Cash Transfer Programmes for Managing Climate Risk: Evidence from a Randomized Experiment in Zambia

Solomon Asfaw, Alessandro Carraro, Benjamin Davis, Sudhanshu Handa, David Seidenfeld and the Zambia Cash Transfer Evaluation Team

Invited paper presented at the 5th International Conference of the African Association of Agricultural Economists, September 23-26, 2016, Addis Ababa, Ethiopia

Cash Transfer Programmes for Managing Climate Risk: Evidence from a Randomized Experiment in Zambia[1]

Solomon Asfaw[1*], Alessandro Carraro[2], Benjamin Davis[1], Sudhanshu Handa[3], David Seidenfeld[4] and the Zambia Cash Transfer Evaluation Team

[1*] Corresponding author: Food and Agriculture Organization (FAO) of the United Nations, Agricultural Development Economics Division (ESA), Viale delle Terme di Caracalla, 00153 Rome, Italy. E-mail: solomon.asfaw@fao.org

[2]CEIS, University of Rome Tor Vergata, Rome, Italy

[3]UNICEF Office of Research – Innocenti, Florence, Italy

[4]American Institutes of Research, Washington DC, USA

Abstract

Cash transfer programmes are increasingly being utilized in order to combat poverty and hunger as well as to building the human capital of future generations. Even though most of these programmes are not explicitly designed to help households manage climate risk, there are good reasons to expect that cash transfers can be good instrument to build household resilience against climatic risk. The goal of this study is to provide an empirical analysis of the effect of weather risk on rural households' welfare using impact evaluation data from the Zambia Child Grant Programme (CGP) together with set of novel weather variation indicators based on interpolated gridded and re-analysis weather data that capture the peculiar features of short term and long term variations in rainfall. In particular, we estimate the impact of weather shocks on a rich set of welfare and food security indicators (including total expenditure, food expenditure, non-food expenditure, calorie intake and dietary diversity) and investigate the role of cash transfer for managing climate risk. We find strong evidence that cash transfer programmes has a mitigating role against the negative effects of weather shocks. Our results in fact highlight how important the receipt of social cash transfer is for households lying in the bottom quantile of consumption and food security distributions in moderating the negative effect of weather shock. Hence, integrating climate change and social protection tools into a comprehensive poverty reduction and social protection strategy should be of primary interest for policy makers and government when setting their policy agenda.

Key words: cash transfer, impact, weather shock, experimental design, Zambia, Africa

[1] This research forms a part of the Protection to Production (PtoP) project and analyses data collected for the impact evaluation of the Zambian Child Grant Programme, which is being implemented by the American Institutes for Research and the University of North Carolina at Chapel Hill under contract to UNICEF-Zambia. The evaluation is commissioned by the Government of Zambia's Ministry of Community Development, Mother and Child Health, with support from DFID, Irish Aid, and UNICEF-Zambia. The members of the evaluation team, include American Institutes of Research (Juan Bonilla, Cassandra Jesse, Leah Prencipe, David Seidenfeld); FAO (Benjamin Davis, Josh Dewbre, Silvio Diadone, Mario Gonzalez-Flores); UNICEF-Zambia (Charlotte Harland Scott, Paul Quarles van Ufford); Government of Zambia (Vandras Luywa, Stanfield Michelo); DFID-Zambia (Kelley Toole); Palm Associates (Alefa Banda, Liseteli Ndiyoi, Gelson Tembo, Nathan Tembo); UNICEF Office of Research (Sudhanshu Handa); University of North Carolina at Chapel Hill (Sudhanshu Handa). We would like to acknowledge Ms. Aslihan Arslan (FAO) for sharing the climate dataset with us. Errors are the responsibility only of the authors, and this paper reflects the opinions of the authors, and not the institutions, which they represent or with which they are affiliated.

1. Introduction

In the last 20 years, unconditional social cash transfer (SCT) programmes have become increasingly relevant in developing countries' policy agendas. Most of the programmes have an impact on the economic livelihoods of beneficiaries (e.g., AIR 2013; Daidone et al., 2014a; Daidone et al., 2014b, Asfaw et al., 2014; Asfaw et al., 2015a; Asfaw et al., 2015b; Pellerano et al., 2014) but are rarely tailored to protect households with low levels of adaptive capacity from weather related shocks because the role of cash transfer programmes as part of an integrated response to climate change in developing countries is still poorly understood. However, there is a growing consensus about the importance of integrating climate risk considerations within the planning and design of new social protection programmes, which can both prevent poor and vulnerable households from falling deeper into poverty and contribute to long-term adaptation to climate change (Kuriakose, 2013). Of the few social protection programmes explicitly designed to address the scenarios described by the IPCC (Davies et al., 2008; Wood, 2011; Bene', 2011), most are issued in South Asia and East Africa (Davies and Leavy, 2007; Arnall, 2009).

Even though most of SCT programmes in SSA are not explicitly designed to help households cope with climate risk, there are good reasons to expect that it can help in building resilience to climate change through improvements in human capital, facilitating changes in productive activities by relaxing liquidity constraints, improve natural resource management and building local economies (e.g., Asfaw et al., 2012). This paper tries to test this proposition taking into consideration a specific form of social protection - Child Grant Programme (CG) in Zambia. Since 2003, Zambia has been operating its SCT programme with the objective of reducing the extreme poverty among beneficiary households. The government unconditionally extended 60 kwacha (ZMW) per month (equivalent to USD 12) to households that had at least a child under the age of five or a disabled child under 14 years and were located in three districts (Kaputa in the northern region, and Kalabo and Shangombo in the western region). The baseline was conducted in 2010, followed up by a second round 24 months later. In these two years, the three districts were hit by floods and droughts (Lawlor et al., 2015), with a large percentage of households (around 42% in 2010 and 71% in 2012) experiencing such weather shocks. As shown in Figure 1 and 2, the average total rainfall and variability of rainfall tend to vary across different regions of Zambia. We register a high variability among the districts targeted by the programme (see table 1); while in northern Kaputa the average annual estimated rainfall was of about 1030 mm.

Given the massive incidence of climate shocks in Zambia, it is crucial to shed light on how households responded to climate instability and whether regular and unconditional small cash payments helped both in mitigating the negative effects of climate variability on smallholders' welfare and food security. In order to shed light on these issues, we carry out an in-depth empirical examination by merging the Zambia's CGP impact evaluation dataset together with weather data. Using both rounds of the panel dataset, we estimate generalized least squares (GLS) random effects and quintile regression models to address the research questions.

2. Programme evaluation design and data

2.1 Description of the CGP

The CGP represents one of the targeting approaches used within the SCT Programme, which was first implemented in 2003 and is still operating to ease extreme poverty and the intergenerational transfer of poverty in Zambia. From 2004 to 2008, the targeting criteria employed within the SCT Programme were based on (i) a 10% inclusive scheme, which targeted incapacitated and destitute households at the bottom 10% of the poor in five different districts, and on (ii) a Social Pension Scheme, which targeted individuals aged 65 years and above.

In 2010, the government, through the Ministry of Community Development, Mother and Child Health (MCDMCH) of the Republic of Zambia, decided to include the CGP among the targeting criteria. The goal of the CGP reflects the goal of the SCT Programme and its objectives are mainly related to a set of five key areas, which include income, education, health, food security and livelihoods. The primary recipient of the transfer is the female in the household that is considered to be the primary caregiver. The amount received by the beneficiaries was about 60 kwacha (ZMW) a month (equivalent to U.S. $12), an amount which the Ministry estimated as adequate to purchase one meal per day for all the household members for one month (AIR, 2013).

The programme was developed in the Northern and Western regions and geographically targeted three different districts: Kaputa in the Northern region and Kalabo and Shangombo in the Western region. A baseline survey was conducted in 2010 as well as a follow-up after 24 months. In the baseline sample, only households with children less than three years old had been targeted in order to ensure that all the beneficiaries received the transfers for the following 24 months.

2.2 Study design, data and randomization effectiveness

The Child Grant Programme impact evaluation was designed with a Randomized Control Trial (RCT) phase-in method. This is the most powerful research design for drawing conclusions about the impacts of programmes on selected outcomes, and involves several phases of random selection (see Seidenfeld and Handa, 2011 for details about the evaluation design). In the first phase, 90 out of 300 Community Welfare Assistance Committees (CWACs) in the three districts were randomly selected. Afterwards CWAC members together with the Ministry staff identified within the selected CWACs all the households with at least one child under the age of three, resulting in more than 100 eligible households for each CWAC. In the third phase, a power analysis tested whether the study was able to detect meaningful effects, and then 28 households were randomly drawn from each of the 90 communities for inclusion into the evaluation, with the final sample size being about 2500 households. Half of the households were then randomly assigned to treatment and control, with treatment households incorporated to receive the benefits starting in December 2010 and control households scheduled to receive the treatment at the end of 2013.

The first panel captured data from 2519 households; half of these households are in control communities and the other half are in treated communities (see Table 2). About 2298 of these households were re-interviewed in the second panel. The attrition rate estimated between the two surveys is of about 8.8 percent: 91.2 percent of the households from baseline are tracked in the 24-month follow-up sample. In table 2, we report the overall attrition rate for the CGP after 24 months. Some of the households in Kaputa, where the highest share of the missing households were located, moved away because of the Cheshi lake drying up, which had previously been the main source of food for them. Seidenfeld et al. (2013) and Daidone et al. (2014b) investigated in detail both differential and overall attrition in terms of outcome indicators of interest. Differential attrition relates to baseline characteristics between treatment and control households that remain at follow-up whereas overall attrition looks at similarities at baseline between the full sample of households and the non-attriters. They did not find any significant differential attrition after twenty-four months, meaning that the benefits of randomization are preserved. The differences in overall attrition are primarily driven by the lower response rate in Kaputa district.

We merge Zambia CGP data with a set of climatic variables based on historical rainfall data at the ward level to control for the effects of levels and variations in rainfall on welfare, food security and productivity. Rainfall data is obtained from Africa Rainfall Climatology version 2 (ARC2) of the National Oceanic and Atmospheric Administration's Climate Prediction Centre (NOAA-CPC) for the period of 1983–2015. ARC2 data are based on the latest estimation techniques, collected on a daily basis and have a spatial resolution of 0.1 degrees (~10 km). These climate data are then matched by ward name with the socio-economic panel, in order to obtain climate variables at ward level. From the climate dataset, we create a unique set of climate indicators. In particular we focus on (i) the historical average precipitation (1980-2010 and 1983-2012), and on (ii) weather shocks (a variable on negative shocks of rainfall) and (ii) rainfall seasonality index as described in the section below.

As reported by Seidenfeld and Handa (2011) and Daidone et al. (2013), the randomization process appeared to be successful. In order to evaluate whether the randomization was performed well, they tested for equivalence between treatment and control groups for a set of indicators, showing statistically significant differences only among a few indicators. In Table 3, we report a selection of descriptive statistics captured by Seidenfeld and Handa (2011) and Daidone et al. (2013) to test for the effectiveness of the randomization process. The results provide information on the sample characteristics and on whether the treatment and control group are statistically different. There are no major significant differences between treated and control households in many targeting indicators.

2.3 Construction of variables

In order to detect shocks in precipitation within our rainfall dataset, we rely on a methodology widely used in the climate shocks literature (Kaur, 2012 and Sarson, 2015) which identifies as negative shocks all the values of the rainfall distributions that are lying below a certain threshold (i.e. the 20th percentile of the distribution). We decided to apply this methodology to a variable that identifies the variation of rainfall outside the historical average of rainfall at the ward level. Similarly to Lobell et al. (2011), we demeaned the dekad precipitation by its historical average and we isolate the shocks from the resulting residuals series.

We apply a three-step methodology. First, for each ward we compute the historical (1983-2010) average of rainfall and use it to demean the actual rainfall, obtaining a series of residuals. Then we compute the average and the standard deviation of the resulting residuals during the historical period (1983-2010) and we identify as shocks the difference between the residuals and the lower bound of the confidence band, which we assume to be twice the standard deviation. In this way, we are able to compute the deviation of the precipitation in millimetres within the rainfall season too. We finally sum up all the deviations from the confidence band. We compute this measure for both the year of the wave and the year before, since the shocks occurring at *t-1* may still have an effect on productivity (and therefore consumption) the following year.

In order to measure the short-term variation within the same season, we construct a discrete Seasonality Index (SI), following the approach suggested by Walsh and Lowler (1981). Our indicator will be equal to one for those wards in which the continuous index is less than 0.4, indicating that the precipitation is evenly distributed among them. The value of the indicator will increase for increasing values of the continuous index, assuming a value of two if the continuous index is greater than 0.4 and less than or equal to 1 and assuming a value of 3 if the continuous index is greater than 1, indicating respectively an increase in the seasonality of rainfalls.

We use FAO approach to construct the Household Dietary Diversity Score (HDDS) based on the guidelines provided by the Food and Nutrition Technical Assistance Project (FANTA) (Swindale and Bilinsky, 2006). Guidelines for the HDDS indicator suggest creating dietary profiles in order to identify the proportion of households/individuals consuming food categories of particular interest. This indicator is built by summing up the different food groups consumed in the last 24 hours before taking the interview. A weight equal to one is applied to each food category of this indicator, as each food group has equal importance in the calculation of the index (i.e. the spices/condiments/beverages group and vitamin-A-rich-vegetables/tubers group have the same importance). The score is within the range 0-12. Summary statistics of key outcome and climate variables are report in table 4.

3. Empirical Model

By relying on the definition of shocks introduced in the previous paragraph, we are foremost interested in the extent of the impacts of: i) the Zambia SCT Programme; ii) the weather shocks, and iii) their interactions, on food security, welfare and productivity in our sample. We use Generalized Least Squares Random Effects (GLS-RE) [2] equation as follows:

[2] The choice of the GLS-RE is mainly driven by the short length of the panel and by efficiency considerations

$$\mathit{\Gamma}_{h,t,i} = \beta_0 + \beta_1 \mathbf{X}_{h,i,t} + \beta_2 \mathbf{K}_{\mathrm{h,i,t}} + \beta_3 CGP_{h,i,t} + \gamma_1 shock_{dt_{i,t}} + \gamma_2 CLIM_{i,t} + \alpha_i + \varepsilon_i$$
(1)

With $\mathit{\Gamma}_{h,t,i}$ representing our dependent variable for household *h* at time *t* in ward *i*, which includes (i) a measure of welfare (total/food/non-food expenditure in natural logs) and (ii) a proxy for food security and nutrition (a measure of dietary diversity or total caloric intake in natural logs). β_0 represents the constant term; $\mathbf{X}_{\mathrm{h,i,t}}$[3] is a vector of variables including household characteristics (age of the head, dependency ratio, household size in adult equivalents, education of the head, number of children within the household); $\mathbf{K}_{\mathrm{h,i,t}}$ is a set of variables measuring natural capital and household wealth, with the former measured by the quantity of land owned by the household (in hectares) and the latter proxied by two different wealth indexes (agricultural and non agricultural[4]) which are based on a range of assets the households own (Filmer and Pritchett, 2001); $CGP_{h,i,t}$ is a dummy variable representing the programme receipt; $shock_{dt_{i,t}}$ denotes the negative rainfall shock registered in each ward in the three years before the survey and finally $CLIM_{\mathrm{i,t}}$ is a vector of variables including average long term rainfall and seasonality index of rainfall in the ward *i* where the household is located. α_i represents the random effects and ε_i represents the heteroskedastic error term. All continuous variables are expressed in natural logarithmic form.

Since we are interested in understanding whether receiving the transfer helps households to manage climate risk, we interact the CGP variable with the climatic variables using the following specification:

$$\mathit{\Gamma}_{h,t,i} = \beta_0 + \beta_1 \mathbf{X}_{h,i,t} + \beta_2 \mathbf{K}_{\mathrm{h,i,t}} + \beta_3 CGP_{h,i,t} + \gamma_2 shock_{dt_{i,t}} + \beta_4 CLIM_{i,t} + \beta_5 (CGP_{h,i,t} * CLIM_{i,t}) + \beta_6 (CGP_{h,i,t} * shock_{dt_{i,t}}) + \alpha_i + \varepsilon_i \qquad (2)$$

Finally, since the impact of weather shocks is usually higher at the lower extreme of the food expenditure/consumption distribution, it is important to empirically assess the impact of the climate variables on different household profiles, in particular the ones lying in the lower tail of the response variables' distributions. We turn to the pooled conditional Quantile Regression (QR) approach, which is preferred to Ordinary Least Squares (OLS) because it has the advantage of being less sensitive to non-normal errors distribution and provides a richer characterization of the data, allowing us to consider the impact of a covariate on the entire distribution of the dependent variable and not only on its conditional mean (Baum, 2013). Moreover, the distribution quantiles are also invariant to monotonic transformations of the dependent variable, e.g. log transformations (Koenker, 2005). Thus, following Koenker and Bassett (1978), the QR corresponding to the model (1) can be expressed as:

$$\mathit{\Gamma}_{h,t,i} = \beta_0^{(p)} + \beta_1 \mathbf{X}_{h,i,t}^{(p)} + \beta_2 \mathbf{K}_{h,i,t}^{(p)} + \beta_3 CGP_{h,i,t}^{(p)} + \gamma_1 shock_{dt}{}_{i,t}^{(p)} + \gamma_2 CLIM_{i,t}^{(p)} + \varepsilon_i^{(p)} \qquad (3)$$

where $0 < p < 1$ indicates the proportion of the population having scores below the quantile at *p*.

---

[3] Given the relative success of random assignment, the inclusion of controls could not be necessary to obtain unbiased estimates of β_0.

[4] The three indexes are constructed using Principal Component Analysis.

4. Results and discussion

This section is organized in three different parts. In the first part, we report and compare the econometric results from the estimation of model (1) using GLS-RE to that from OLS for each of the outcome variables introduced in the previous section. In the second part, we present the evidence obtained by the estimation of model (2) in which we control for the interactions between the CGP and the climatic variables. In the third part, we will introduce the QR estimates by plotting the results for the potential differential effects of some selected covariates on various quantiles in the conditional distribution of our response variables.

To save space, we discuss Table 5 and 6 jointly. Table 5 presents the results obtained from GLS-RE and OLS estimates of the CGP, climate variables and other determinants on total expenditure, food/non-food expenditure, while Table 6 displays the estimates on daily caloric intake and the dietary diversity index. We see that the coefficients related to the CGP receipt are positive and statistically significant in all the specifications considered, implying that the CGP increases the welfare and food-security of households, which is consistent with the findings reported in AIR (2013). In particular we register an increase of about 19% in total household expenditure, finding that within total expenditure, the CGP has a slightly higher effect on food expenditure (+20%) compared to non-food expenditure (+18%). Although the effect on the value of food expenditure is positive and statistically significant, it is important to know whether this is translated into an improvement of energy intake and of the types of food consumed by the household. While caloric intake plays an important role in households meeting their food security needs, a more varied diet is fundamental to ensure the necessary amount of micronutrients, particularly for children. We find that, as a result of an increase in the food expenditure, the quantity and quality of food consumed increased under the CGP receipt, meaning that households being in a programme benefit more in terms of food security than non-targeted households.

The results clearly show the importance of climatic variables on our set of welfare and food security indicators. Within a rain-fed agricultural system like that in Zambia, precipitation is among the primary determinants of agricultural households' production function. Thus, the water requirements for the different crops should be met in order to improve crops productivity and, in turn, the households welfare. In Table 5, we observe a slightly positive and statistically significant correlation of the long-term average rainfall with all the outcome variables. The only exception is its impact on the household dietary diversity index, which is not statistically significant. In terms of magnitude, we find that increasing the amount of rainfall by 1 millimetre leads to a very slight but positive (+0.1%) improvement in welfare and food security.

In this paper as discussed in the preceding section, we defined rainfall shock as deviations of the quantity of rainfall from the lower limit of the confidence bound computed with respect to the average historical rainfall. This information is fundamental to interpreting the model coefficients. We notice that in the model specification the relationships between our rainfall shock variable and the dependent variables are always negative and statistically significant, meaning that the higher the shortage of water the worse is the household response in terms of welfare and food security. A possible explanation of this effect could be that the decline in rainfall has an initial negative impact on agriculture and livestock production and other water-intensive activities. The decline in volume of production will thus affect households' purchasing power, forcing them to enforce their coping mechanisms. Households react to weather shock by employing a wide range of possible strategies, like reducing consumption, such as shifting diets towards cheaper food. Households often initially respond to weather shocks in terms of decreasing expenditures on certain non-essential items (i.e. clothing, medical treatments) and moving towards a higher reliance on public relief and, when possible, to safety net programmes (Skoufias, 2003, Pandey and Bandhari, 2009). However, even though households try to adapt to minimizing the impact of these shocks, some are not able to smooth consumption over the year. This often results in a diminution of the quantity and quality of the diet, with a drop in the number of meals per day and a progressive decrease of the daily caloric intake, which in our sample we estimate to be around -1.7%. With respect to the seasonality index variable, which captures the effects of both the magnitude and concentration of rainfall during the rainy season, results show that it has a negative impact on all the outcome variables. Results also show that households with a higher number of members spend more on food/non-food items, and consume a higher amount of calories at the expense of the quality of their diet. This finding is confirmed by the regression on the household dietary diversity score, which shows the household dietary diversity score to be negatively related with household size. This argument has encountered a broad interested among economists for a long time. One possible explanation for this phenomenon is described in the seminal work of Deaton and Paxson (1998), which states that the larger the household, the better off per capita are the people within it. Their underlying reason for this is economies of scale or, in other words, the gain to be derived from public (to the household) or shared goods. Results from Table 5 and 6 also show that households with better-educated heads are always associated with increased welfare and food security. Expenditure and food security are somewhat lower in households with a higher number of children aged less than five, but at the same time, they are positively related with the amount of land owned and the agricultural/non-agricultural wealth indexes. Since they reflect the ability in re-investing the income earned in the previous periods in agricultural or non-agricultural assets, the two indexes introduced within this paper are good proxies for household wealth. Households with higher wealth indexes have a higher level of consumption, suggesting that they are less vulnerable to poverty.

After looking at the average impact of social cash transfers and climate variables, we try to investigate whether social cash transfer instruments can help households either mitigate the ex-ante climate risk or manage ex-post, reducing the negative effect of high rainfall variability on welfare. While policy actions by government and donor communities that increase household access to some services cannot directly reduce climate variability, extra resources made available through policy actions may help households either mitigate the ex-ante climate risk or manage ex-post. Therefore, we interact the rainfall shock variable and the average historical rainfall variables with the dummy for CGP receipt, following the specification reported in model (3). Table 7 and 8 presents the full estimation results with the interaction variables.

In all our estimates, the coefficients of the interaction term between weather shock and CGP are positive and highly significant supporting the proposition that cash transfer programmes play a critical role in moderating the negative effect of weather shock. The magnitude of the interaction coefficient for most of the outcome variables is around 0.03, meaning that for people benefiting from the programme, the response variables increase even if households are subject to a shock. Our results confirm the findings of authors like Eriksen et al. (2005), who found a positive relationship between the ability of people to draw on extra sources of income and the ability to withstand droughts in Tanzania and Kenya. Cash transfers can thus help Zambian smallholders to better respond to climate shocks. However, even though we find a positive relationship for the shock-CGP interaction variable, we do not find a statistically significant relationship when interacting the programme with the long-term average rainfall variable. Many of the effects of climate change, such as the gradual variation in precipitation (or temperature) patterns, might slowly weaken livelihoods without being classified as disasters; for this reason, the greatest benefits of social cash transfers accrue to those households who are enrolled in the programme for a certain amount of time. With just two waves of data, it is thus reasonable to not find any effect on a long lasting stepwise variation of the climatic conditions.

Figures 3 and 4 show the pooled quantile regressions results for our outcome variables and shed light on the heterogeneous impact of CGP. Figure 3 includes three different panels for factors affecting the household level daily caloric intake (which is the only dependent variable we report) that show the variation in the beta coefficients of (i) the CGP dummy variable, (ii) the average total rainfall in the long term and (iii) the weather shock variable, respectively. In Figure 4, we plot the effect of the interaction term ($CGP*shock_{dt}$) across the quantiles of the distribution of the whole set of dependent variables.

In Figure 3 panel (a) we observe that the effect of the CGP is significant in the first half of the distribution (until the 60^{th} percentile) and that it is stronger for the bottom part of the caloric intake distribution. This effect is positive and decreases as the household reaches the top of the daily caloric intake distribution. When turning to the effect of the average rainfall on intake distribution, however, the coefficient is slightly positive and its change in magnitude is small among the quantiles. Panel (c) shows the impact of the weather shock on daily caloric intake. Its impact decreases as we move towards the top quantiles, and as we expected, it has a greater effect among the poorest of the poor.

From Figure 4a to 4e, we focus on the variation of the impact of the interaction term with respect to total expenditure, food/non-food expenditure, daily caloric intake and dietary diversity. The QR estimates for the effect of the interaction on value of total expenditure are always significant (with the exception of the tails of the distribution), and the relationship does not change across the different quantiles, remaining positive but quite flat. Households benefiting from the programme respond positively to climate disruptions regardless of their economic status. This is true also for the other welfare outcomes, for which we do not register any negative statistically significant relationships. When looking at the non-food expenditure QR, we notice that cash transfers have a higher mitigating effect on households at the bottom of the value of non-food expenditure and that this decreases substantially as one moves up the distribution. Households from the 80th percentile until the top of the distribution obtain a positive but not significant effect from the social cash transfer. A positive and statistically significant pattern is also registered for the food expenditure all across the different quantiles with a slightly increasing trend moving to the top of the distribution. Finally, as regards our two food security indicators, we register a positive and statistically significant effect for both the daily caloric intake and the household dietary diversity score distribution. While for the former we register a positive impact with a decreasing pace all across the quantile distribution, for the latter we find statistically significant results only between the 10^{th} and 40^{th} percentile, with a higher effect on the lower quantiles. Again, the mitigating effect of the CGP is higher for the lowest quantiles of the distribution meaning that poorer households are much more protected against the negative effects of climate instability than richer ones.

5. Conclusions

With events such as droughts and floods becoming increasingly frequent, this work aims to quantitatively assess the role of cash transfer in mitigating the negative effects of weather shock on welfare, food security and productivity using the Zambia CGP impact evaluation dataset combined with historical climate data. We also tried to examine heterogeneities impact along the different quantiles of the reference dependent variables.

We find that social cash transfers have significant positive effects on the welfare and food security status of households. With regards to the effect of climatic variables on welfare and food security, we find that the long term average rainfall positively influence expenditure and food intake while negative rainfall shock and seasonality index have a negative effect on our outcome variables. The most interesting result is that the cash transfer programme has a mitigating effect on the negative effect of weather shocks. Considering the limited attention given by the literature towards the relationship between social cash transfers and climate change, this finding is quite relevant since social cash transfers can be part of a valuable *ex-ante* strategy to help the poor adapt to climate change. The mechanisms of adaptation to climate change have received great interest in the last decade, but a concrete linkage between environmental policies and social protection is still missing and deserves supplementary attention both at institutional and academic level, especially considering the heterogeneous effects of social cash transfers on the different households.

Our results also highlight how important the receipt of social cash transfer is for households lying in the bottom quantile of consumption and food security distributions, so integrating climate change and basic social protection tools into a comprehensive poverty reduction and social protection strategy should be of primary interest for policymakers and governments when setting their policy agendas. As poverty reduction instruments, often the targeting of social protection interventions would tend to include mainly economic (wealth and income) related criteria. It is critical to move from a narrow targeting to a multidimensional approach, which would also include economic, social, as well as environmental risks and vulnerabilities as targeting criteria. One critical first step would be aiming to overlap income poverty and food security maps, with vulnerability maps linked to climate change. Public works, including productive safety nets and other kind of public works can be designed in such a way as to contribute to meet increase household income, while at the same time engaging communities in climate smart agriculture and generating of 'green jobs' in areas such as waste management, reforestation and soil erosion prevention. Overlapping access to social protection and access to key financial services such as credit and weather insurance can also be important to reduce uncertainty and impacts of climate variability.

References

American Institutes for Research (AIR). (2013). 24-Month Impact Report for the Child Grant Programme. Washington DC, USA.

Arimond M, Ruel M. (2004) - Dietary diversity is associated with child nutritional status: evidence from 11 demographic and health surveys. J Nutr.134:2579-85

Asfaw, S., Davis, B., Dewbre, J., Handa, S. and Winters, P. (2014). Cash transfer programme, productive activities and labour supply: Evidence from randomized experiment in Kenya. Journal of Development Studies, 50(8):1172-1196.

Asfaw, S., Pickmans, R., Alfani, F. and Davis, B. (2015a). Productive Impact of Ethiopia's Social Cash Transfer Pilot Programme, PtoP project report, FAO, Rome

Bruckner M, Ciccone A (2011) Rain and the democratic window of opportunity. Econometrica 79(3):923–947

Daidone, S., Davis, B., Dewbre, J., Gonzalez-Flores, M., Handa, S., Seidenfeld, D. & Tembo, G., (2014b). Zambia's Child Grant Programme: 24-month impact report on productive activities and labour allocation PtoP Project Report, FAO, Rome.

Daidone, S., Pellerano, L., Handa, S., & Davis, B. (2015). Is Graduation from Social Safety Nets Possible? Evidence from Sub-Saharan Africa. IDS Bulletin, 46(2), 93-102.

Davies, M. and Leavy, J., 2007 Connecting social protection and climate change adaptation, IDS In Focus Policy Briefing 2.

Deaton, A.S., Paxson, C., 1998. Economies of scale, household size, and the demand for food. Journal of Political Economy 106, 897–930.

Dell M, Jones BF, Olken BA (2012) Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics 4(3):66–95

Dixon, J, Gulliver, A. & Gibbon D. (2001) - Farming systems and poverty Food and Agricultural Organization of the United Nations and World Bank, Rome and Washington, DC (2001)

Eriksen, S.H., Brown, Kelly, P.M., The dynamics of vulnerability: locating coping strategies in Kenya and Tanzania - The Geographical Journal, Vol.171, No. 4, December 2005, pp. 287–305

Filmer, D., & Pritchett, L. (2001). Estimating wealth effects without expenditure data—or tears: An application to educational enrolments in states of India. *Demography*, 38(1), 115–132.

Hoddinott, J. (2002) - Measuring Dietary Diversity: A Guide. Food and Technical Assistance Project (FANTA), Washington, DC.

IPCC, (2014): Working Group II contribution to the IPCC Fifth Assessment Report Climate Change 2014: Impacts, Adaptation, and Vulnerability.

Kaur, 2012. Nominal wage rigidity in village labor markets (No. w20770). National Bureau of Economic Research.

Koenker, R. (2005). Quantile regression. Econometric Society Monographs. Cambridge University Press.

Kuriakose, A. T., Heltberg, R., Wiseman, W., Costella, C., Cipryk, R., & Cornelius, S. (2013). Climate-Responsive Social Protection. Development Policy Review, 31(s2), o19-o34.

Lawlor, K., Handa, S., Seidenfeld, D. and the Zambia Cash Transfer Evaluation Team (2015). Cash Transfers and Climate-resilient development: Evidence from Zambia's Child Grant Programme, Innocenti Working Paper No.2015-03, UNICEF Office of Research, Florence.

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. Science, 333(6042), 616-620.

Miguel E, Satyanath S, Sergenti E (2004) Economic shocks and civil conflict: An instrumental variables approach. Journal of political Economy 112(4):725–753

Pandey, S., Bhandari, H., 2009. Drought, Coping Mechanisms and Poverty: Insights from Rainfed Rice Farming in Asia. Seventh Discussion Papers, Asia and the Pacific Division, IFAD

Rosenzweig MR, Binswanger HP (1993) Wealth, weather risk and the composition and profitability of agricultural investments. The Economic Journal pp 56–78

Seidenfeld, D. & Handa, S. (2011). Zambia's Child Grant Program: Baseline Report. Washington, D.C. American Institutes of Research. November.

Seidenfeld, D., Handa, S. & Tembo, G. (2013). 24-Month Impact Report for the Child Grant Programme. Washington, D.C. American Institutes of Research, September.

Skoufias, E., 2003. Economic crises and natural disasters: coping strategies and policy implications. World Dev. 7, 1087–1102.

World Bank (2009) - World Development Report 2010: Development and Climate Change, World Bank, Washington DC

Table 1 – Long Term (1983-2010) climatic characteristics of targeted districts

	Average rainfall (mm)	CoV rainfall
Kaputa	1030.99	0.58
Kalabo	834.57	0.81
Shangombo	730.51	0.88

Source: own elaboration

Table 2 - Baseline and Follow-up household sample sizes by district and treatment status

	Baseline			Follow-up			Attrition (%)
	C	T	Total	C	T	Total	
Kaputa	420	419	839	337	343	680	19.0
Kalabo	420	420	840	403	405	808	3.8
Shangombo	419	421	840	405	405	810	3.6
Overall	1259	1260	2519	1145	1153	2298	8.8

Source: AIR, 2013

Table 3 - Baseline comparisons between treatment and control groups

Selected Variables	Treatment	Control	diff	t-stat
Household Characteristics				
Household Size	5.75	5.65	-0.1	-1.18
Children < 5 y.o.	1.88	1.93	0.04	1.44
HH Consumption (AE)				
Food	53.3	50.4	3	1.56
Non-food	17.6	16.8	0.7	1.14
Own-produced	21	19.2	1.7	1.43
Location Variables				
Distance to food market	14.79	21.46	6.67**	5.01
Distance to health facility	9.32	9.4	0.08	0.18
Income sources				
HH farming	76.83%	78.95%	-2.13%	-1.286
HH herding livestock	49.29%	47.42%	1.87%	0.937
Any HH member in waged labor	11.11%	10.25%	0.86%	0.703
HH received any transfer	30.00%	26.61%	3.39%*	1.89
Subsidies				
HH receiving farm input subsidy	2	2	0	0.71
HH receiving a food security pack	0	0	0	-1.06
Production				
Value of harvest	403.8	398.1	5.7	0.211
Value of sales	73.4	80.4	-7	-0.435
HH selling crops	20.48%	25.10%	-4.62%**	-2.769
Value of own consumption	207.1	206.4	0.7	0.065
Self-Reported Shocks				
Household affected by drought	0.04	0.06	0.01	1.2
Household affected by flood	0.03	0.07	0.04**	4.54
Household affected by any shocks	0.18	0.2	0.02	1.34

Source: AIR (2011), Daidone et al. (2013)

Table 4 - Descriptive Statistics

	2010			2012		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Ln Total expenditure	2174	5.27	0.68	2174	5.55	0.60
Ln Tot exp. food items	2174	11.13	0.88	2174	11.63	0.59
Ln HH Food consumption	2174	11.75	0.77	2174	12.22	0.63
Ln Non-food expenditure	2174	10.68	0.81	2174	11.06	0.74
Ln Total Kcal consumed by HH	2174	8.52	1.02	2174	8.81	0.93
Ln Household Dietary Diversity Score	2174	1.67	0.35	2174	1.88	0.29
HH received CGP	2174	0	0	2174	0.50	0.50
Ln Female size	2174	0.99	0.49	2174	0.99	0.51
Ln HH size (AE)	2174	1.36	0.44	2174	1.41	0.42
Ln HH head average education	2174	0.48	1.82	2174	0.46	1.83
Ln # Members (<5 y.o.)	2174	0.56	0.43	2174	0.46	0.53
Dependency ratio	2174	0.48	1.11	2174	0.53	1.08
Ln Operated land	2174	-1.82	2.04	2174	-1.10	1.78
Non-agricultural wealth index	2174	0.01	1.02	2174	0.01	1.02
Agricultural wealth index	2174	0.02	1.02	2174	0.00	1.01
Tropical livestock unit (TLU)(total)	2174	0.38	3.14	2174	0.35	1.53
HH made loan repayment	2174	0.01	0.10	2174	0.02	0.14
Ln Total average rainfall (1983 t)	2174	896.15	147.72	2174	899.29	140.77
Negative deviation of rainfall (-)	2174	4.22	6.51	2174	4.44	7.03
Seasonality index	2174	0.48	0.50	2174	0.48	0.50

Table 5 – Average impact on welfare GLS-RE vs OLS

	Ln Total expenditure				Ln Tot food expenditure				Ln Non-food expenditure			
	RE		OLS		RE		OLS		RE		OLS	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
HH received CGP	0.194***	(0.021)	0.197***	(0.021)	0.205***	(0.023)	0.206***	(0.023)	0.183***	(0.027)	0.185***	(0.027)
Ln Total Average Rainfall (mm)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.000*	(0.000)	0.000	(0.000)
Negative deviation of rainfall (mm)	-0.029***	(0.003)	-0.026***	(0.003)	-0.033***	(0.003)	-0.031***	(0.003)	-0.014***	(0.004)	-0.012***	(0.004)
Seasonality Index	-0.057*	(0.026)	-0.061*	(0.027)	-0.113***	(0.029)	-0.118***	(0.029)	-0.061	(0.032)	-0.066*	(0.032)
Ln Female Size	0.048*	(0.020)	0.050*	(0.021)	0.054*	(0.024)	0.055*	(0.024)	0.010	(0.026)	0.012	(0.027)
Ln HH Size (AE)	0.259***	(0.027)	0.256***	(0.028)	0.224***	(0.032)	0.219***	(0.032)	0.371***	(0.033)	0.373***	(0.034)
Ln HH Head Average Education	0.033***	(0.005)	0.034***	(0.005)	0.029***	(0.006)	0.030***	(0.006)	0.043***	(0.006)	0.044***	(0.006)
Ln # Members (<5 y.o.)	-0.059**	(0.022)	-0.058*	(0.023)	-0.050	(0.034)	-0.050	(0.035)	-0.063*	(0.027)	-0.062*	(0.027)
Dependency Ratio	0.002	(0.009)	0.002	(0.009)	0.012	(0.010)	0.013	(0.011)	0.004	(0.013)	0.003	(0.013)
Ln Operated Land	0.032***	(0.005)	0.031***	(0.005)	0.037***	(0.006)	0.036***	(0.006)	0.013*	(0.006)	0.013*	(0.006)
Non Agricultural Wealth Index	0.206***	(0.010)	0.201***	(0.010)	0.177***	(0.011)	0.175***	(0.012)	0.244***	(0.012)	0.237***	(0.012)
Agricultural Wealth Index	0.030**	(0.011)	0.030**	(0.011)	0.029*	(0.011)	0.029*	(0.011)	0.018	(0.012)	0.018	(0.012)
TLU (total)	0.010	(0.007)	0.010	(0.007)	0.015*	(0.007)	0.015*	(0.007)	0.002	(0.005)	0.001	(0.005)
HH made loan repayment	0.171**	(0.066)	0.168**	(0.064)	0.126	(0.072)	0.123	(0.071)	0.202*	(0.099)	0.204*	(0.097)
Constant	4.013***	(0.146)	4.109***	(0.150)	10.578***	(0.167)	10.673***	(0.172)	10.147***	(0.187)	10.210***	(0.185)
Observations	4348		4348		4348		4348		4348		4348	
r2	0.327		0.328		0.274		0.275		0.276		0.276	

Note: Robust standard-errors in parentheses, level of significance is *** p<0.01, ** p<0.05, * p<0.10. Errors are clustered at enumerator area level.

Table 6 – Average impact on food and nutrition security GLS-RE vs OLS

	Ln Total Kcal consumed by HH				Ln Household Dietary Diversity Score			
	RE		OLS		RE		OLS	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
HH received CGP	0.126***	(0.034)	0.129***	(0.034)	0.151***	(0.011)	0.152***	(0.011)
Ln Total Average Rainfall	0.002***	(0.000)	0.002***	(0.000)	-0.000	(0.000)	-0.000	(0.000)
Negative deviation of rainfall (mm)	-0.017***	(0.004)	-0.016***	(0.004)	0.001	(0.001)	0.001	(0.001)
Seasonality Index	-0.072*	(0.036)	-0.072	(0.037)	-0.083***	(0.013)	-0.083***	(0.014)
Ln Female Size	0.054	(0.034)	0.056	(0.034)	0.029**	(0.011)	0.030**	(0.011)
Ln HH Size (AE)	0.224***	(0.042)	0.221***	(0.043)	-0.032*	(0.014)	-0.033*	(0.014)
Ln HH Head Average Education	0.033***	(0.008)	0.033***	(0.008)	0.018***	(0.003)	0.018***	(0.003)
Ln # Members (<5 y.o.)	-0.085*	(0.036)	-0.085*	(0.036)	-0.017	(0.010)	-0.016	(0.010)
Dependency Ratio	0.021	(0.014)	0.021	(0.014)	0.010*	(0.004)	0.011*	(0.005)
Ln Operated Land	0.040***	(0.007)	0.038***	(0.008)	0.017***	(0.002)	0.018***	(0.002)
Non Agricultural Wealth Index	0.169***	(0.015)	0.169***	(0.015)	0.083***	(0.005)	0.082***	(0.005)
Agricultural Wealth Index	0.056***	(0.015)	0.054***	(0.015)	0.010	(0.005)	0.010	(0.005)
TLU (total)	0.020**	(0.007)	0.020**	(0.007)	0.002	(0.001)	0.003	(0.002)
HH made loan repayment	0.056	(0.093)	0.056	(0.092)	-0.005	(0.033)	0.000	(0.033)
Constant	6.385***	(0.217)	6.437***	(0.222)	1.905***	(0.073)	1.909***	(0.074)
Observations	4348		4348		4348		4348	
r2	0.202		0.202		0.263		0.263	

Note: Robust standard-errors in parentheses, level of significance is *** p<0.01, ** p<0.05, * p<0.10. Errors are clustered at enumerator area level.

Table 7 – Heterogeneous impact of SCT on welfare GLS-RE vs OLS

	Ln Total expenditure				Ln Total food expenditure				Ln Non-food expenditure			
	RE		OLS		RE		OLS		RE		OLS	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
HH received CGP	0.274	(0.199)	0.306	(0.197)	0.248	(0.233)	0.280	(0.231)	-0.115	(0.264)	-0.073	(0.260)
Ln Total Average Rainfall (mm)	0.002***	(0.000)	0.002***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001*	(0.000)	0.001*	(0.000)
Negative deviation of rainfall (mm)	-0.039***	(0.004)	-0.038***	(0.004)	-0.045***	(0.005)	-0.044***	(0.005)	-0.024***	(0.005)	-0.024***	(0.005)
CGP*rainfall shock	0.030***	(0.005)	0.032***	(0.005)	0.032***	(0.006)	0.033***	(0.006)	0.028***	(0.007)	0.030***	(0.007)
CGP*tot average rainfall	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Constant	3.859***	(0.174)	3.909***	(0.178)	10.426***	(0.204)	10.481***	(0.210)	10.101***	(0.226)	10.109***	(0.222)
Observations	4348		4348		4348		4348		4348		4348	
r2	0.340		0.340		0.285		0.285		0.290		0.290	

Note: Robust standard-errors in parentheses, level of significance is *** p<0.01, ** p<0.05, * p<0.10. Errors are clustered at enumerator area level. All estimation control for the same set of variables reported in table 5.

Table 8 - Heterogeneous impact of SCT on food and nutrition security, GLS-RE vs OLS.

	Ln Total Kcal consumed by HH				Ln Household Dietary Diversity Score			
	RE		OLS		RE		OLS	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
HH received CGP	-0.063	(0.329)	-0.124	(0.329)	0.288**	(0.107)	0.333**	(0.109)
Ln Total Average Rainfall (mm)	0.003***	(0.000)	0.002***	(0.000)	0.000	(0.000)	0.000	(0.000)
Negative deviation of rainfall (mm)	-0.027***	(0.006)	-0.026***	(0.006)	-0.003	(0.002)	-0.003	(0.002)
CGP*rainfall shock	0.029***	(0.008)	0.029***	(0.008)	0.011***	(0.003)	0.012***	(0.003)
CGP*tot average rainfall	0.000	(0.000)	0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
Constant	6.306***	(0.269)	6.355***	(0.277)	1.821***	(0.088)	1.803***	(0.089)
Observations	4348		4348		4348		4348	
r2	0.211		0.210		0.267		0.267	

Note: Robust standard-errors in parentheses, level of significance is *** p<0.01, ** p<0.05, * p<0.10. Errors are clustered at enumerator area level. All estimation control for the same set of variables reported in table 6.

Figure 1 - Total amount of Rainfall (1983-2010) and Zambia CGP wards

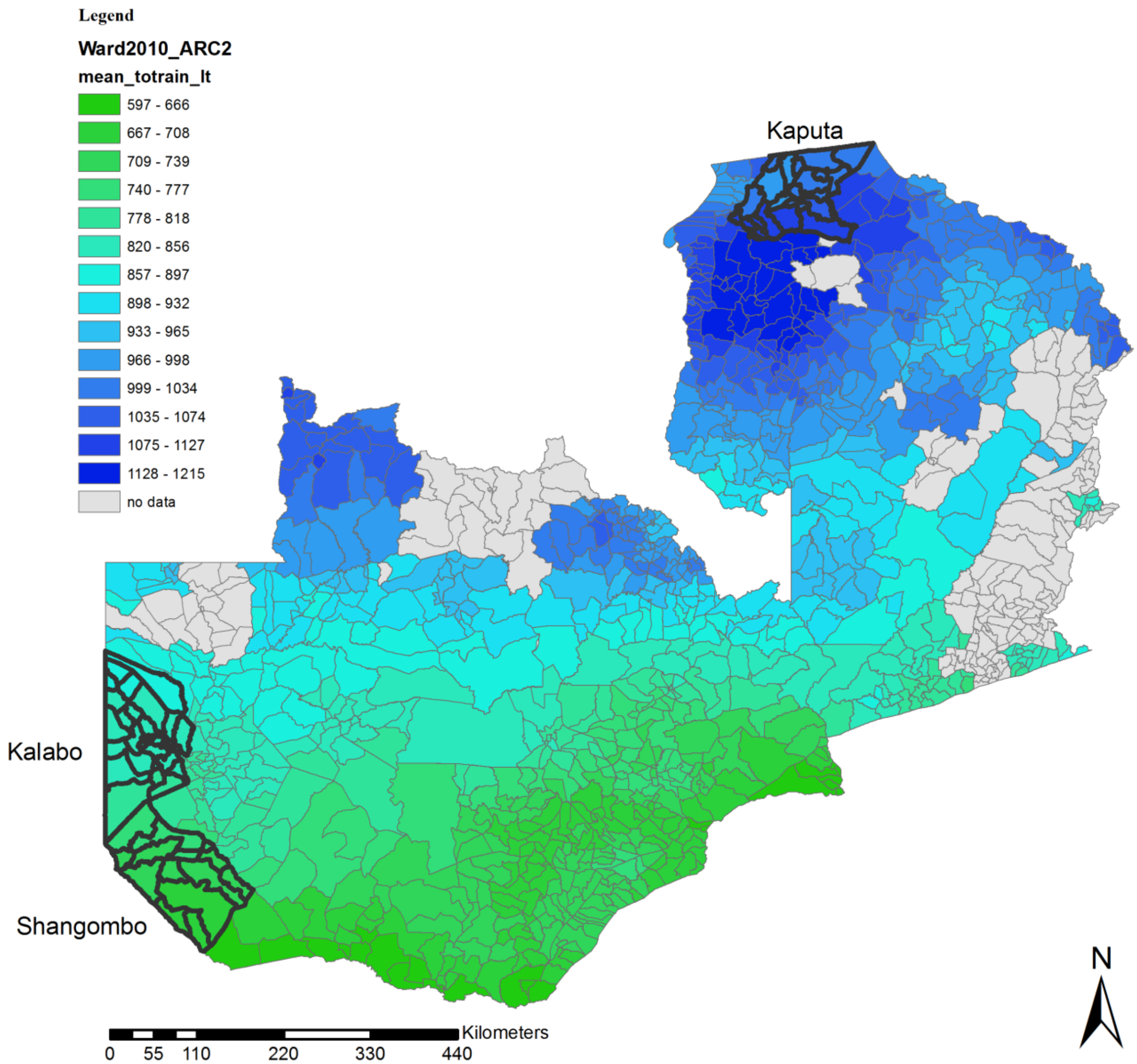


Figure 2 - Coefficient of Variation (CoV) of rainfall (1983-2010) and Zambia CGP wards

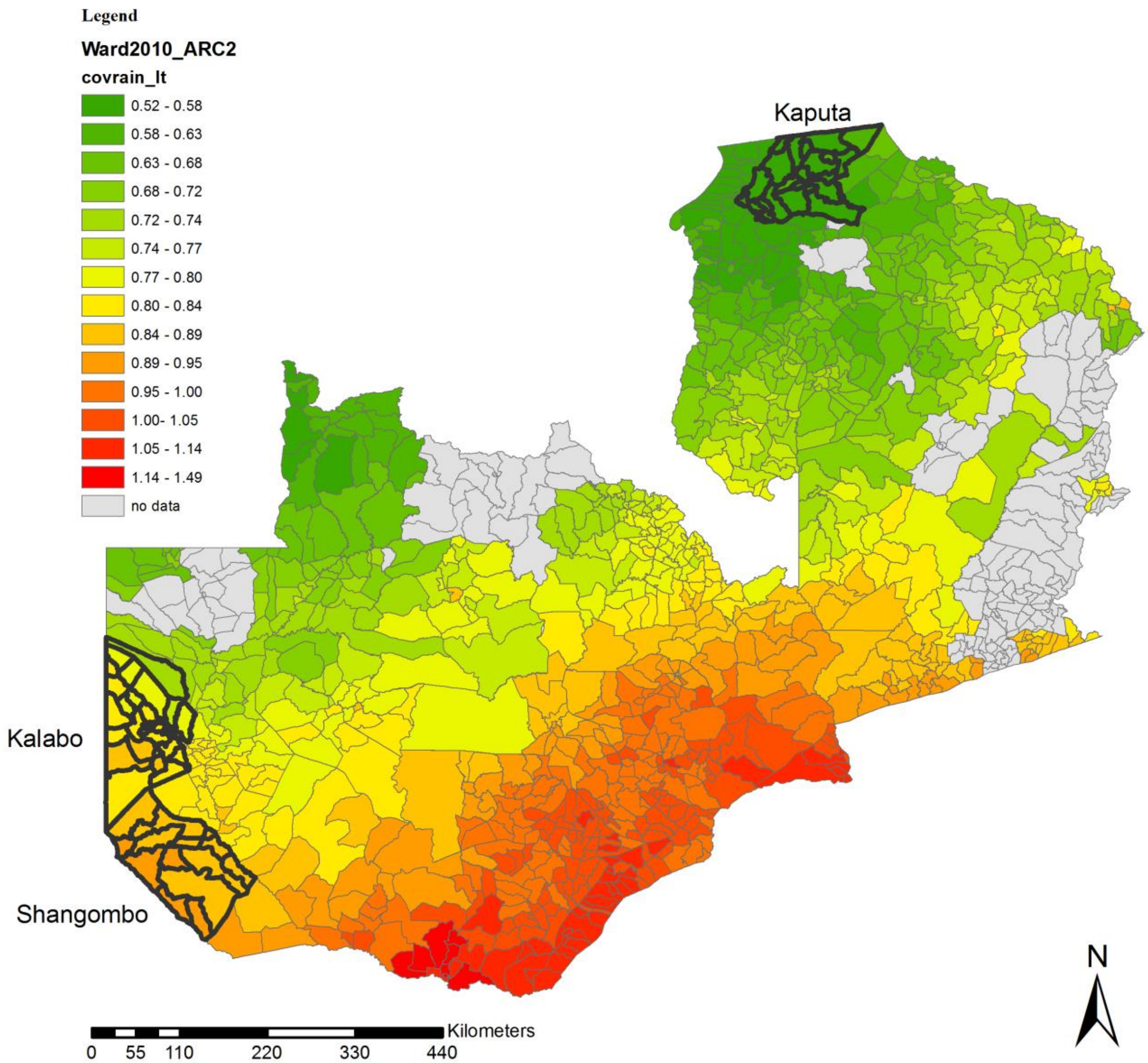


Figure 3 – Quantile Regression plots – Daily caloric intake

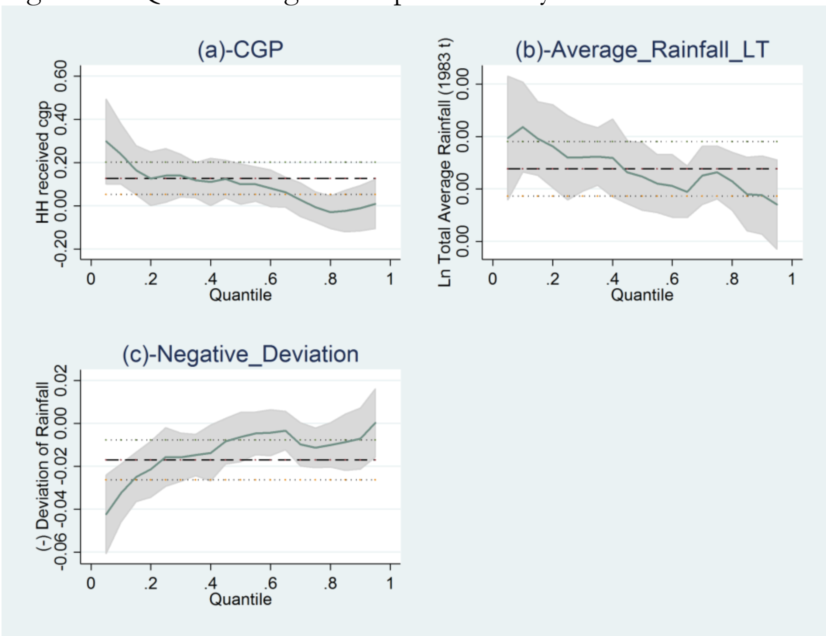
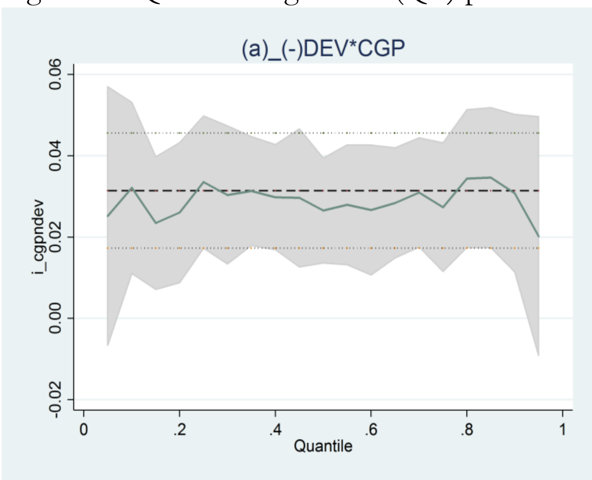
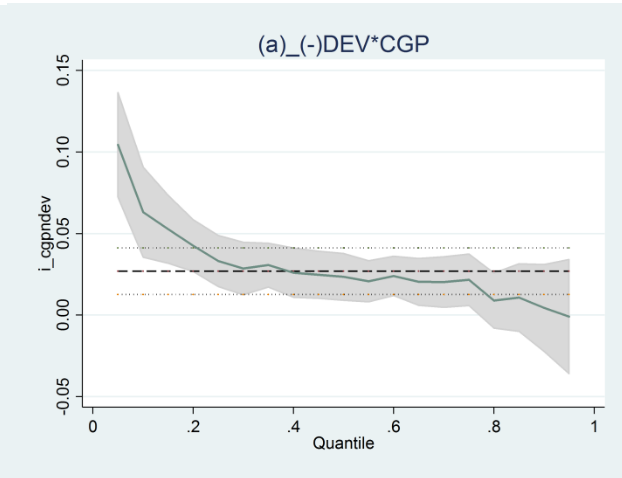


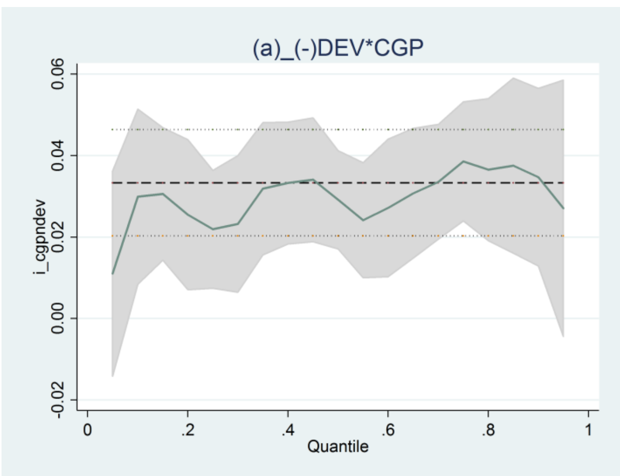
Figure 4 – Quantile Regression (QR) plots



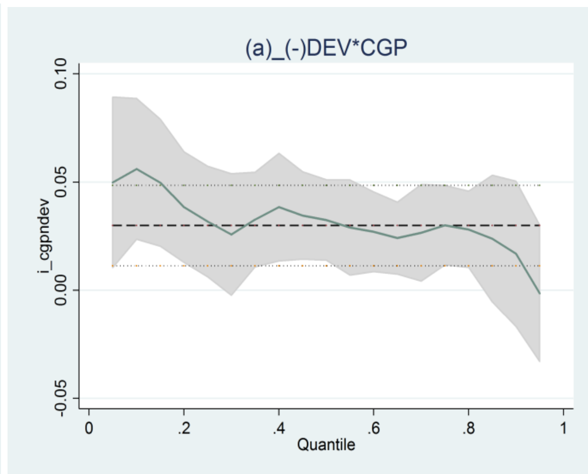
a) Total expenditure



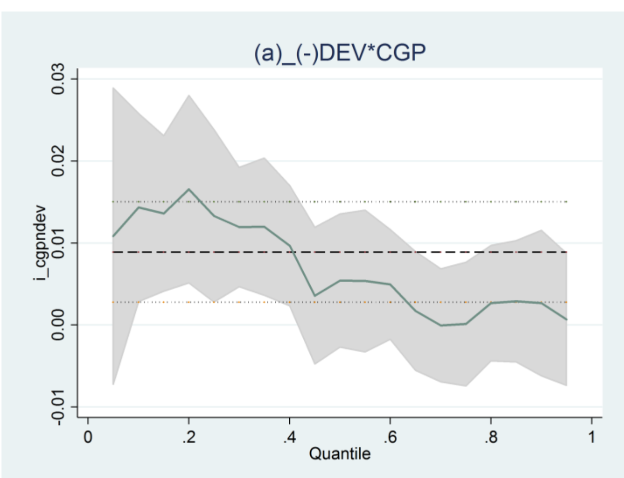
b) Non-food Expenditure



c) Food expenditure



d) Daily caloric intake



e) Household dietary diversity score