as well. While the total number of children in the control sample in 2002 is 530, only 239 of these children were in the baseline ie, have been in the program for the 2 years of the experiment. The analysis is restricted to this subgroup.

The surveys gathered information on individual, household and community level variables. At the individual level detailed information was collected on education and school enrolment, direct and indirect costs of all school related expenditures, illnesses in the previous six months and health care expenditure. For all children under 5 years detailed information was gathered on immunization, health checks, weight measurements. In the additional module each child was weighed and heights recorded by the surveyor and entered. The survey however does not include detailed information on earnings and income, instead detailed information on all household consumption is available.

The unobserved distribution of WAZ under treatment, $F_H^{**}(h)$, is estimated using the specification in equation (8). Table 2 provides means of the covariates for the control sample used in the forecasting exercise. The specification includes the two key policy related variables - consumption and school costs of the household. It also includes other variables referred to in the previous section as the vector Z, that are likely to influence the health of the child such as individual characteristics - mother's age, child's age and gender. The literature often cites "sibling effects" as a determinant of child health, where greater the number of siblings below a certain age, smaller is the amount of

Table 2: Means of covariates in estimation sample

	2002
Household consumption	17,854.97
Mother's age	29.96
Child's age in months	43.89
School costs	206.07
Number of children under 5 years	1.86
Distance to pharmacy (hours)	1.72
Distance to nurse (Kms)	8.73
Distance to public transport (Kms)	5.87

resources available per child. To capture these effects, number of children aged under 5 years in the household is included. To capture time-related costs of accessing health care two community level variables - distance to the nearest form of public transport and travel time in hours to the nearest nurse are included. Most areas in the program have limited access to formal health care with the most likely being a health post or a trained nurse. Also included in the specification is the travel time in hours to the nearest pharmacy which is expected to capture the effect of treatments not captured by visiting a health care worker. If the time costs for parents are high due to waiting times to see a health care worker then parents might choose over-the-counter medication as a first point of medical care. The measure of consumption included is expected to capture effects of having access to clean water and sanitation which are largely determined by economic status and hence these two variables are not included separately in the model. Following this argument the main specification does not include a variable to capture the education of either the mother or the head of the household. Both these variables have a large number of zeros. To test for specification robustness, the models are re-estimated including education of the household head and gender of the child.

The school costs for all children in the family eligible for the school components are estimated using a two part model with the same specification of variables for both parts. Due to the small sample size the model is estimated jointly for boys and girls. The variables include characteristics of the household head such as age, gender, employment and years of education. Child related variables - age and gender, and household composition variables - number of children aged under 5, number of children between 7 and 13 and the number of adults. Log of household consumption is included as a measure of economic status. In addition, as a measure of opportunity and time costs of schooling, the distance of the household to the nearest primary school is included. The variable number of children aged under 5 in the household is also an indicator of the opportunity costs which could involve caring for younger siblings in the household.

5 Results

5.1 School costs

As discussed in the earlier sections, the first step was to estimate the school costs for the children eligible for the school transfer but not enrolled in school. The results from the *two part model* are listed in Table 3. Column 1 provides the estimates for the *probit* participation model for school enrolment. The binary indicators of different age groups show that younger children are more likely to enrol in school. The coefficients are positive and statistically significant. As the children grow older (age 13) they are less likely to enrol. The coefficient on gender provides more insight and shows that boys are less likely to enrol in comparison to girls and may indicate that boys begin employment earlier. Most of the households in the sample cultivate lands and the gender difference may also be related to the negative coefficient on employment of the household head. This variable largely reflects land cultivation for coffee in Nicaragua which is the primary occupation of most of these households. It could mean that boys may begin to work in the farms much earlier than girls. The results show that household wealth (as measured by consumption) has a positive and statistically significant effect on enrolment, with households having greater wealth being more likely to enrol. Also important is the composition of the household. Families with children under the age of 5 years are less likely to have older children enrolled in school. This variable is included as a measure of the opportunity costs of schooling where older children if not employed may be expected to provide care for younger siblings. A similar negative and statistically significant effect is observed for distance to school, with children being less likely to enrol if schools are far away. The coefficient on the variable- number of children of the same age (ie 7-13 years) in the household is positive. This possibly indicates a sharing of resources that enables them to participate in school. The other key determinant of enrolment in the model is the years of education of the household head, with a positive coefficient that is statistically significant; the greater the levels of education of the household head, the higher is the likelihood of children enrolling in school. The age of the household head and gender ie. if the household head is male, have a positive influence on the likelihood of children in this age group enrolling in school.

Column (2) of Table 3 shows the results from the *generalized extended linear model* or the *extended estimating equations approach* of Basu & Rathouz (2005). As can be expected, school costs increase with age and the coefficients are statistically significant with children aged 11 years having the largest school costs. Wealthier families spend more on education as do families where the household head has more years of education. School costs are lower for households where there are children between the ages of 7-13 reflecting economies of scale. Children of the same age group may be likely to share limited resources available including books and supplies across classes and age groups. A similar negative effect is observed for children under 5 years and could mean that expenditure on education is constrained by large family size and could reflect the opportunity costs

Table 3: Estimates of the model for School Costs

VARIABLES	(1) Probit Enrolment	(2) EEE School Costs
age8	0.495**	-0.004
	(0.191)	(0.073)
age9	0.383**	0.181**
	(0.169)	(0.072)
age10	0.581***	0.163*
	(0.187)	(0.058)
age11	0.720***	0.340***
	(0.212)	(0.107)
age12	0.450**	0.195**
	(0.989)	(0.091)
age13	-0.024	0.222*
	(0.221)	(0.118)
Gender	-.310***	-0.088
	(0.115)	(0.054)
Full Wealth (log)	0.292**	0.632***
	(0.125)	(0.088)
Distance to school	-0.008***	-0.001
	(0.002)	(0.001)
No. of adults	0.035	-0.001
	(0.414)	0.024
Children under 5	-0.217***	-0.022
	(0.074)	(0.045)
Children 7-13	0.127*	-0.092**
	(0.069)	(0.036)
HHH gender	0.061	-0.088
	(0.275)	(0.112)
HHH age	0.021	-0.001
	(0.007)	(0.004)
HHH yrs of ed	0.168***	0.028
	(0.047)	(0.023)
HHH works	-0.245	-0.149
	(0.293)	(0.134)
Constant	-2.170	-5.73***
	(1.217)	(0.809)
λ		0.914***
		(0.194)
θ_1		0.693***
		(0.051)
θ_2		1.246***
		(0.123)
Observations	785	657

Robust standard errors in parentheses, clustered at the household level

*** p<0.01, ** p<0.05, * p<0.1

of schooling as observed in the participation model for enrolment. Gender, age and employment of the household head all have negative effects on school costs but are not statistically significant. Expenditure tends to be lower when women are the head of the household. The negative coefficients on the age and work of the household head could once again reflect opportunity costs of working on the land if the household head is elderly or employed in cultivation.

As discussed in the section on empirical specification, the *extended estimating equations approach* allows for a flexible link and variance function, both of which are estimated from the data. The value of $\lambda = 0.914$ is close to an identity link function while $\theta_1 = 0.693$ and $\theta_2 = 1.246$ together are close to a Gamma distribution which requires $\theta_1 > 0$ and $\theta_2 = 2$.

5.2 Ex post - distributional impact

The quantile effects provide information on the total change from the RPS program at different points of the WAZ distribution. Figure 3 plots the quantiles for the year 2002. 90% confidence intervals are also plotted calculated by bootstrapping the standard errors. Also plotted as a horizontal dotted line on the graph for comparison is the average treatment effect from the double difference estimates. The average treatment effect on the treated is the difference between the changes in the treatment and control groups before and after the program was implemented. This parameter assumes a constant treatment effect across all quantiles, equal to the average value. The quantile effects in the graph show the vertical distance between the quantile functions in the treatment and control groups displayed in Figure 2. Without the assumption of rank preservation no interpretation on treatment effects for individuals is made. Hence the results in this paper are interpreted as the impact of RPS on shifting the distribution of WAZ without any reference to individuals at different quantilies of the distribution.

Overall the graph shows that WAZ is greater in the treatment group than in the control group with positive quantile effects in all but the highest quantile where a negative but statistically non-significant effect is observed. The greatest impact is seen at the lowest quantile and the difference decreases from the lowest percentile to the highest indicating that children with the worst WAZ scores ie those that are malnourished show the biggest improvement. Table 4 column 1 shows the changes between the lowest, middle and highest quantiles of WAZ. The negative magnitudes show that the inequality declines across the distribution of WAZ in both the lower (Q50-Q10) and upper (Q90-Q50) segments of the distribution. These findings suggest that the average impact does not necessarily reflect an accurate picture and that nutrition does improve more for those who are malnourished.

5.3 Ex ante - distributional impact

Figures 4(a),4(b) and 4(c) graph the results of the partial contribution of the cash transfer to the total change in the distribution of WAZ using the semiparametric methods of Chernozhukov

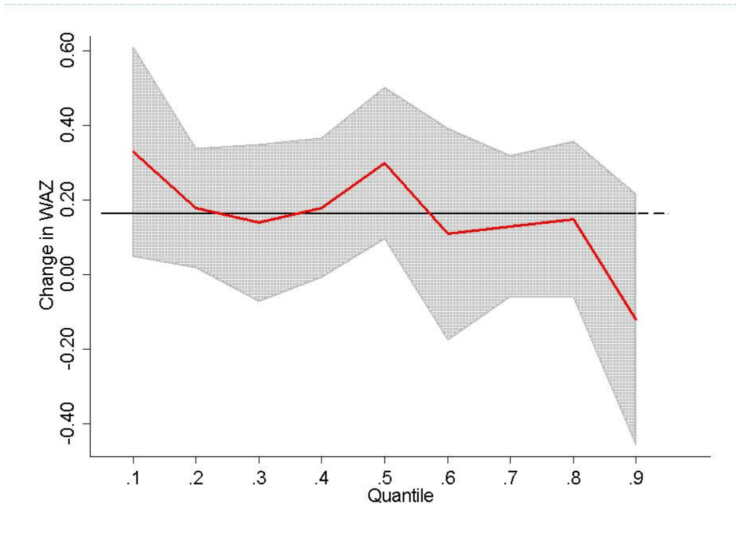
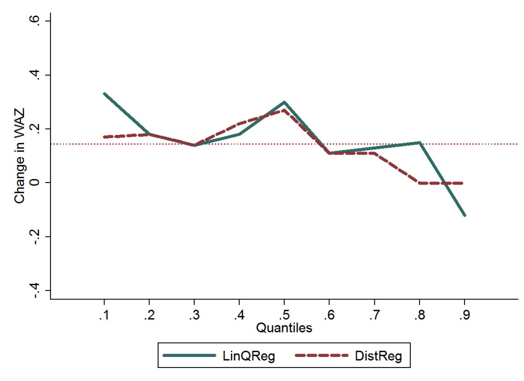


Figure 3: Ex-post Quantile Treatment Effects

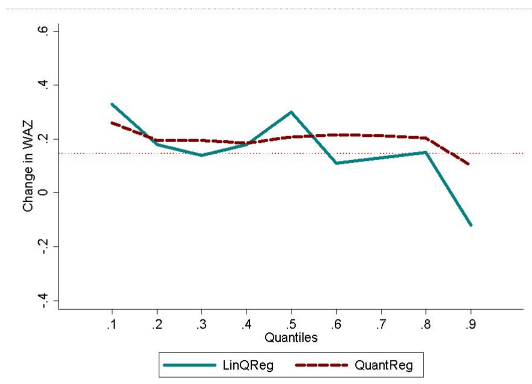
et al. (2009) and Melly (2005) and the nonparametric method of Rothe (2010). In all three graphs the solid line represents the *ex post* quantile effects discussed above and the horizontal dotted line represents the average effect from the double difference estimates. Overall the methods have the same direction as the *ex post* results and show the greatest change at the lowest and middle quantiles of the WAZ distribution. Columns 3, 4 and 5 of Table 4 show the results across quantiles, measured in standard deviations. A comparison of the estimates shows that across most quantiles, the distributional regression and nonparametric approaches are similar in estimates. In the current specification however the quantile regression approach over predicts the effect across all quantiles of the upper segment of the distribution. While the nonparametric method shows results quite similar to the distributional regressions, none of the estimated effects in the nonparametric approach are statistically significant. The reported results for this approach are bias-corrected effects from bootstrapping the standard errors. Like the Machado & Mata (2005) approach the method is sensitive to the random draws due to the small sample size and the results are less robust than the other approaches.

Table 4 also shows the change in inequality across quantiles. As in the *ex post* case the quantile regression approach shows a decline in inequality in both the upper and lower segments of the distribution of WAZ. The same trend is seen for the upper quantiles (Q90-Q50) using distributional regressions and the nonparametric approach. Both these methods however show an increase in inequality in the Q50-Q10 segment of the distribution.

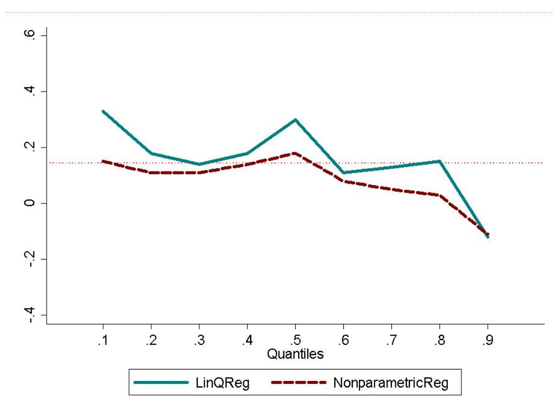
As discussed earlier the methods allow recovery of the entire distribution of WAZ under treatment. This permits tests for stochastic dominance between the treated (predicted) and untreated distributions. In both the semiparametric approaches tests for stochastic dominance of a positive



(a) Distributional Regression - Chernozhukov et al (2010)



(b) Quantile Regression - Melly (2005)



(c) Nonparametric Regression - Rothe (2010)

Figure 4: Ex ante Quantile Policy Change

Table 4: Decomposition of the estimated change in the WAZ distribution

Quantiles	Total Change	Distributional Regression	Quantile Regression	Nonparametric Regression
Q10	0.33	0.17	0.26	0.15
	(0.121)	(0.118)	(0.102)	(0.248)
		51.51%		
Q20	0.18	0.18	0.20	0.11
	(0.109)	(0.114)	(0.101)	(0.249)
		100%		
Q30	0.14	0.14	0.19	0.11
	(0.099)	(0.117)	(0.102)	(0.276)
		100%		
Q40	0.18	0.22	0.19	0.14
	(0.112)	(0.138)	(0.984)	(0.309)
		122%		
Q50	0.30	0.27	0.21	0.18
	(0.102)	(0.127)	(0.099)	(0.300)
		90%		
Q60	0.11	0.11	0.22	0.08
	(0.129)	(0.099)	(0.102)	(0.296)
		100%		
Q70	0.13	0.11	0.21	0.05
	(0.102)	(0.114)	(0.108)	(0.263)
		84.61%		
Q80	0.15	0.00	0.20	0.03
	(0.102)	(0.188)	(0.113)	(0.294)
		0%		
Q90	-0.12	0.00	0.10	-0.11
	(0.237)	(0.194)	(0.118)	(0.307)
		0%		
Q90-Q10	- 0.45	-0.17	-0.31	-0.26
Q90-Q50	-0.42	-0.27	-0.26	-0.29
Q50-Q10	-0.03	0.10	-0.05	0.03

Bootstrapped standard errors in parentheses shift in the WAZ distribution ($QTE(\tau) > 0$ for all τ) fail to reject the hypothesis of an improvement in the WAZ scores across all quantiles (Kolmogorov-Smirnov statistic p-values of 0.975 and 0.825 for distributional and quantile regressions respectively). In addition to the above specification for the model a further specification including years of education of the household head and gender of the child was estimated. This variable includes a large number of zeros. The estimations show no change in the results of the distributional regressions but show much quantitatively larger estimates in the quantile regression approach across all quantiles. The nonparametric approach shows similar results to the original specification. In general the predicted results all have the same direction as the experiment. The distributional regression approach seems to perform better than the quantile regression approach across all quantiles and is more stable than the nonparametric approach in small samples. Based on this, the distributional regression approach is considered the main set of results and applied to the simulations that follow and in decomposing the contribution of the cash transfer to the total change observed in the *ex post* results.

In interpreting the *ex post* results it is important to recognize that they are in effect after *two years* of program intervention including the various conditionalities, while the *ex ante* model is the partial contribution of a one year cash transfer. If the conditionalities relating to health do have a positive influence on a short term outcome such as WAZ then the *ex ante* results should be lower than the outcomes from the experiment. This may particularly be the case at the lowest quantiles of WAZ where undernourished children are also more likely to belong to families not investing in preventive care due to resource constraints. This is reflected in the results of the lowest quantile. The partial contribution of the cash transfer to the total change is also shown in table 4 for the distributional regression approach. This factor shows systematic variation across the distribution and explains 52% of the total change at Q10 but almost 90 % at the median. The contribution is increasing in the lower part of the distribution (Q10-Q50) suggesting that factors such as preventive health checks, growth monitoring or immunizations and health education workshops may be equally important in explaining improvements in WAZ for the most malnourished. But for those who are more likely meeting or almost meeting the program requirements such as immunizations/health checks, the contribution of the cash transfer is larger. At the upper tail of the distribution where children are not undernourished the overall program and hence the cash transfer component has no contribution. While these results at a first glance are much larger than the findings of O'Donnell et al. (2009) and Glewwe et al. (2004) who show that consumption/income growth does not explain much the change in HAZ scores, it should be noted that the overall experimental impacts in this paper are quite small in magnitude across all quantiles. The *ex post* experimental evaluation found that 2 years of RPS (Maluccio & Flores 2005) decreased the percentage of underweight children ($WAZ < -2.0$) by 6.2 percentage points. Also, the population here is from an experiment which targeted extremely poor households in rural Nicaragua rather than the nationally representative random sample used in the other surveys and may be more likely to benefit from cash transfers.

Table 5: Quantile Policy Simulations - Distributional Regressions

	(1)	(2)	(3)	(4)
Quantiles	Total change	Main Specification	Food security transfer	Unconditional transfer twice program amount
Q10	0.33	0.17	0.00	0.04
	(0.121)	(0.118)	(0.058)	(0.128)
Q20	0.18	0.18	0.04	0.18
	(0.109)	(0.114)	(0.061)	(0.115)
Q30	0.14	0.14	0.05	0.14
	(0.099)	(0.117)	(0.053)	(0.112)
Q40	0.18	0.22	0.03	0.12
	(0.112)	(0.138)	(0.036)	(0.107)
Q50	0.30	0.27	0.04	0.19
	(0.102)	(0.127)	(0.058)	(0.131)
Q60	0.11	0.11	0.03	0.03
	(0.129)	(0.099)	(0.047)	(0.141)
Q70	0.13	0.11	0.05	0.11
	(0.102)	(0.114)	(0.037)	(0.150)
Q80	0.15	0.00	0.00	0.03
	(0.102)	(0.188)	(0.048)	(0.189)
Q90	-0.12	0.00	0.00	0.06
	(0.237)	(0.194)	(0.071)	(0.228)

Bootstrapped standard errors in parentheses

In table 5 the results of the decomposition from two policy simulations are presented along with bootstrapped standard errors in parenthesis. The first simulation (3) models a cash transfer equal to the food security transfer. In this simulation all families receive the food security component only, irrespective of whether they also have children eligible for the school component. In the second simulation (4) all families receive double the program amount as an unconditional cash transfer. The first simulation results in very little change in the WAZ distribution with much lower estimates when compared to the original program specification in column (2), indicating that the size of transfer and the conditionality of the school transfer is important in determining outcomes. The estimates also show very little variation across quantiles. The second policy simulation also shows predictions lower than the original specification across most quantiles but particularly so at the lowest quantile and the median. Even at double the financial outlay, the health related conditionalities seem critical to changing the WAZ distribution as indicated by the small contribution of the cash transfer. The variation observed in the original specification is also not as obvious in this simulation.

6 Conclusion

This paper combines a simple behavioural model with new empirical estimation strategies to forecast the contribution of the cash transfer component of Nicaragua's conditional cash transfer program to the total change in the distribution of weight-for-age Z scores for children aged under 5 years. The application in this paper recovers the entire unobserved unconditional distribution of WAZ under the cash transfer. This facilitates forecasting the partial contribution of the cash transfer by comparing the predicted distribution with the observed pre-treatment distribution. The empirical procedure uses three different estimators - two semiparametric and one nonparametric in their specification. This first, uses linear quantile regression to estimate the conditional distribution pre-treatment and integrates this function across the distribution of the covariates under the program. The second differs by using distributional regressions to estimate the conditional distribution in the first stage - in this case a series of binary regression models are estimated at various cutoffs of the WAZ distribution. The third uses a nonparametric Kernel regression to estimate the first step and as in the other approaches averages over the distribution of the covariates under treatment. All three procedures provide estimates of the unconditional distribution of the outcome under the cash transfer. The total change from RPS is estimated from the randomized experiment using linear quantile regression.

The *ex post* linear quantile regression shows that the RPS program resulted in the greatest improvement at the lower part of the distribution of WAZ, particularly at the lowest quantile and median. No assumptions are made about rank preservation and hence inference is restricted to changes in the distribution of WAZ pre and post treatment. The results for the cash transfer component show that the distributional regression approach performs better and is more stable and more precise than the nonparametric and quantile regression approaches. Tests for stochastic dominance show that the cash transfer does improve WAZ across all quantiles however, the least change is seen as expected in the highest quantiles where children are already in good health.

The cash transfer component makes the least contribution to the total change in the lowest quantile, indicating that the health related conditionalities play an important role in improving child health outcomes for the most malnourished. Simulations of alternate policy scenarios indicate that providing just the food security transfer makes little improvement in the WAZ distribution while providing an unconditional cash transfer double the size of the original program outlay does not result in a major change in the results from the original specification.

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