Do Cash Transfers Promote Food Security? The Case of the South African Child Support Grant

d'Agostino, Giorgio and Scarlato, Margherita and Napolitano, Silvia

Department of Economics, Università degli Studi Roma Tre

2 February 2016

Do Cash Transfers Promote Food Security? The Case of the South African Child Support Grant

Giorgio d'Agostino, Margherita Scarlato*, Silvia Napolitano

Department of Economics, Università degli Studi Roma Tre

Abstract

This paper evaluates the causal effect of the Child Support Grant (CSG) implemented in South Africa on household food consumption and dietary diversity. The analysis uses the National Income Dynamics Study (NIDS) covering 2008, 2010-2011 and 2012, and carries out a regression discontinuity design exploiting the increase in the age limit criteria for eligibility for the program. Our results show that the CSG have proved to be effective in increasing total food expenditure per adult equivalent but has not significantly changed the dietary habits of the beneficiary households, nor has the program resulted in any stronger effect for the most vulnerable subgroups of the beneficiary population. To analyse the external and internal validities of the results, a comparison between non-parametric, semi-parametric and parametric estimates is presented.

Keywords: Food security, Cash transfers, Regression discontinuity design, Africa.

JEL code: I32, I38, C33, O55

1. Introduction

A number of studies have recently evaluated the impact of cash transfers (CTs) targeted to the poorest and most vulnerable people in sub-Saharan African countries, and a positive role in promoting human capital, health and productive activities has been documented (World Bank 2015). CTs may also affect food security because, by addressing the lack of purchasing power of poor households, they contribute to improving food purchases and access to more good-quality food (Alderman 2014; Bassett 2008). However, the evidence on the impact of CTs on food security in sub-Saharan Africa is not conclusive, since it is still not clear in what conditions they increase the consumption level of food and whether consumption gains are translated into improved nutritional status for household members (Alderman 2014; Manley *et al.* 2013; Slater *et al.* 2014).

In this paper we contribute to this literature by evaluating the impact on food security of the Child Support Grant (CSG), a CT program introduced in South Africa in 1998 with the aim of supporting children in poverty and poor households. At the demise of the apartheid regime in 1994, South Africa underwent significant political and social advances and rapid economic growth, both of which have led to steady progress in reducing poverty (Leibbrandt *et al.* 2011; Leibbrandt

*Corresponding author: Margherita Scarlato, Department of Economics, Università degli Studi Roma Tre, Via Silvio D'Amico 77, 00145, Roma, e-mail:margherita.scarlato@uniroma3.it.

and Levinsohn 2011). However, food insecurity remains widespread: 35% of the population is vulnerable (Kirsten 2012) and about 25% of children under age of 6 are classified as stunted by malnutrition (Manyamba *et al.* 2012). Food insecurity in South Africa is not due to a shortage of food, but rather to insufficient access as a result of structural poverty and inequality dynamics with a strong racial footprint (Aliber 2001; Du Toit 2011; Manyamba *et al.* 2012). In this context, CT programs aimed at eradicating extreme poverty[1] play a central role in addressing food insecurity and represent one of the pillars of the Integrated Food Security Strategy established in 1996 (South African Department of Agriculture 2002), although, to date, South Africa has no CT aimed at reducing food insecurity directly.

Although the CSG is the major CT program, its impact on food security has only been analysed in a few studies. Using data from the General Household Survey and the Labor Force Survey, Williams (2007) found that CSG beneficiaries aged between 7 and 17 years more probably attended school and suffered less hunger. Analysing an original survey of households in low-income areas and focus group discussions, Delany (2008) found that beneficiary households allocated a larger proportion of their expenditure to essential goods, such as food, and that more than three-quarters of the CSG recipients stated that food was the main expenditure covered by the grant. Samson *et al.* (2008) showed a reduction in hunger among children under 7 years of age, using a household panel extracted by the EPRI (Economic Policy Research Institute) from repeated cross-sections of the National General Household Surveys. Agüero *et al.* (2010), using data from the KwaZulu-Natal Income Dynamic Study, evaluated the impact of the CSG on anthropometric indicators which are widely used in nutritional assessment. Focusing on children in the first 36 months of life, the study found that the CSG improved childhood nutrition as measured by child height-for-age. Last, Coetzee (2013) evaluated the same impact in children under 14 on health, nutrition and education and found a few positive effects on the well-being of beneficiary children. Overall, these studies indicate that the CSG has positive effects on outcome variables connected to food security. However, a proper evaluation of this connection is still lacking.

This paper partially fills the gap by evaluating the causal impact of the CSG on the food expenditure of the beneficiary households[2] with a fuzzy regression discontinuity (RD) design. On the basis of a longitudinal survey provided by the National Income Dynamics Study (NIDS) covering 2008, 2010-2011 and 2012, the paper exploits the discontinuous variation induced by the expansion in eligibility due to child age criteria. As from January 1 2010, eligibility for the CSG was extended for children born on or after January 1 1994 until their 18th birthday; those born before 1994 lost eligibility at age 14. As a result of this policy change, a discontinuous increase occurred in the probability of

---

[1]South Africa has several types of social grants targeted to children, older persons and people with disabilities, amounting to 3.5/4 percent of GDP (Department Social Development 2010). By March 2015, these programs had reached almost 16.5 million people, representing more than 25% of the population (South African Social Security Agency, SASSA 2015).

[2]Although food expenditure is only a proxy of food security, in the case of low-income households it estimates information closely related to access to food, which is an important dimension of food security.

being a CSG beneficiary during the age interval 14-17 for children born after January 1 1994. This discontinuity provides a natural experiment for examining the causal effects of the program across birth cohorts. Using this identification structure, we explore whether CSG participation is effective in improving total food expenditure per adult equivalent and dietary diversity[3] for the beneficiary families who have a child that was eligible up to the age of 18.

In this perspective, we estimate the effect of the CSG by using the local polynomial (LP) estimator (Calonico *et al.* 2014) and then compare the results with the parametric estimates obtained with an instrumental variable (IV) approach.

Three major concerns arise in this analysis. First, the regression discontinuity estimates are valid locally, where "locally" means only for the birth cohorts close to the January 1 1994 cutoff. However, we are interested in more general causal effects not restricted to these cases. The external validity of the evaluation requires that the outcomes for the treated and non-treated populations away from the cutoff to be constant. To check whether the external vality assumption holds, we analyse the constancy of the local average treatment effect (LATE) for birth cohorts away from the January 1 1994 cutoff by comparing the results obtained from the IV estimator with those from the inverse distance weight (IDW) estimator[4]. Since the IDW provides higher weights for cohorts near the cutoff, if the LATE is constant, we do not expect to find significant differences between the IDW and IV estimates.

Secondly, not all households with a child in the eligible age range receive the CSG, since they must also meet an eligibility requirement based on income means test scores, and this criterion has changed over time. A selection bias may therefore emerge if we do not take into account how participation in the program varies with changes in the income requirement. The database does not allow us to examine these changes explicitly. In addition, since households may manipulate their income to satisfy the income eligibility criteria, the internal validity assumption may be violated. To overcome these shortcomings, following van der Klaauw (2002), a two-step propensity score (PS) procedure was applied. If the income requirement does not influence the estimated results, no significant difference is found between the two-step PS and the IV estimates.

Lastly, we ascertain that the causal estimates are robust within specific population subgroups. We emphasize that, in this analysis, significant differences may emerge because the CSG was designed to focus on poor households which had been excluded from social assistance programs during apartheid (Pauw and Mncube 2007), particularly Africans, and ones living in marginalized rural areas (Lund *et al.* 2008). Thus, we expected that the potential outcome would not be homogeneous with respect to the entire population (Angrist 2004). Hence, as a further robustness check, we used elasticity

[3]To estimate dietary diversity, we use expenditure disaggregated by food groups as a proxy measure. As Hoddinott and Yohannes (2002) state, a more varied diet is associated with better nutritional quality of food expenditure and yields improved outcomes in food security.

[4]For an application of this approach, see, for example, Pieroni and Salmasi (2015).

measures based on the PS estimates, obtained in the two-step procedure, to compare the potential outcome of the subgroups with that of the entire population and account for the differences between them[5]. Since elasticities may be interpreted in terms of the percentage variation in the outcome variable caused by a 1% increase in the treated population, they also allow us to verify whether the CSG program was successful in having a stronger impact on the target subgroups, i.e., the households which are most vulnerable to poverty and food insecurity.

Our results show that the monetary transfers provided by the CSG proved to be effective in increasing total food expenditure per adult equivalent, with an impact, on average, of about R53. The variation is quite large, given that the mean value of food expenditure for adult equivalent is only R500 in our sample. This result was confirmed by a comparison between non-parametric, semi-parametric and parametric estimations and thus is very robust. Our analysis also confirms that the estimated parameters are constant away from the cutoff and that the results are homogeneous across various population subgroups. We may thus interpret the causal effects of the CSG unconditionally to the birth cohorts which are not close to the cutoff. In terms of policy implications, this analysis shows that the CSG did not have a greater effect on the population subgroups which were more vulnerable to food insecurity with respect to the others. When dietary diversity is analysed, we find robust positive results only for carbohydrates, which represent the major food group in the total food expenditure of the treated households (with a share of 23%). This result indicates that the CSG did not lead to significant changes in the dietary habits of the beneficiary households and did not improve the dietary diversity of the poor households.

The paper proceeds as follows: Section 2 describes the dataset and the identification strategy; Section 3 provides an overview of the empirical framework used to estimate the causal impact of the CSG on food expenditure; Section 4 discusses the results, and Section 5 concludes.

2. Identification strategy and dataset

2.1. Identification strategy

CSG benefits are provided each month to eligible beneficiaries[6] and are paid to the primary caregiver[7]. As mentioned in Section 1, the eligible population is determined according to a means test and child age, and these criteria have changed over time. *Figure 1* shows the timeline of policy

[5]This approach is close in spirit to the analysis of Becker *et al.* (2013).

[6]The grant is given for each beneficiary child up to a maximum of six children per caregiver. The transfer was fixed at a level of R100 per month in 1998, but this increased over years reaching R280 in 2012 (and R320 in 2014). As from 2008, the amount of the grant has been adjusted every year for inflation.

[7]The primary caregiver is defined as the person who takes primary responsibility for meeting the daily care needs of the child, without payment. In 98% of cases, the caregiver is a woman of the household where the child lives (Agüero *et al.* 2010).

changes in the eligible population and in the amount of the grant, from 1998, when the program was introduced, to the last year of our evaluation (2012).

In the case of income criteria, the means test was initially based on household income, and the ceiling was fixed at the nominal level of R800 in urban areas and R1,100 in rural areas for ten years. However, in 1999, to increase take-up rates, the government altered this rule to one which considered only the income of the primary caregiver plus her/his spouse (Agüero *et al.* 2010; Woolard and Leibbrandt 2010). Eligibility was expanded again in 2008: the Department of Social Development defined the income ceiling as ten times the value of the grant paid to the single primary caregiver of the child (double for married caregivers), so that the means test automatically keeps pace with inflation (Agüero *et al.* 2010; Woolard and Leibbrandt 2010).

Fig. 1.— *Timeline of CSG implementation*

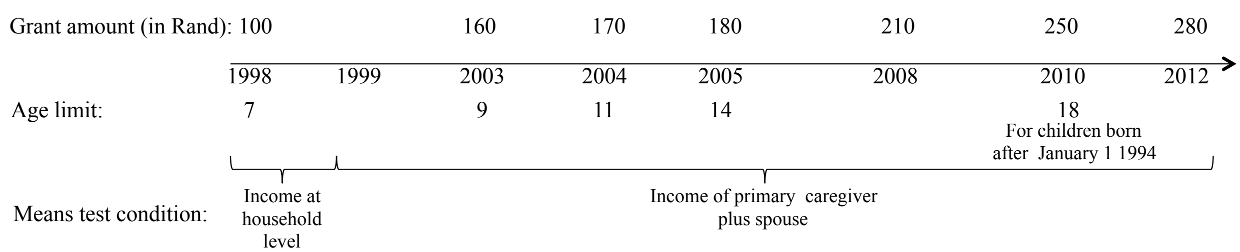


Figure 1 also shows changes in age limit criteria. When the program was introduced in 1998, age eligibility was limited to children under 7 years old, but it was later gradually raised: in 2003, it was extended to children up to their 9th birthday, in 2004 up to their 11th, and in 2005 up to their 14th. From January 1 2010, eligibility was further extended, so that children born after January 1 1994 were eligible until their 18th birthday, whereas those born before that date lost eligibility at 14 (Bor 2013; Van der Berg *et al.* 2010; Woolard and Leibbrandt 2010).

Policy changes in age eligibility criteria have been gradual since 2005, whereas in 2010 a large discontinuity in implementation occurred. This discontinuity allows a clear-cut natural experiment to be carried out, by looking at the causal effects of the CSG and comparing the estimates across birth cohorts. We apply this identification structure to analyse the external effect on household food expenditure produced by the sudden increase in the probability of receiving the CSG grant for children aged 14-17, among cohorts born on or after January 1 1994. The analysis is based on a comparison between the food expenditure behavior of households with no eligible children and that with eligible children in the specified cohorts.

2.2. Dataset

The National Income Dynamic Study (NIDS) is a dataset implemented by the South African Labour and Development Research Unit (SALDRU) of the University of Cape Town, and represents the first nation-wide panel study in South Africa. The NIDS was available for the waves 2008, 2010-2011 and 2012, and allowed a face-to-face longitudinal survey of households resident in South Africa. Its aim was to follow a sample of household members and register changes in household compositions and migrations and several dimensions of well-being (e.g., incomes, expenditures, assets, access to social services, education, health, employment).

From the entire dataset, households with no children or with children who were not born in the period 1990-1998 were dropped. This procedure was followed because the evaluation required a sample of households with children in the age range 14-17 who experienced the policy change. Since our panel data covers the period 2008-2012, we needed to include children born since 1990, and to remove those born after 1998, who are always eligible for the CSG. Using this framework, we obtained a sample of households with children in the age range from 10 (in 2008) to 22 (in 2012). We then restricted the data to households with only one child receiving the CSG and also extracted a sample in which the household composition remained unchanged during the three survey periods, to ensure the absence of migration between different provinces and areas. After these modifications, we obtained a sample of 1,336 households with one beneficiary child, for a total of 4,010 units.

Table 1: *Total food expenditure per adult equivalent and shares of food groups*

	Full-sample		Control		Treatment	
	mean	s.d.	mean	s.d.	mean	s.d.
Total food expenditure per adult equivalent	500.460	497.196	556.419	532.096	394.815	403.085
Share of food groups in total food expenditure:						
Carbohydrates	19.401	18.532	17.476	17.366	23.035	20.065
Dairy products	4.203	5.123	4.257	5.119	4.101	5.130
Proteins	15.939	15.911	16.384	16.480	15.099	14.747
Vitamins	5.857	6.386	5.828	6.342	5.912	6.471

Notes: Total food expenditure per adult equivalent is monthly expenditure at household level, adjusted by an adult equivalent scale. Analysis of food groups is valid for period 2008-2011, as NIDS stopped reporting such data after 2011.

The dataset provided expenditure data at household level and included both total food expenditure and food expenditure disaggregated by food group. We used these variables due to our interest in analysing aspects of food security related to economic access to a sufficient quantity of food, and to the the quality of food consumed (Hoddinott and Bassett 2008; Hoddinott and Yohannes 2002).

In more in detail, the first variable of interest is monthly food expenditure at household level, adjusted by an adult equivalent scale[8]. The other variables were obtained by disaggregating the

[8]The variable is the result of the aggregation of four separate sources of food expenditure: i) expenditure for food items; ii) value of food items received as gifts; iv) value of food items received as payment; v) value of self-produced food items. To obtain the total food expenditure, the survey considers 32 food items in ten major categories: i) cereals, ii) meat, iii) fish, iv) dairy products, v) fats, vi) fruit, vii) vegetables, viii) sweets, ix) beverages, x) other food expenses. In order to yield expenditure at constant prices, it was adjusted according to the monthly and provincial

total food expenditure per adult equivalent into four food groups: i) carbohydrates, given by the sum of the expenditure on cereals such as samp, flour and bread, mealie meal, rice and pasta; ii) dairy products, iii) proteins, given by the sum of expenditure on meat and fish; iv) vitamins, comprising expenditure on fruit and vegetables. Analysis of food groups was carried out for the period 2008-2011, since NIDS stopped reporting such data after 2011.

Table 1 reports means and standard deviations (s.d.) for the outcome variables in question, separated into control and treatment groups. As an initial outcome, the first raw data show that considerable differences arise when the total food expenditure per adult equivalent is considered: the mean in the treated group is about R394, compared with about R556 in the control group. The standard deviation is also much higher in the control group.

In addition, when the four shares of food expenses in the total food expenditure per adult equivalent are compared, *Table 1* shows that the largest difference between treated and control groups regards the mean value of the share of carbohydrates, which is about 6 % higher in the treated group. As shown in the literature, the poorest people in South Africa have little variety of diet and consume more cereals and fewer items in other food groups compared with the rest of the population[9].

Table 2 lists household characteristics in the entire sample (for both periods, 2008-2012 and 2008-2011) and both groups. In the sample for 2008-2012, the first remarkable difference between the groups is due to the share of households living under the food poverty line[10], defined as the threshold under which individuals cannot purchase sufficient food to provide them with an adequate diet. This share is 44% of treated units and only 32% of controls. Other significant differences are found when geographical location, race, gender and employment status are considered. In more detail, we find that the majority of households in the treated group live in rural areas (57%), and also have household heads who are Africans (86%), women (69%) and receiving no education (26.5%), compared with the control group.

Consumer Price Index (CPI) (December 2012 = 100). Household food expenditure was also adjusted according to a per adult equivalent scale, to account for economies of scale at household level. Following Woolard and Klasen (2005), we applied the formula commonly used for poverty and welfare analyses in South Africa, thus obtaining the total food expenditure per adult equivalent at constant price ($Adult\ Equivalent\ Scale = \frac{Household\ Income}{(Adult\ +\ 0.5{*}Children)^{\ 0.9}}$).

[9]For an extensive discussion on dietary diversity in South Africa, see Labadarios *et al.* (2011) and South African Department of Health (2013).

[10]For the definition of the two poverty lines, see del Ninno and Mills (2015) and *Appendix A*.

Table 2: Descriptive statistics

	Sample 2008-2012				Sample 2008-2011			
	Sample	Control	Treated	Difference	Sample	Control	Treated	Difference
Province								
Western Cape	0.146	0.175	0.088	0.087	0.144	0.173	0.088	0.085
Eastern Cape	0.134	0.124	0.154	-0.030	0.135	0.126	0.154	-0.028
Northern Cape	0.064	0.070	0.053	0.017	0.063	0.069	0.053	0.016
Free State	0.084	0.093	0.067	0.026	0.085	0.094	0.067	0.027
KwaZulu-Natal	0.235	0.197	0.310	-0.113	0.237	0.198	0.311	-0.113
North West	0.051	0.043	0.066	-0.023	0.051	0.044	0.066	-0.022
Gauteng	0.117	0.140	0.074	0.066	0.114	0.135	0.075	0.060
Mpumalanga	0.070	0.065	0.081	-0.016	0.070	0.065	0.078	-0.013
Limpopo	0.098	0.094	0.107	-0.013	0.100	0.096	0.108	-0.012
Poverty								
Food poverty line	0.362	0.321	0.442	-0.121	0.293	0.255	0.368	-0.113
Poverty line	0.329	0.309	0.369	-0.060	0.338	0.307	0.399	-0.092
Geographical location								
Rural	0.442	0.374	0.573	-0.199	0.450	0.383	0.580	-0.197
Urban	0.558	0.626	0.427	0.199	0.550	0.617	0.420	0.197
Number of household members								
1 or 2	0.135	0.147	0.113	0.034	0.124	0.133	0.105	0.028
3	0.227	0.211	0.258	-0.047	0.235	0.215	0.274	-0.059
4	0.212	0.213	0.211	0.002	0.216	0.215	0.218	-0.003
5	0.174	0.179	0.165	0.014	0.173	0.179	0.162	0.017
≥ 6	0.252	0.250	0.254	-0.004	0.252	0.258	0.240	0.018
Head of household by race								
African	0.768	0.719	0.862	-0.143	0.768	0.719	0.862	-0.143
Colored	0.171	0.195	0.124	0.071	0.171	0.195	0.124	0.071
Asian/Indian/White	0.061	0.086	0.014	0.072	0.061	0.085	0.014	0.071
Head of household by gender								
Female	0.617	0.578	0.692	-0.114	0.588	0.550	0.661	-0.111
Male	0.383	0.422	0.308	0.114	0.412	0.450	0.339	0.111
Head of household by education								
No schooling	0.182	0.138	0.265	-0.127	0.201	0.153	0.291	-0.138
Primary	0.185	0.154	0.246	-0.092	0.196	0.165	0.255	-0.090
Secondary	0.515	0.542	0.464	0.078	0.499	0.532	0.437	0.095
Tertiary	0.118	0.167	0.025	0.142	0.105	0.151	0.018	0.133
Head of household by age								
	49.085	48.166	50.869	-2.703	49.967	49.181	51.491	-2.310

Notes: Descriptive statistics of district of residence of household and interview's month are omitted. For definitions of food poverty line and poverty line, see *Appendix A*.

3. Empirical framework

An RD design is as good as random in the neighborhood of the discontinuity cutoff (*local random assignment*), when the observed individuals do not have complete control over the variable which assigns them to treatment[11] (Lee 2008; Lee and Lemieux 2010). In the case of the CSG, access to three more years of transfers is determined by the children's age. As a consequence, individuals have approximately the same probability of receiving an assignment variable which is just above (receiving treatment) or below (denied treatment) the cutoff date of the treatment, and internal validity is not a problem. In this case, local random assignment implies that the discontinuity gap at the cutoff identifies the treatment effect of interest (τ), or that:

$$\lim_{\epsilon \downarrow 0} Pr(Y|X = c + \epsilon) - \lim_{\epsilon \uparrow 0} Pr(Y|X = c + \epsilon)) = \tau \tag{1}$$

where X is the assignment variable (in our analysis, the birth cohort of children) which is deterministically related to crossing cutoff c (January 1 1994), Y is the outcome variable of interest, and ϵ determines the neighborhood in which local random assignment is satisfied.

Since participation in the CSG program was not compulsory, some households with eligible children did not apply for the grant. Thus, treatment variable $T \in \{0, 1\}$ is not deterministically related to the cutoff and a fuzzy RD design is required. In this way, we take into account the fact that only for those households which applied to the program and gained eligibility to three more years of the CSG we may expect a variation after crossing the cutoff related to the year of birth. A further assumption must also be satisfied to identify the fuzzy RD design:

$$\lim_{\epsilon \downarrow 0} Pr(T = 1|X = c + \epsilon) \neq \lim_{\epsilon \uparrow 0} Pr(T = 1|X = c + \epsilon) \tag{2}$$

where the continuity assumption refers to the probability of being treated by the CSG in the neighborhood of the cutoff. Therefore, in the fuzzy RD design, the treatment effect is obtained by dividing the increase in the relationship between Y and X at c (equation 1) by the difference of the probability that applicant households will be treated before or after the cutoff (equation 2). The treatment effect in the fuzzy RD design (defined as τ_F) is:

$$\tau_F = \frac{\lim_{\epsilon \downarrow 0} E(Y|X = c + \epsilon) - \lim_{\epsilon \uparrow 0} E(Y|X = c + \epsilon)}{\lim_{\epsilon \downarrow 0} E(T|X = c + \epsilon) - \lim_{\epsilon \uparrow 0} E(T|X = c + \epsilon)}. \tag{3}$$

When the local random assignment holds, equation 3 provides an unbiased estimate of a weighted version of the LATE, in which the impact of the program is evaluated on individuals who were assigned to the treatment group and actually participated in it (compliers) compared with those who were assigned to the treatment group but did not participate in the program (non-compliers) (Jacob *et al.* 2012).

The first approach followed here was to estimate equation 3 through a local polynomial (LP) estimator, which approximates the regression functions above and below the cutoff by means of weighted polynomial regressions, with weights computed by applying a kernel function to the distance of

[11] Formally, this hypothesis ensures that the stochastic error component in the assignment variable is continuously distributed.

each observation from the cutoff[12]. The LP does not impose any functional form or introduce any relevant characteristic of the household and, hence, represents a benchmark for parametric and semi-parametric estimations. It is also useful for inspecting the link between assignment variable X and treatment variable T, described in equation (2).

In addition, since equation 3 shows a close analogy between the fuzzy RD design with the Wald formulation of the treatment effect, an IV setting can also be applied. It requires the monotonicity and excludability related to the assignment variable when crossing the cutoff (Hahn *et al.* 2001). When these assumptions hold, the treatment effect in the fuzzy RD design can be written as:

$$\tau_F = E[Y(1) - Y(0)|household\ is\ a\ complier,\ X = c] \tag{4}$$

where $Y(0)$ and $Y(1)$ represent the values of the outcome variable before and after the cutoff, respectively. To estimate equation 4 in an IV framework, when the monotonicity assumption holds, we impose a linear form on the two-sided relationship among the assignment variable, the treatment dummy and the outcome variable[13]. The first-stage regression is:

$$\begin{aligned} T &= \alpha_o + \alpha_1 X + W'\alpha_2 + \alpha_3 trend + \alpha_4 trend^2 + \sum_{r=1}^{R} \gamma_r^1 D_r + \sum_{r=1}^{R} \gamma_r^2 (D_r \times trend) \\ &+ \sum_{r=1}^{R} \gamma_r^3 (D_r \times trend^2) + \sum_{m=1}^{M} \gamma_m^1 D_m + \sum_{m=1}^{M} \gamma_m^2 (D_m \times trend) + \sum_{m=1}^{M} \gamma_m^3 (D_m \times trend^2) + \Psi \end{aligned} \tag{5}$$

where W is a matrix of the relevant characteristics of households and heads of households, Ψ is an error term, and a second-order polynomial time trend ($trend$ and $trend^2$) is included to take into account non-linear patterns of food expenditure [14].

Regional D_r and district D_m dummies and their interactions with the second-order polynomial time trend are also introduced. The reduced form equation is:

$$\begin{aligned} Y &= \beta_0 + \beta_1 X + W'\beta_2 + \beta_3 trend + \beta_4 trend^2 + \sum_{r=1}^{R} \theta_r^1 D_r + \sum_{r=1}^{R} \theta_r^2 (D_r \times trend) \\ &+ \sum_{r=1}^{R} \theta_r^3 (D_r \times trend^2) + \sum_{m=1}^{M} \theta_m^1 D_m + \sum_{m=1}^{M} \theta_m^2 (D_m \times trend) + \sum_{m=1}^{M} \theta_m^3 (D_m \times trend^2) + \Phi. \end{aligned} \tag{6}$$

Lastly, the IV estimates of the outcome variable are obtained by the ratio of the reduced-form coefficients of the assignment variable in equations 6 and 5, that is, $\delta_1 = \beta_1/\alpha_1$. The structural

[12]The main shortcoming of the LP approach concerns the choice of the most appropriate bandwidth. We follow Calonico *et al.* (2014) for the best choice.

[13]As stressed by Jacob *et al.* (2012), more sophisticated functional forms may also be used as robustness checks of the linear formulation.

[14]We apply to food expenditure the procedure used by Pieroni *et al.* (2013) and Pieroni and Salmasi (2015) to capture non-linear patterns in food consumption.

equation is:

$$\begin{aligned} Y &= \delta_0 + \delta_1 T + W'\delta_2 + \delta_3 trend + \delta_4 trend^2 + \sum_{r=1}^{R} \lambda_r^1 D_r + \sum_{r=1}^{R} \lambda_r^2 (D_r \times trend) \\ &+ \sum_{r=1}^{R} \lambda_r^3 (D_r \times trend^2) + \sum_{m=1}^{M} \lambda_m^1 D_m + \sum_{m=1}^{M} \lambda_m^2 (D_m \times trend) + \sum_{m=1}^{M} \lambda_m^3 (D_m \times trend^2) + \Omega. \end{aligned} \tag{7}$$

To account for non-linearities, we also present estimation results which were obtained by introducing a third-degree polynomial of the assignment variable into equations 5, 6 and 7. In order to check for the external validity assumption, we must also verify whether the outcomes of the treated and non-treated groups away from the cutoff are constant. In this perspective, we analyse the constancy of the LATE when the considered birth cohorts are far from the January 1 1994 cutoff by comparing the results obtained by the IV with the IDW estimators (Pieroni and Salmasi 2015).

Since we can only identify the impact of the CSG on the outcome variable caused by the variation of the age limit, but we do not have complete control over the effects of the change in the income eligibility rule, the selection process is not perfectly known and an omitted variable bias may arise in the estimations. In addition, households are able to manipulate their income threshold. Thus, the internal validity assumption may also turn out not to be realistic anymore. Following van der Klaauw (2002), the selection bias may be overcome by replacing T with its propensity score $E[T|X]$ in equation 5. In this case, a two-step procedure is required and, thus, in the first stage we specify the PS function in the fuzzy RD design (van der Klaauw 2002; You 2013). The propensity score in the RD framework thus reads:

$$E[T|X] = f(X) + \mu\ 1(S \geq c) \tag{8}$$

where $f(X)$ is a continuous function in c which may be estimated parametrically or semi-parametrically. In the present context, it is defined as a third-degree polynomial of the assignment variable.

The estimated propensity score can then replace treatment variable T in equation 7 to estimate δ_1. The second-step equation is:

$$\begin{aligned} Y &= \delta_0 + \delta_1 [T|X] + W'\delta_2 + \delta_3 trend + \delta_4 trend^2 + \sum_{r=1}^{R} \lambda_r^1 D_r + \sum_{r=1}^{R} \lambda_r^2 (D_r \times trend) \\ &+ \sum_{r=1}^{R} \lambda_r^3 (D_r \times trend^2) + \sum_{m=1}^{M} \lambda_m^1 D_m + \sum_{m=1}^{M} \lambda_m^2 (D_m \times trend) + \sum_{m=1}^{M} \lambda_m^3 (D_m \times trend^2) + \Omega \end{aligned} \tag{9}$$

so that we can compare the parameters estimated with the IV method with those obtained with the two-step PS procedure.

Lastly, we recall that the potential outcome in specific population subgroups may not be homogeneous with respect to the entire population (Angrist 2004). Hence, we calculate elasticity measures based on the PS estimates obtained in the two-step procedure, and carry out a a further robustness check by comparing the result of the subgroups with that of the entire population, to verify whether significant differences emerge.

In more detail, we extend equation 9 by introducing interaction terms between the PS estimates and the dummy variables describing, one by one, five subgroups of the population which may present substantial differences in the potential outcomes. Defining the matrix including the five interaction terms as W^2, we obtain:

$$\begin{aligned} Y &= \delta_0 + \delta_1[T|X] + W'\delta_2 + W^{2'}\delta_3 + \delta_4 trend + \delta_5 trend^2 + \sum_{r=1}^{R}\lambda_r^1 D_r + \sum_{r=1}^{R}\lambda_r^2 (D_r \times trend) \quad (10) \\ &+ \sum_{r=1}^{R}\lambda_r^3 (D_r \times trend^2) + \sum_{m=1}^{M}\lambda_m^1 D_m + \sum_{m=1}^{M}\lambda_m^2 (D_m \times trend) + \sum_{m=1}^{M}\lambda_m^3 (D_m \times trend^2) + \Omega \end{aligned}$$

where, to allow for the correct identification of equation 10, we must assume that the interaction variables are continuous at the cutoff and uncorrelated with the error term, conditional on W (Becker *et al.* 2013). With the estimated parameters, we construct elasticity measures using the integration terms and PS estimates. The elasticity measures allow us to compare the effects of policy changes on varying population subgroups and to interpret the results in terms of the percentage variation in the outcome variable caused by a 1% increase in the treated population.

4. Results and robustness analysis

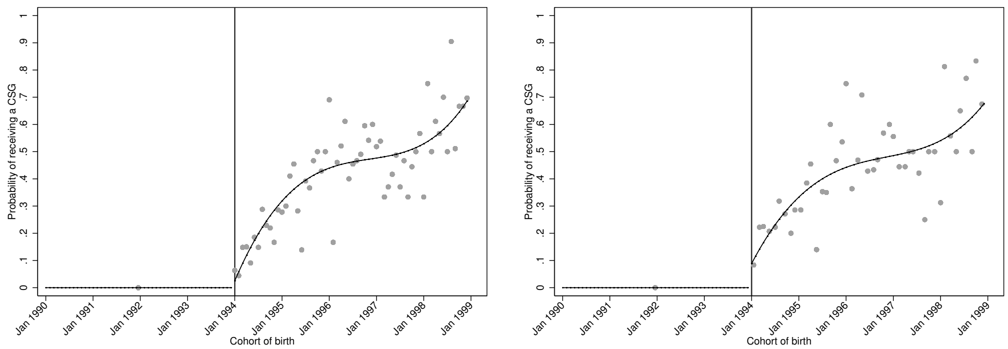
This Section presents the estimates of the causal effects of the CSG on total food expenditure per adult equivalent and shares of food groups. The results for the full sample 2008-2012 are given, together with those excluding 2012 for the shares of food groups.

Figure 2 shows the results of the estimation of equation 2, which links assignment variable X (the birth cohort of children) to treatment status T (the probability of participating in the CSG), with the LP estimator. A comparison of the two plots confirms the fuzzy nature of the RD design showing that, one month after the policy change, about 3% (7% in the second sample) of households participated in the CSG. The probability of entering the program rapidly increases along the birth cohorts, reaching about 70% of the households in 1998.

Figure 3, panel (a) shows the estimates of the causal effects of the CSG on the first outcome variable, total food expenditure per adult equivalent, obtained through the LP estimator. The other four panels replicate the same analysis, being outcome variables the shares in total food expenditure of: i) carbohydrates, ii) dairy products, iii) proteins, and iv) vitamins.

Panel (a) of *Figure 2*, clearly shows a discontinuity in the food expenditure per adult equivalent around the January 1 1994 cutoff: before that date, the expenditure pattern remained quite constant along the birth cohorts, but after it participant households showed an increase in food expenditure per adult equivalent of about R50.

Fig. 2.— LP estimates: birth cohort and treatment status



(a) Sample 2008-2012 (b) Sample 2008-2011

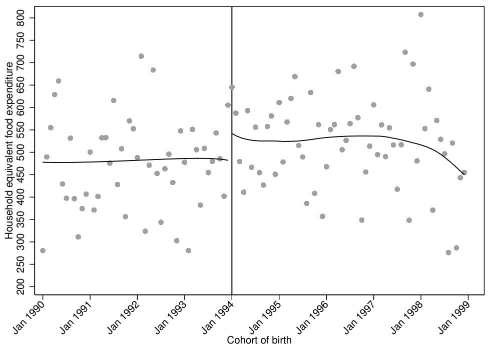
Notes: Construction of evenly spaced bins follows Calonico *et al.* (2014).

A similar pattern is also found in the shares of carbohydrates and dairy products in total food expenditure, in panels (b) and (c) respectively. In both cases there is a positive variation in expenditure shares after the cutoff due to the expanded CSG age eligibility rule. Conversely, a poorly defined result appears for the protein share (panel d), and no discontinuity in the vitamin share (panel e). As the last four plots were obtained with data up to 2011, i.e., only one year after the policy change, and as the LP estimator requires an extensive number of observations, these results should be considered with caution.

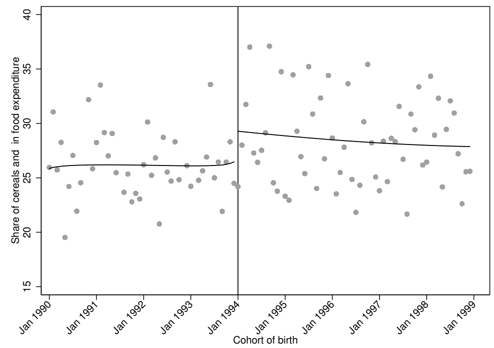
Lastly, when the five plots are compared, a third-degree polynomial is used by the LP estimator to approximate the total food expenditure patterns, although, except for the protein, a linear functional form approximates the behavior of the variables in the neighborhood of the cutoff quite well.

Table 3 lists the estimates of food expenditure per adult equivalent, comparing the results for the IV, IDW and two-stage PS estimators. In each case we consider a linear functional form (1) an then a non-linear one (2), which uses a third-degree polynomial, as suggested by the LP estimator. When the results obtained from the two-step PS estimator are analysed, the non-linear form is introduced in $f(X)$, as in equation 8.

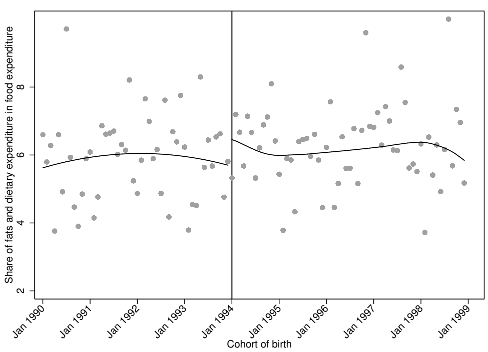
Fig. 3.— LP estimates: impact of CSG on total food expenditure per adult equivalent and shares of food groups



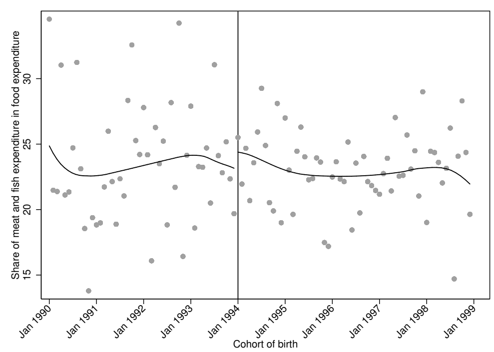
(a) Total food expenditure per adult equivalent



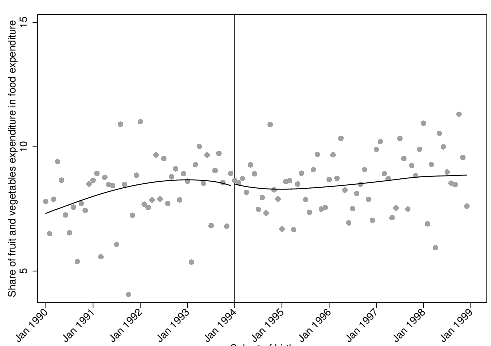
(b) Share of carbohydrates*



(c) Share of dairy products*



(d) Share of proteins*



(e) Share of vitamins*

Notes: (*) Analysis of food groups valid for 2008-2011. Construction of evenly spaced bins follows Calonico *et al.* (2014).

Table 3: Impact of CSG on total food expenditure per adult equivalent

	Instrumental variable		Inverse Distance Weight		Propensity score	
	(1)	(2)	(1)	(2)	(1)	(2)
Child Support Grant (CSG)	55.337 ***	54.202 ***	55.402 ***	54.199 ***	52.357 ***	53.964 ***
	(20.040)	(19.589)	(19.919)	(19.511)	(19.547)	(19.176)
Constant term	1046.445 ***	1232.174 ***	1440.459 ***	1225.300 ***	1221.254 ***	1432.057 ***
	(184.109)	(78.246)	(191.673)	(76.888)	(77.864)	(187.934)
Fixed effects	yes	yes	yes	yes	yes	yes
Linear and quadratic trends	yes	yes	yes	yes	yes	yes
Selected covariates	yes	yes	yes	yes	yes	yes
Cragg-Donald F statistic	1359.645	499.282	1337.016	492.801		
	(0.000)	(0.000)	(0.000)	(0.000)		
Kleibergen-Paap F test statistic†	1433.471	510.756	1442.713	511.839		
	(0.000)	(0.000)	(0.000)	(0.000)		
R^2	0.676	0.676	0.677	0.677	0.681	0.682
Adjusted R^2	0.658	0.658	0.659	0.659	0.663	0.664
No. of observations	3399	3399	3399	3399	3399	3399

Notes: In all specifications, dependent variable is total food expenditure per adult equivalent (see the list of the selected covariates in Section 2). Robust standard errors are shown in brackets. Asterisks: *p-value* levels (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$). For each model, linear (1) and non-linear specification (2) is shown. When two-step PS procedure is applied, non-linearities are introduced only in first-stage regression. Tests for weak instrument hypothesis and first-stage F statistics and Wald statistics based on Cragg and Donald (1993) and Kleibergen and Paap (2006). † Confidence intervals for Kleibergen-Paap F test statistic follow Bazzi and Clemens (2013).

Table 4: Impact of CSG on food expenditure by food group

	Carbohydrates		DAIry products		Proteins		Vitamins	
	IV	PS	IV	PS	IV	PS	IV	PS
Child Support Grant (CSG)	2.267 **	2.022 **	0.808 **	0.753	0.196	-0.233	1.230 **	1.019
	(1.150)	(1.030)	(0.405)	(0.483)	(1.216)	(1.176)	(0.557)	(0.588)
Constant term	32.921 ***	32.716 ***	5.768 ***	5.685 ***	9.164	9.270	14.986 ***	14.898 ***
	(7.440)	(7.359)	(2.156)	(2.185)	(5.772)	(5.774)	(4.379)	(4.391)
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Linear and quadratic trends	yes	yes	yes	yes	yes	yes	yes	yes
Selected covariates	yes	yes	yes	yes	yes	yes	yes	yes
Cragg-Donald F statistic	866.207		866.207		866.207		866.207	
	(0.000)		(0.000)		(0.000)		(0.000)	
Kleibergen-Paap F test statistic†	930.615		930.615		930.615		930.615	
	(0.000)		(0.000)		(0.000)		(0.000)	
R^2	0.361	0.361	0.090	0.094	0.222	0.222	0.097	0.106
Adjusted R^2	0.321	0.321	0.034	0.038	0.174	0.174	0.042	0.051
No. of observations	2193	2193	2193	2193	2193	2193	2193	2193

Notes: The dependent variables are shares of food groups in total food expenditure per adult equivalent. In all specifications, dependent variable is total food expenditure per adult equivalent (see the list of the selected covariates in Section 2). Robust standard errors are shown in brackets. Asterisks: *p-value* levels (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$). For each model, linear (1) and non-linear specification (2) is shown. When two-step PS procedure is applied, non-linearities are introduced only in first-stage regression. Tests for weak instrument hypothesis and first-stage F statistics and Wald statistics based on Cragg and Donald (1993) and Kleibergen and Paap (2006). † Confidence intervals for Kleibergen-Paap F test statistic follow Bazzi and Clemens (2013).

All specifications include province and district dummies, and also linear and quadratic trends to account for the non-linear patterns of food expenditure (Pieroni *et al.* 2013; Pieroni and Salmasi 2015), together with the household and head of household characteristics (see Section 2). For each specification, we test for weak instruments. In more detail, we run a test for weak instruments and report first-stage F statistics and Wald statistics based on the Cragg and Donald (1993) and Kleibergen and Paap (2006) generalisation to non-independently and non-identically distributed errors, together with the $p - values$ (Bazzi and Clemens 2013).

Overall, we find that the non-parametric and parametric estimations show very similar variations, due to the CSG policy change. That is, from the linear (1) and non-linear (2) specifications of the IV estimator, we find a variation in food expenditure per adult equivalent which ranges between R54 and R55 and this variation is significant at 1%.

Considering the full sample (see *Table 1*), this variation corresponds to a mean increase of 10% in total food expenditure per adult equivalent. The under-identification and weak instrument tests show that the assignment variable accounts for the entire endogeneity appearing in the IV estimations.

Moving to columns 3 and 4, we use the IDW estimator to check for the constancy of IV results in the birth cohorts away from the January 1 1994 cutoff. Both linear and non-linear specifications show that the estimated parameter does not differ, in terms of standard deviation, from other estimated with IV method. Also in this case, first-stage tests show that the instrument is neither under nor weakly identified.

A similar result is found when the two-step PS is compared with the IV results. It should be noted that the two-step PS is used to analyse the robustness of the results when the identification mechanism is not completely known. In the present case, it shows that variations in participation in the CSG caused by the change in the income cutoff do not affect the IV results, since there are no differences in the standard deviations between the IV and two-step PS estimates. This result is not surprising, because the program does not implement any proper control of the households' income level after they pass the initial means test and are involved in the program.

Table 4 extends the previous analysis to the shares of food groups in the total food expenditure per adult equivalent. In depth, the table compares the results from a linear specification of the IV and two-step PS estimations[15]. The results for the IDW estimator are given in *Appendix B*.

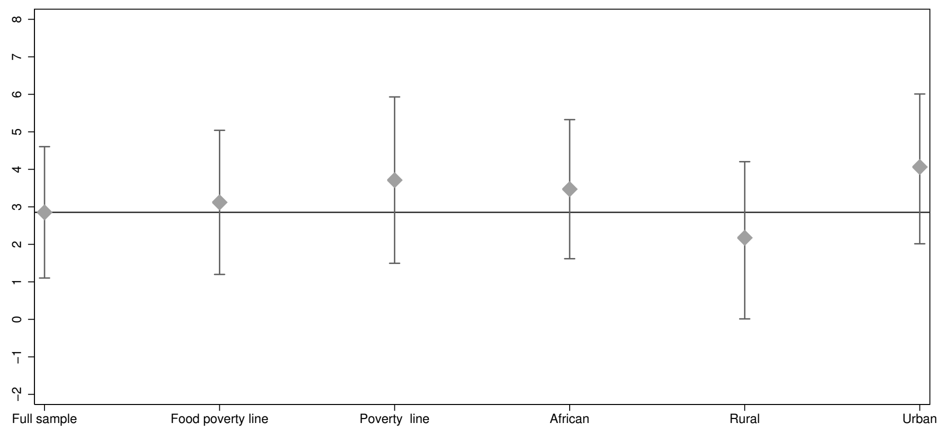
When the carbohydrate share is analysed, we find a variation of about 2% in expenditure produced by the policy change. Again, this result is similar to that found by the LP estimator and does not change in the two-step PS and IDW estimations (not reported). Less robust but still significant results are found when the shares of dairy products and vitamins are accounted for in the IV specification: the beneficiary families increase the share of expenditure for diary products by 0.8% and that for vitamins by 1.2%. However, these results become non-significant at 10% level when the two-step PS and IDW estimators are used. Instead, no significant variations are found when the share of proteins in total expenditure per adult equivalent is examined.

It should be emphasized that carbohydrates are the major food item consumed by the treated households (on average, 23% of total food expenditure per adult equivalent), and these results thus indicate that the program grants were not sufficient to allow the beneficiary households to make significant changes in their dietary habits. However, we must also use caution because, when

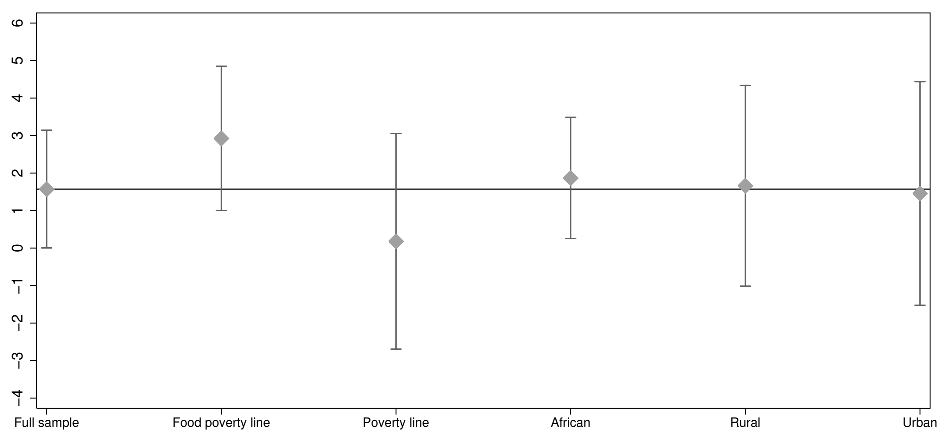
[15] Omitted non-linear specifications are available from the authors.

considering food shares, the restricted sample (2008-2011) may be too short to account for the whole effect of CSG policy change.

Fig. 4.— *Elasticity measures: total food expenditure per adult equivalent and share of carbohydrates*



(a) Total food expenditure per adult equivalent



(b) Share of carbohydrates

To complete the analysis, *Figure 4* shows the elasticity measures for total food expenditure per adult equivalent and the share of carbohydrates. We do not report the other three panels (for dairy products, proteins and vitamins) since the estimated parameters are not robust across differing estimation methods (see Table 4). *Figure 4* shows the results for the total population and some population subgroups, which are the households under both the food poverty line and the poverty line, households in which the head is an African and households living in rural and urban areas. It should be recalled that the main targets of the CSG program are the subgroups most vulnerable to poverty and food insecurity, i.e. households living under the food poverty line, Africans, and those living in rural areas. The elasticity measure allows us to compare the various subgroups with the entire population in terms of the percentage effect of the variation in their participation in the program after the policy change and to check its homogeneity.

Figure 4, panel (a) shows that, although some differences between the subgroups and full-sample estimates are found, all the subgroups elasticities plot in the same confidence interval as the full-sample elasticity. In this case, the analysis shows that a 1% variation in participation in the program produces a 3% increase in total food expenditure per adult equivalent, at a significance level which is less than 5%.

We find a higher variability when the rural/urban groups are analysed. *Figure 4* shows that a 1% increase in participation in the program for the households living in urban areas produces a positive variation in the food expenditure per adult equivalent, which is double that estimated for rural areas. This result may be explained by the fact that rural areas in South Africa are geographically isolated and marginalised, so that food availability is a serious problem (Kirsten 2012). Several studies have found a higher percentage of food insecurity in rural areas in South Africa (Kirkland *et al.* 2013). However, we must also recall that, as Aliber (2009) stresses, rural households spend less than their urban counterparts on food purchases because they have their own production. In principle, measures of food expenditure are designed to capture this information, but the imputed value is probably smaller than the true one. In this case, the effect of the CSG on food security in rural areas in our analysis would be underestimated.

When the carbohydrate share is analysed, we find more variability between the full-sample elasticity measure and those for the population subgroups, but the results are significant at 5% level only for households under the food poverty line and ones in which the head is African. In more detail, the elasticity measure for beneficiaries under the food poverty line is about double that of the full sample, even though it falls in the same confidence interval. This result is in line with existing literature, which states that poor dietary variety is a problem concerning mainly the poorest people, who consume far more cereals and fewer fruit, vegetables, dairy products and meat than other population subgroups (Labadarios *et al.* 2011; South African Department of Health 2013). In the case of the subgroup of households with an African head, the elasticity is very close to that of the full sample.

Overall, these results indicate that the CSG has proved to be effective in supporting the food expenditure of its beneficiary households, but the amount of the grant is not high enaugh to produce a significant change in the dietary habits of very poor beneficiaries and to guarantee a nutritionally varied food basket. Our findings also show that the CSG has failed to improve the food security of the most disadvantaged groups with a greater effect than in the others. This study suggests that an integrated social protection program, specifically targeting adequate resources and social services to the most food-insecure households, would contribute more effectively to increasing food and nutrition status of very poor households in South Africa.

5. Conclusions

This paper estimates the impact of the South African CSG on food security. We used the dataset provided by the National Income Dynamics Study covering 2008, 2010-2011 and 2012, and carried out an RD design to estimate the effect caused by the program on total food expenditure per adult equivalent and dietary diversity. Our results show that the transfers provided by the CSG have proved to be effective in increasing total food expenditure per adult equivalent, which rises by about R53. This variation is quite large, as the mean food expenditure per adult equivalent in our sample was only about R500. This result is very robust, being confirmed by a comparison among non-parametric, semi-parametric and parametric estimations. Our analysis also confirms the constancy of the estimated parameter when the cutoff diverges, which means that we can interpret the causal effect of the program unconditionally to it.

When dietary diversity is analysed, we find robust positive results only when the share of carbohydrates in the total food expenditure per adult equivalent is included. Since this is the largest food group consumed by the treated households (23% of total food expenditure), this result indicates that the CSG has not been effective in making significant improvements in the dietary habits of the beneficiary households.

Lastly, the estimates of the elasticity measures for total food expenditure and the share of carbohydrates do not show any significant differences among differing population subgroups. This means that the statistical results are homogeneous. It also suggests that the CSG, at variance with its stated objective, has not produced a significantly stronger effect for the poorest population subgroups who are the most vulnerable to food insecurity.

Overall, the policy implication of our study is that the current design of the CSG, which only provides a small grant for each beneficiary child, and its strategy of gradually raising the eligible population, has not been appropriate to guarantee a significant reduction of deprivation for the most vulnerable households. A more effective approach would be to implement a specific, comprehensive strategy to reduce food insecurity and deliver additional grants and ancillary social services to the most vulnerable households. In addition, income-generating programs and enhancement of small-scale agricultural activities remain crucial in increasing household access to food in the most poverty-stricken areas, which are the rural ones.

Appendix A: Poverty line boundaries

We examine the Statistics South Africa (StatsSA) money metric measure of poverty in the country (Statistics South Africa, StatSA 2007a; Statistics South Africa, StatSA 2007b) following a "cost of basic needs" approach, as reported by Ravallion (1998). This approach determines a consumption bundle considered adequate for basic consumption needs and its estimated cost. Following del Ninno and Mills (2015), we examine two poverty lines:

- *food poverty line (FPL)*: the level of consumption below which individuals are unable to purchase sufficient food to provide them with an adequate diet;
- *poverty line (PL)*: the level of consumption which allows individuals to purchase both adequate food and non-food items.

The FPL is calculated as the cost of satisfying the daily energy requirement for an average person for one month, which, according to the South African Medical Research Council, is 2,261 calories per person (Statistics South Africa, StatSA 2007b). The food basket is composed of food items commonly consumed by all expenditure-ranked household groups and usually recommended for a balanced diet. Median quantities of the reference food basket, as purchased by reference households, were then derived from data on food expenditure at household level, with the CPI for food in September 2000. The PL includes non-food expenditure such as accommodation, electricity, clothing, schooling for children, transport, and medical services, among other things.

The two poverty lines are measured in per adult equivalent terms, assuming that resources are equally shared in the households without any differences based on age, gender or spouse status. The two poverty lines are also expressed in rand per month and are annually adjusted according to CPI data, which track the rate of change in the price of goods and services purchased by consumers (see *Table A1*).

Table A1: Poverty line boundaries

Year	Food poverty line	Poverty line
2008	259	507
2010	307	594
2011	321	620
2012	339	655

Notes: Poverty line boundaries extracted from Statistics South Africa (StatsSA) money metric measure of poverty (Statistics South Africa, StatSA 2014).

Appendix B: Impact of CSG on food expenditure by food groups, IDW estimation

	Carbohydrates		Dairy products		Proteins		Vitamins	
Child Support Grant (CSG)	2.646	**	0.336		-0.233		0.998	*
	(1.154)		(0.476)		(1.267)		(0.577)	
Constant term	27.252	***	5.994	***	23.225	***	8.228	***
	(0.501)		(0.161)		(0.451)		(0.184)	
Fixed effects	yes		yes		yes		yes	
Linear and quadratic trends	yes		yes		yes		yes	
Selected covariates	yes		yes		yes		yes	
Cragg-Donald F statistic	843.345		843.345		843.345		843.345	
	(0.000)		(0.000)		(0.000)		(0.000)	
Kleibergen-Paap F test statistic†	987.625		987.625		987.625		987.625	
	(0.000)		(0.000)		(0.000)		(0.000)	
R^2	0.361		0.090		0.222		0.097	
Adjusted R^2	0.321		0.034		0.174		0.042	
No. of observations	2301		2301		2301		2301	

Notes: The dependent variables are shares of food groups in total food expenditure per adult equivalent. In all specifications, dependent variable is total food expenditure per adult equivalent (see the list of the selected covariates in Section 2). Robust standard errors are shown in brackets. Asterisks: *p-value* levels (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$). For each model, linear (1) and non-linear specification (2) is shown. When two-step PS procedure is applied, non-linearities are introduced only in first-stage regression. Tests for weak instrument hypothesis and first-stage F statistics and Wald statistics based on Cragg and Donald (1993) and Kleibergen and Paap (2006). † Confidence intervals for Kleibergen-Paap F test statistic follow Bazzi and Clemens (2013).

REFERENCES

Agüero, J., Carter, M. R. and May, J. (2007). Poverty and inequality In the first decade of South Africa's democracy: what can be learnt from panel data from KwaZulu-Natal? *Journal of African Economies*, 16 (5), 782–812.

Agüero, J., J., Carter, M. and Woolard, I. (2010). The impact of unconditional cash transfers on nutrition: the South African Child Support Grant. International Poverty Centre Discussion Paper No.39, UNDP, New York.

Alderman, H. (2014). Can transfer programs be made more nutrition-sensitive? IFPRI Discussion Paper No.1342, IFPRI, Washington D.C.

Aliber, M. A. (2001). Study of the incidence and nature of chronic poverty and development policy in South Africa: an overview. Chronic Poverty Research Centre Working Paper No.1, University of Manchster, Manchester.

Aliber, M. (2009). Exploring Statistics South Africa's national household surveys as sources of information about household-level food security. *Agrekon*, 48 (4), 384-409.

Angrist, J. D. (2004). Treatment effect heterogeneity in theory and practice. *The Economic Journal*, 114 (494), 52–83.

Bassett, L. (2008). Can conditional cash transfer programs play a greater role in reducing child undernutrition? World Bank Social Policy Discussion Paper No.835, The World Bank, Washington DC

Bazzi, S. and Clemens, M. A. (2013). Blunt instruments: Avoiding common pitfalls in identifying the causes of economic growth. *American Economic Journal: Macroeconomics*, 5 (2), 152–86.

Becker, S. O., Egger, P. H. and von Ehrlich, M. (2013). Absorptive capacity and the growth and investment effects of regional transfers: a regression discontinuity design with heterogeneous treatment effects. *American Economic Journal: Economic Policy*, 5 (4), 29–77.

Bor, J. (2013). Cash transfers and teen pregnancy in South Africa: evidence from a natural experiment. Northeast Universities Development Consortium (NEUDC) Conference, Harvard University.

Calonico, S., Cattaneo, M. D., Titiunik, R. et al. (2014). Robust data-driven inference in the regression-discontinuity design. *Stata Journal*, 14 (4), 909–946.

Coetzee, M. (2013). Finding the benefits: estimating the impact of the South African Child Support Grant. *South African Journal of Economics*, 81 (3), 427–450.

Cragg, J. G. and Donald, S. G. (1993). Testing identifiability and specification in instrumental variable models. *Econometric Theory*, 9 (2), 222–240.

del Ninno, C. and Mills, B. (2015). Introduction, in Del Ninno, C. and Mills, B. (eds.), Safety nets in Africa. The World Bank, Washington D.C.

Delany, A. (2008). Review of the child support grant: uses, implementation and obstacles. United Nations Children's Fund, Johannesburg.

Department of Social Development (2010). An Overview of South Africa's Social Security System. Republic of South Africa, Pretoria.

Du Toit, D. (2011). Food security. Department of Agriculture, Forestry and Fisheries, Republic of South Africa, Pretoria.

Hahn, J., Todd, P. and Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, 69 (1), 201–209.

Hoddinott, J. and Yohannes, Y. (2002). Dietary diversity as a food security indicator. Food and Nutrition Technical Assistance Project, Academy for Educational Development, Washington D.C.

Hoddinott, J. and Bassett, L. (2008). Conditional cash transfer programs and nutrition in Latin America: assessment of impacts and strategies for improvement. UN-FAO, Washington D.C./Rome.

Jacob, R. T., Zhu, P., Somers, M.-A. and Bloom, H. S. (2012). A practical guide to regression discontinuity. MDRC, New York.

Kirkland, T. M., Kemp, R. J., Hunter, L. M. and Twine, W. M. (2013). Toward improved understanding of food security: a methodological examination based in rural South Africa. *Food, Culture & Society*, 16 (1), 65–84.

Kirsten, J. F. (2012). The political economy of food price policy in South Africa. UNU-WIDER Working Paper No.102, UNU-WIDER, Helsinki.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133 (1), 97–126.

Labadarios, D., Steyn, N. P. and Nel, J. (2011). How diverse is the diet of adult South Africans? *Nutrition* Journal, 10 (33). 1–11.

Lee, D. S. (2008). Randomized experiments from non-random selection in U.S. House elections. *Journal of Econometrics*, 142 (2), 675–697.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48, 281–355.

Leibbrandt, M. and Levinsohn, J. (2011). Fifteen years on: household incomes in South Africa. NBER Working Paper No. 16661, NBER, Cambridge Mass.

Leibbrandt, M., Wegner, E. and Finn, A. (2011). The policies for reducing income inequality and poverty in South Africa. SALDRU Working Paper No. 64, University of Cape Town, Cape Town.

Lund, F., Noble, M., Barnes, H. and Wright, G. (2008). Is there a rationale for conditional cash transfers for children in South Africa? *Transformation: Critical Perspectives on Southern Africa*, 70, 70–91.

Manley, J., Gitter, S. and Slavchevska, V. (2013). How effective are cash transfers at improving nutritional status? *World Development*, 48, 133–155.

Manyamba, C., Hendriks, S., Chilonda, P. and Musaba, E. (2012). Factors contributing to inequalities in food security in South Africa: implications for agricultural policy. Paper presented at conference 'Strategies to overcome poverty & inequality', University of Cape Town, Cape Town.

Pauw, K. and Mncube, L. (2007). Expanding the social security net in South Africa: opportunities, challenges and constraints. DPRU Working Paper No. 127, University of Cape Town, Cape Town.

Pieroni, L., Lanari, D. and Salmasi, L. (2013). Food prices and overweight patterns in Italy. *The European Journal of Health Economics*, 14 (1), 133–151.

Pieroni, L., and Salmasi, L. (2015). Does cigarette smoking affect body weight? Causal estimates from the clean indoor air law discontinuity. *Economica*, 82 (328), 671–704.

Ravallion, M. (1998). Poverty lines in theory and practice. The World Bank, Washington DC.

Samson, M., Heinrich, C., Williams, M., Kaniki, S., Muzondo, T., Mac Quene, K. And Van Niekerk, I. (2008). Quantitative analysis of the impact of the child support grant. Economic Policy Research Institute, Cape Town.

Slater, R., Holmes, R. and Mathers, N. (2014). Food and Nutrition (in)Security and Social Protection. OECD Development Co-operation Working Papers No.15, OECD, Paris.

South African Department of Agriculture (2002). The integrated food security strategy for South Africa. Republic of South Africa, Pretoria.

South African Department of Health (2013). South African National Health and Nutrition Examination Survey (SANHANES 1). Republic of South Africa, Pretoria.

South African Social Security Agency, SASSA (2015). A statistical summary of social grants in South Africa. Fact sheet: Issue No. 2, Pretoria.

Statistics South Africa, StatSA (2007a). A discussion note: constructing comparable household survey data for the analysis of poverty in South Africa (1995 - 2000). Statistics South Africa, Pretoria.

Statistics South Africa, StatSA (2007b). A national poverty line for South Africa. Statistics South Africa, Pretoria.

Statistics South Africa, StatSA (2014). Poverty trends in South Africa. An examination of absolute poverty between 2006 and 2011. Statistics South Africa, Pretoria

Van der Berg, S., Siebrits, F. K. and Lekezwa, B. (2010). Efficiency and equity effects of social grants in South Africa. Stellenbosch Economic Working Papers No.15, Stellenbosch University, Cape Town.

van der Klaauw, W. (2002). Estimating the effect of financial aid offers on college enrollment: a regression-discontinuity approach. *International Economic Review*, 43 (4), 1249–1287.

Williams, Martin J. 2007. The social and economic impacts of South Africa's child support grant. PhD diss. Williams College, Williamstown.

Woolard, I., Harttgen, K. and Klasen, S. (2010). The evolution and impact of social security in South Africa. European Report on Development, Dakar

Woolard, I and Klasen, S. (2005). Determinants of income mobility and household poverty dynamics in South Africa. *Journal of Development Studies*, 41 (5), 865–897.

Woolard, I. and Leibbrandt, M. 2010. The evolution and impact of unconditional cash transfers in South Africa. SALDRU Working Paper No. 51, University of Cape Town, Cape Town.

World Bank (2015). The State of social safety nets. The World Bank, Washington D.C.

You, J. (2013). The role of microcredit in older children's nutrition: quasi-experimental evidence from rural China. *Food Policy*, 43, 167–179.