Feed Thy Neighbour: how Social Ties shape Spillover Effects of Cash Transfers on Food Security and Nutrition

ALESSANDRO CARRARO AND LUCIA FERRONE

Feed Thy Neighbour: how Social Ties shape Spillover Effects of Cash Transfers on Food Security and Nutrition

Alessandro Carraro[1], Lucia Ferrone[2]

[1]UNICEF Office of Research Innocenti

[2]Department of Economics and Business, University of Florence

Abstract. – Economic development in Sub Saharan African countries is strongly tied to households' ability to cope with exogenous events affecting their well-being. Using data from the Lesotho Child Grant Program dataset we provide evidence on whether households' food security and nutrition are influenced by the presence of a particular network structure, and if there is any spill-over effect of the program on ineligible households living in treated villages. We take advantage of information on money and in-kind transfers to build a set of indicators representing quantitatively and qualitatively the network architecture of each household. We find relevant spill-over effects of the CGP on the food security and nutrition of ineligible households living in treated villages and embedded in a social network.

1. Introduction

Development economists have long assumed that social interactions help modelling economic exchange, because formal institutions are often fragile and must be accompanied by interpersonal forms of trust and dependence (Fafchamps, 2006). This is central especially in the developing world where risk sharing is among the most relevant coping mechanisms adopted by poor households to face adverse shocks (Rosenzweig and Stark, 1989; Townsend, 1994; Ligon et al 2001, Fafchamps, 2003). Extended families and kinship networks provide many forms of protection and insurance against external events or risks affecting the poor, both at private and public level (Cox and Fafchamps, 2008). For example, forms of networks like labour sharing are very helpful against health risks (Krishnan and Sciubba, 2004), child fostering enables children's care and school attendance (Akresh, 2005 and Ksoll, 2007) and resource pooling facilitates protection of public goods (Baland and Platteau, 2000).

Risk sharing in less developed countries remains principally informal, due to institutions' weaknesses or lack of proper policy agendas, and households differentiate risks through informal loans, transfers, and interpersonal exchanges of food, assets, and cash. This is particularly relevant in the Basotho culture, where nuclear and extended families' relations are deep-rooted within the society. In fact, according to the report by Oxford Policy Management (OPM, 2014), who conducted the evaluation for the pilot of the Lesotho Child Grant Programme (CGP), Lesotho's poor rely on their neighbours for help, from whom they receive in-kind assistance, usually in the form of clothing or food, although there are also households lending/sharing livestock to/with others living in the community. In developing economies, the provision of cash is being increasingly used as a practical social protection tool, which can be safely issued and that can allow poor households to improve their consumption, food security and livelihood strategies. Even though these interventions are likely to influence all the households residing in the same community, the literature on programs evaluation is usually concentrated on the estimation of the program impacts only on the those directly benefiting of the transfers. This could result in an underestimation of the actual effect of the programs: considering that kinship, inter-household relationships, and community informal social networks are a fundamental "economic relief strategy" for the majority of households living in the local community. In this regard Barca et al. (2014) recognized that Social Cash Transfers (SCT) positively enter within communities' risk sharing networks by improving beneficiaries' economic conditions as well as their economic partnerships with non-recipient households, reducing the gaps between poor households, better-off households and the local establishment. Beneficiaries can thus become an active part of the community, they can rely less on their families by reducing their financial aid needs and facilitating the spreading of financial contributions to other families in their social network (Barca et al., 2014).

Started in 2009, the Lesotho Child Grant Programme (CGP) is one example of unconditional social cash transfer programme developed to reduce malnutrition, improve health and increase school enrolment among Orphans and Vulnerable Children (OVC). The program has had a broad range of impacts, such as increasing the spending on children, improving school enrolment, providing protection against food and nutrition insecurity, boosting farm production, and positive effects on the local economy (Taylor et al., 2013; Pellerano et al. 2014; Tiwari et al. 2016; Prifti et al. 2019). Concerning the latter, the local economy-wide impact evaluation (LEWIE) model developed by Taylor et al. (2013) for the CGP found that the transfers had the potential to lead to relatively large income multipliers. Thus, benefits from the CGP program may ultimately lead to positive consequences for society as a whole through different types of interactions. If this is the case, the positive effects documented for programme recipients represent only a portion of the overall effect of CGP. As the CGP injects cash into the local economy, beneficiaries but also non-beneficiaries in treated communities may have an advantage. Spill-over effects towards non-beneficiaries may occur by stimulating the demand for goods and services in the local economy. The increased expenditure is then likely to convey immediate impacts from beneficiaries to non-beneficiaries either in the community or outside it. Analysing spill-over effects is thus essential in determining whether the contribution of unconditional social cash transfers is effective at reducing poverty and food insecurity. This is where the objective of this paper fits in.

Our goal is twofold: first we will establish whether households who benefit from the transfers indirectly affect the welfare and food security perceptions of non-recipients living in the same community; secondly, we will investigate how this effect could propagate if households were to pool the risk with a wider social network.

We expect a spill-over effect on non-eligible groups in communities where the CGP is in operation: if ineligible households can rely on a deep network pattern, CGP may cause an increase in welfare and food security for these households. To the best of our knowledge this is the first study that uses social networks to shed light on the mechanisms through which cash transfers' spill-over effects occur.

We draw from the Lesotho CGP baseline and follow-up household survey data which has a special focus on the networks and informal transfers to and from the households. The targeting has been performed following a community-Randomised Controlled Trial (RCT) design, with a village-level randomization of the program irrespective of the households' eligibility. Eligibility criteria included the presence of at least one child within in the household and qualification as either ultra-poor or very poor with proxy-mean testing and validation procedures within the community.

Our findings suggest that CGP can act as insurance for non-beneficiary households: the programme increases food security in a range of indicators for non-eligible households in treated villages, and more so for households with stronger and closer ties.

The remainder of the paper is as follows. Section 2 provides a review of the existing works on social networks with a specific attention to those linked with social assistance. Section 3 briefly describes the program. Section 4 presents our data and outlines our empirical strategy. Section 5 introduces the main results, focusing on the impact of the program in Lesotho, on the spillover effects and on whether and why being connected with other households has an influence in the program response. Section 6 concludes.

2. Literature review

An increasing plethora of works on social networks has focused on insurance and protection against external events. This followed a decade in which households' risk pooling attracted the interest of many development economists (e.g. Mace, 1991; Cochrane, 1991; Townsend, 1994). In his eminent study on Indian communities, Townsend (1994) was among the first who assumed that risk sharing took place at the network, rather than at village or community level. This sparked an interest in understanding at what level exactly risk-sharing takes place. Udry (1994) started to analyze how households pool risk through close connections, highlighting the role of the economic exchanges among them (i.e. lending and borrowing strategies) and arguing about the importance of the village-level networks, underlining the relevance of geographic proximity in creating networks. A vast literature also analyzed the economic role of transfers and gifts between households either shedding light on their role as risk sharing mechanisms (e.g. Rosenzweig, 1988; Rosenzweig and Stark, 1989; Fafchamps and Lund, 2003) or testing whether they would favor consumption smoothing (Dercon and De Weerdt, 2006). Other research also focused on the type of linkages among households, showing that most transfers between households took place between close relatives (e.g. Lucas and Stark, 1985; Ellsworth, 1989; Lund, 1996; Fafchamps and Gubert, 2007). However, not all the households' links are equally helpful. For example, Kinnan & Townsend (2012) analyzed the type of networks which were the most supportive to the households for consumption smoothing and investments. Households linked to banks achieved significantly better consumption smoothing than unconnected households, while investments appeared to be facilitated by kin networks. Baird and Grey (2014) found that traditional inter-household exchanges and the attached social ties decline and change as the households develop new diversification strategy. Social networks have also long been studied in their relationship with migration (see, for example, Fawcett, 1989; Palloni et al., 2001) as well as gender (Kumar, 2019). Recently, social networks have been found as one of the main forces driving migration intentions (Manchin, Orazbayev, 2018), both internal and international. While migrants' household own social network increases political participation (Batista, Seither, Vicente, 2019). Kumar et al. (2019) find that women's self-help groups

increase participation and awareness of entitlement and public services in their social networks. Karlan et al. (2009) are among the first who analyze transfers' flows through networks, considering the indirect paths across them as well. They employ data on time spent with other individuals in order to build-up the network, and they demonstrate that both direct and indirect paths add in the same way to risk pooling. Building on this framework, Ambrus, Mobius & Szeidl (2014) indicate that the level of informal insurance is contingent to the network expansiveness.

Our paper speaks also to the literature examining the relationship between networks and cash transfers, but the empirical works based on the interplay between design/development of social cash transfers and social networks with their relative spill-over effects are quite scarce. Angelucci et al. (2010, 2014) were among the first to make progress in this area. In their first paper, Angelucci et al. (2010) studied whether the effects of the Progresa conditional cash transfer program on secondary school enrolment varied according to the characteristics of the network. By employing a first difference OLS regression model, they showed that there was no evidence of increased bargaining power of treated women, and that there was no effect of larger number of spouse links to school enrolment. They also found a limited indirect treatment effect of the program among non-eligible households in the family network: resources are not transferred from eligible to non-eligible households within the same village. In their following work, Angelucci et al. (2014) found that the randomized Progresa conditional cash transfer in Mexico is pooled within kin network, thus allowing members to both better smooth consumption and make higher-return investments. Larger and more closely linked networks achieve better consumption smoothing than smaller and less closely linked networks, though they exhibit similar investment responses. Results from Angelucci et al. (2014) suggest that network architecture, and not just bilateral links, matters for risk sharing. Other relevant contributions on SCT and their spillover effects are the ones by Angelucci and De Giorgi (2009) and Beegle et al. (2015), who looked at the indirect effects of cash transfer programs on ineligibles and untreated households. Strupat and Klohn (2018) investigate the role of the National Health Insurance Scheme (NIHS) program in Ghana on informal transfers and find that the implementation of the NHIS displaces informal transfers made within one's social-network to help pay for medical expenses. An effect similar to the one observed by MacAuslan and Riemenschneider (2011), who find negative impacts on social relations from two cash transfer programmes in Malawi and Zimbabwe. However, in an earlier work, Attanasio, Pellerano, and Reyes (2009) find evidence of increased cooperation among targeted communities in Cartagena, Colombia. A similar finding is the conclusion of Valli, Peterma, and Hidrobo (2018), who find that a social protection programme (including cash and food transfer) increased social cohesion of Colombian refugees in host communities in Ecuador. Daidone et al. (2015) find that the Ghana Livelihood Empowerment Against Poverty (LEAP) cash transfer has positive effect on the participation of beneficiary households in informal risk-sharing networks, suggesting that the transfer has a crowding-in effect on social safety nets. Positive spill-over effects of cash transfers on the local economy are also found in Kenya (Thome et al., 2013), and Malawi (FAO, 2019).

Summarizing, it appears from the available evidence that effects of cash transfers on social networks and spill-over effects are quite dependent on a) the context and the specific programme b) the specific outcome being investigated: while positive economic spill-overs are more commonly observed, the impacts on social relations are more nuanced. However, a gap in the evidence remains as to what is the synergy between social cash transfers and social networks: our work aims at shedding light on this question.

3. Lesotho's Child Grant Programme

The Lesotho Child Grants Programme has the primary objective of improving "the living standards of Orphans and other Vulnerable Children (OVC) so as to reduce malnutrition, improve health status, and increase school enrolment among OVCs" (OPM, 2014). The programme is run by the Ministry of

Social Development, with financial support from the European Commission and technical support from UNICEF-Lesotho. Launched as pilot program in April 2009 with the coverage of 10,000 beneficiary households (phase 1) in 5 districts, the coverage was expanded at the end of 2013 (phase 2), reaching 19,800 households and providing benefits for approximately 65,000 children across 10 districts in Lesotho. Within 10 Community Councils selected for the Phase 1 – Round 2 expansion of the programme, half of all 96 Electoral Divisions were randomly assigned to be covered by the pilot (treatment), while the other half were to be covered after the end of the evaluation study (control). Electoral Divisions were assigned to either group in public lottery events. The control group was selected on the basis of a randomized controlled trial (RCT) design, in such way ensuring that it was fully comparable to the treatment group. The beneficiaries are selected through a combination of Proxy Means Testing (PMT) and community validation and registered in the National Information System for Social Assistance (NISSA). The study took place in five Districts: Qacha's Nek, Maseru, Leribe, Berea and Mafeteng.

Baseline and follow-up panel surveys collected information for a sample of CGP-eligible and non-eligible households in treatment and control communities. The baseline survey fieldwork took place between June and August 2011, comprising around 3000 households. The follow-up survey fieldwork took place in 2013 at the same time of the year to avoid seasonality bias. A total of 3102 households were surveyed; 1531 program eligible households (766 treatments and 765 control) to be used for the impact evaluation analysis, with the remaining 1571 program ineligible households to be used for targeting analysis and spill-over effects. Besides the household survey, two other questionnaires were implemented: the community and business enterprise questionnaires. The program, which is oriented towards poor and vulnerable households with children, is set up in a way such that the cash is disbursed quarterly with a flat transfer of money of M360 (US$36) at baseline, and between M360 (US$36) and M750 (US$75)[1] at follow-up. However, the payment schedule was not followed over the study period, and the recipients got the entire amount in lumpier transfers than expected.

4. Data and analytical methods

(a) Data, network structure and indicators

The number of households included in the baseline survey is 3,054, evenly distributed across treated and control villages and between eligible and non-eligible households. Children moving away from their original households were also included in the follow-up survey. The number of households in the second wave is 2,212, and they include the new or split households, where any of the baseline children had resettled (see Table 1 for further details). The registered attrition rate, which is estimated to be of 6%, decreases the sample size and can lead to selection bias, which in turn may determine a variation in the sample characteristics and generates incorrect estimates. In order to avoid this issue, we employ analytical weights to correct for the selective non-response (Daidone et al. 2014, OPM 2014). The final number of households included in the econometric analysis is equal to 4302, evenly distributed among the two years.

<INSERT TABLE 1 ABOUT HERE>

Given the objectives of this paper we are especially interested in the characteristics of the social network. Differently from studies that rely on individual information about direct bilateral linkages, to define our network we use a different framework, using both direct and indirect connections. Figure 1 displays the Lesotho CGP networks map, consisting of 535 nodes and 333 ties. We plot only households with available information on eligibility and treatment status, while connections involving households

---

[1] CGP has been indexed to number of children as follows: (1) Households with 1-2 children M360 (US$ 36) quarterly; (2) Households with 3-4 children M600 (US$ 60) quarterly; and (3) Households with 5 and more children M750 (US$ 75) quarterly (OPM, 2014).

without any information associated and relative nodes have been suppressed. The network map gives a snapshot of the network architecture of households involved in money transfers at baseline[2]. Treated households consisted of 312 nodes and 195 arcs, while control household consist of 224 nodes and 138 arcs. As a result of the randomization process, defined at community level, it is fairly evident that treated (in grey) and control (in white) households are perfectly divided in two groups that do not interact at all, with connections likely to happen only within the same village type (either treated or control). Ineligible (squares) and eligible (circles) households do communicate between each other emphasizing the potential for spill-over effects of the program. Overall in both sub-samples (treatment and control) the majority of households show low degree centrality, meaning that they contribute little to network connectivity. The highest number of nodes shows a null or 1-degree connection, and only 1.6-1.8% of nodes receives more than two ties. Among them the vast majority is associated to ineligible households for both treated and control villages. This low in-degree centrality is confirmed by the index of network density reported in table A1 in Annex A. Neither treated nor control villages show a dense network. A more detailed description of the network is provided in Annex A.

<INSERT FIGURE 1 ABOUT HERE>

For each household, we construct a set of indicators for the strength of the social networks by referring to the section on Network and Informal Transfers included within the CGP's Household questionnaire. The module is divided in three sub-modules where respondents give answers on transfers to and from non-resident members. The interviewer asks if there is any non-resident HH member included in the roster and whether he/she has sent the household any money or in-kind assistance over the last 12 months. Other questions include how much has been given to the household and if the recipient household sent any money to non-resident household members over the last 12 months. If there are no transfers to non-resident household member, the interviewer investigates whether any other member/group of members outside the household (friend or neighbor) lent or helped with any money, food or consumables, labor or time, or work animals/equipment to support the household. The amount of the contribution as well as the relationship to the household, name, sex and location are finally included in the questionnaire. Every household has a unique identification code, so that it is possible to track them through the different modules[3].

Given their importance in the broader social networks literature, measures of network size, function and composition will represent the key feature of our network analysis. Our picture of household's network characteristics relies on a set of different indicators which capture both qualitative and quantitative network features. First of all, we look at the total number of non-resident members with which the household has an interaction, either as recipient or sender, as described above. Following Adams et al. (2002) we assess the households' network size by summing up the **total** number of connections (money - food – labour - agricultural equipment) per household. This indicator gives a quantitative measure of the depth of the network. Secondly, we frame the qualitative dimension of the social networks by computing a set of qualitative indicators for the different types of linkages. The first dimension we consider is the relationship closeness, since people may prefer helping their own kin rather than friends or neighbors. It is in fact widely recognized that food or financial inflows largely follow well established paths between individuals with deep social connections (Udry and Conley, 2004). For example, this happens between wife and husband, between siblings, close friends, among members of the extended family or neighbors. We model the relationship closeness by assigning to each linkage a scale of values ranging from 1 to 3, where 1 represents the closest linkage (i.e. family), 2 the intermediate linkage (i.e. friend) 3 the most distant one (i.e. neighbor). Therefore, the smaller the value associated to

---

[3] We do not observe the identity for all the second nodes, whether they belong to poor or non-poor households

it, the closer the relationship within the dyad. We calculate the Relationship Closeness Index (RCI) as $RCI_j = \frac{\sum_{i=1}^{n} R_{ij}}{n_{ij}}$, with R_{ij} representing the relationship level between the two nodes for each linkage i in each household j, and n_{ij} the number of linkages per household j. However, when dealing with social networks it must be considered that husbands and wives tend to pool risks differently (Goldstein, 2002). Several studies have shown how the differences on the network structure are gender based (Fischer, 1982; Moore, 1990). For instance, men's networks consist of fewer kin with respect to women's, who represent also the kin-keepers within the family. To address this issue, we construct the Gender Balance network Index (GBI). The GBI is a dummy variable equal to 1 if the share of networks established with women non-resident members outweighs those established with men.

Finally, a dimension of geographic proximity is derived to capture the degree of geographical closeness between the kin. For each household we compute a geographic proximity index (GPI) equal to $\frac{\sum_{i=1}^{n} CL_{ij}}{n_{ij}}$ where CL_{ij} represents the contributor's location for each linkage i and n_{ij} being the number of linkages. The contributor's location is represented by a scale ranging from 1 to 6[4], which increases as the distance from the household position increases. The result is a value computed at household level which returns the mean physical distance within the dyad.

Some descriptive statistics of the variables used in the study are reported in Table 2, which gives information on the context for a set of standard household characteristics. These include household size, which is expressed in adult equivalents, age of the head of household, highest year of education of the head of household, a dummy for female headed households (1=female), the number of children within each family and the number of orphans living in the household. Data on per capita nominal consumption was also collected and disentangled in food and non-food nominal consumption. We show a generalized increase in the three dimensions of consumption overtime (see Figure 2 for a summary). To better understand household expenditure decisions, we included also the budget share[5] devoted to different food and non-food items. The share of budget devoted to food expenditure (65%) remains higher with respect to non-food expenditure (35%) over time. Our consumption bundle was formed by cereals, fruit and vegetables for what concerns food expenditure, and by health care, services and education for what concerns non-food expenditure.

<INSERT FIGURE 2 ABOUT HERE>

Together with consumption, we also include information on food security in our analysis. The survey aimed at analysing the household's food supply during different months of the year, following the Household Food Insecurity Access Scale (HFIAS). As reported by Coates *et al* (2007) the questions used to create such scale "represent universal domains of the household food insecurity (access) experience" and can be employed to classify households and populations in a scale such that their food insecurity status can be monitored overtime. These questions, which we report in Table 3, ask whether the respondent felt that the (i) amount of food (any kind) that any household member (adult or child) ate during the past twelve months was smaller than they felt they needed due to a lack of resources, (ii) had to eat fewer meals than the number typically eaten in the food secure households in their area or (iii) was aware of adults or children within the household that went to sleep hungry[6]. Perception of food insecurity is widespread among the sampled households. This makes the introduction of these variables relevant for our analysis. On average, three out of four respondents declared that adults ate small/fewer

---

[4] CL =1 represents the closest location (i.e. the village), CL=2, neighboring village; CL=3, closest town; CL=4, Maseru; CL=5 elsewhere in Lesotho; while CL = 6 the outermost place (i.e. other country).

[5] We define budget share as the percentage of money (on the overall available budget) dedicated to each food/non-food category.

[6] Not all the households answered to the HFIAS questions. This lead to a reduction in the final number of observations in the sample.

meals in the 12 months before the survey, and around 40% went to sleep hungry. Figures for children are still high but are 10% lower (on average) with respect to adults. Moreover, a very high percentage of households (around 82%) admitted to face food scarcity in the past 12 months, with around 4 months of some/severe food shortage and 3.5/4 months of sufficient food.

<div align="center"><INSERT TABLES 2 and 3 ABOUT HERE></div>

(b) Econometric strategy

As the Child Grant Program injects cash into the local economy, its effects will spread to both beneficiaries and non-beneficiaries: spill-over effects towards non-beneficiaries may occur by stimulating the demand for goods and services in the local community. The increased expenditure is then likely to convey immediately impacts from beneficiaries to non-beneficiaries either in the community or outside of it. We are interested in investigating a) whether there are spill-over effects of the program on those households who do are not eligible for the transfer, but are located in treated villages b) what is the role of household's social networks in conveying these effects. To assess the impact of the program we employ the differences-in-differences (DD) approach considering ineligibles living in treated villages as intended-to-treat (ITT). Eligibles are initially excluded from the analysis. The DD approach is particularly suitable to our case given that: (i) the households are tracked over both waves, (ii) the sample is stratified to draw eligible and non-eligible groups within each village. In such a randomized setting where treatment and control are similar the DD approach is sufficient to generate unbiased estimates of the impact of the program.

We start by introducing the regression equivalent for the difference in difference estimator:

$$(y_{it}| Inelig = 1) = \delta_0 + \delta_1 ITT_{it} + \delta_2 S_t + \delta_3 (S_t * ITT_i) + \sum \delta_i C_i + \varepsilon_{it} \tag{1}$$

With y_{it} representing the transfers (food/labour/agricultural inputs) among the households; ITT_{it} is a dummy equal to 1 for intent-to-treat household i is and 0 otherwise; S_t is a time dummy equal to 1 for the follow-up round and 0 for the baseline; $S_t * ITT_i$ is the interaction term computed between intervention and time dummies, and ε_{it} represents the error term. In order to control for differences in the composition of the two groups we added vector C_i, that included the households' demographic composition, head of household characteristics, district dummies, vectors of prices, wages and shock variables as representative of household and community characteristics. This set of variables has two purposes, firstly it captures the observable differences at the baseline which can impact on y_{it}, then it conveys general explanatory information in the estimation of y_{it}. δ's coefficients are vectors representing respectively the intercept (δ_0), the magnitude of time invariant differences among treated and control (δ_1), the overtime variation (δ_2), and the difference in difference estimator (δ_3). Equation (1) can also be written in differences

$$\Delta y_{it} = \delta_0 + \delta_1 T_{it} + \sum \delta_i C_i + \varepsilon_{it} \tag{1a}$$

With $\Delta y_{it} = y_{i1} - y_{i0}$ representing the difference in the outcome variable before and after the treatment. T_{it} is a dummy equal to 1 if the household i is treated and 0 otherwise; ε_{it} represents the noise. Compared to (1), δ_1 represents the double difference estimator - the coefficient capturing the treatment effect. With only a two waves' panel available, model (1) and (1a) correspond to a Fixed Effect (FE) model. Since the variables of interest - like in many difference in difference setups - only vary at group level, and outcome variables are often serially correlated (Huber, 1967; Moulton, 1990) all the standard errors reported in the results are clustered at community level. Since the control variables

are also correlated across observations, the usual OLS standard errors would have led to a bias in the estimation of the treatment effects' standard errors, leading in turn to overestimated significance levels (Kezdi, 2004). Here we adopt the cluster robust standard error (CRSE) where the correlation across groups equals zero as with fixed effects, but allows for the variation in the within group correlation. The mechanism behind the CRSE is that as the number of cluster increases, so does the approximation to the real standard error estimate.

We then move one step forward, exploring whether the network affects households' welfare and food security. We assume that the household's total, food/non-food consumption as well as the budget share in food/non-food items depend on the household's network size, the household's eligibility status (*i.e.* ineligible, ineligible in treated village (ITV), treated villages) and the households' characteristics. We are expecting that (i) eligibles are worse off with respect to ineligibles in both groups, that (ii) eligibles in the treated group are better off with respect to eligibles in the control group, (iii) there is a spill-over effect of the program from eligible to ineligible households in treated communities. Similarly to Angelucci (2009), we model the network and spillover effects on ineligibles living in treated villages by using the following reduced form:

$$Y_{it} = \alpha_0 + \beta_1 Treat_{it} + \beta_2 Inelig_{it} + \beta_3 ITV_{it} + \beta_4 Nwk_{it} + \gamma_1 \mathbf{X}_{it} + \gamma_2 \mathbf{Z}_{ct} + \varepsilon_{it} \qquad (2)$$

Where Y_{it} is the dependent variable (total/food/non-food consumption, share of budget devoted to food/non-food) for the household i at time t. $Treat_{it}$ is the program participation variable, $Inelig_{it}$ represents a dummy for ineligible households, and finally ITV_{it} is a household level indicator which is equal to 1 for ineligible households living in treated villages whose coefficient (β_3) returns the spillover effect of the program. Nwk_{it} represents the set of social networks' characteristics of the household, as explained above. $\mathbf{X}_{it}$ is a vector of time-invariant household characteristics, $\mathbf{Z}_{ct}$ is a set of price, wage and shocks vectors included at community level c and at time t, and finally ε_{it} is a normally distributed error term.

We first estimate the general specification of the model (2) and then we control for the heterogeneous effect of the different network characteristics with the CGP, including an interaction term between the ITV dummy variable and each of the network indicators. Given that households in each group are absorbing the intervention differently, these interaction terms help capturing the differential network effects across the eligible/ineligible groups.

We use a Mundlak-Chamberlain correction to the Random Effects (RE) model, to control for unobserved heterogeneity, which leads to the estimation of a correlated random effects model (CRE)[7]. The CRE approach, which was proposed by Mundlak (1979) and relaxed by Chamberlain (1980, 1982) unifies the fixed and random effects estimation approaches, allowing for correlation between the time invariant unobserved characteristics assuming $v_i|x_i \sim N(\varphi + \overline{\mathbf{x}}_i \omega, \sigma_\tau^2)$, with σ_τ^2 representing the variance a_i in the equation $v_i = \theta_i + \overline{\mathbf{x}}_i \omega + \tau_i$, and $\overline{\mathbf{x}}_i = T^{-1} \sum_{r=1}^{T} \mathbf{x}_{ir}$ the vector of time averages. To implement the CRE framework in equation (2), we include as explanatory variables the vector of variables containing the means $\overline{\mathbf{x}}_i$ of all time-varying controls (Wooldridge, 2002).

Finally, we investigate to what extent the probability of food insecurity occurrence among adults and children is affected by the extent and characteristics of the program and the family network. This is done by building up a Pooled Logit model which makes use of our set of food insecurity access dichotomic variables. We employ a Poisson regression model, as reported in equation (3), to evaluate the spillover

---

[7] As pointed out by several works, with short panels FE models are usually not consistent and can only give estimates of time-varying variables (Ricker-Gilbert *et al.* 2011; Arslan *et al.*, 2015).

effects of the program on the number of months in which the household faces food insecurity (e.g. number of months in which the household has sufficient food, number of months the household faces some food shortage, number of months the household has to face extreme food shortage). In the econometric specification of the model, y_{it} represents the outcomes of household i at time t. We move from equation (2) to a Poisson model specification using the same control variables specified previously:

$$E(y_{it}|Treat_{it}; Inelig_{it}; \text{ITV}_{it}; Nwk_{it}; \mathbf{X}_{it}; \mathbf{Z}_{ct}) =$$
$$= \exp(\beta_1 Treat_{it} + \beta_2 Inelig_{it} + \beta_3 \text{ITV}_{it} + \beta_4 \text{Nwk}_{it} + \gamma_1 \mathbf{X}_{it} + \gamma_2 \mathbf{Z}_{ct}) \quad (3)$$

5. Results

5.1. Indirect effects of the program on transfers among households: difference in difference model.

We start by exploring whether there is an overall effect of the Lesotho Child Grant Program on money and in-kind transfers (food, labour and agricultural inputs) among the ineligible households living in treated villages with respect to their control counterparts. Results presented in Table 4 show the indirect impact of the CGP over a set of different cash/in-kind transfers including food, agricultural inputs and labour. We demonstrate that the CGP had a relevant effect in strengthening the households' mutuality measures concerning food exchange, both from outside and from within the village. Indeed, the effects of the program appear to be strongly significant: we register a 16-18% increase in food exchanges from inside and outside the village, respectively. Contrary to the expectations, we do not find significant effects of the program in labour and agricultural input exchanges.

< INSERT TABLE 4 HERE >

5.2. Indirect effects of CGP on welfare and food security

We then investigate how households' social ties channel the increase in mutuality caused by the CGP. We start by introducing the results from equation (2) which evaluates both the direct impact of the CGP on treated households' outcomes of interest and its indirect impact on ineligible households' living in the same village of the treated ones. Table 5 shows the analysis on total/food and non-food consumption, Table 6 the impact on the budget shares, while pooled logit and Poisson regression results are displayed in Table 7. Results in this section are introduced in the form of elasticities computed at covariates means, which implies that the coefficients for continuous variables yield the percentage variation in the outcome variable for a 1% variation in the explanatory variable, while coefficients for the dummy variable return the percentage change in the dependent variable if the dummy shifts from zero to one.

The program has a positive effect on total and non-food consumption but shows a non-significant effect on food consumption. The indirect effect of CGP on ITVs captures the variation in consumption with respect to eligible households in treated villages. Overall, ineligibles are better off than eligible households, with coefficients that are always positive and statistically significant. When looking at the ineligibles in treated villages, we find negative and statistically significant coefficients, showing that in the three dimensions of consumption ITVs are worse off with respect to treated eligibles.

The impacts of the networks indicators vary across the quantitative and qualitative indicators. First, we find that the number of linkages developed by each household is a strong predictor of consumption. This form of mutual insurance facilitates the transfer of cash/in-kind resources among households and produces an overall increase in welfare by households who manage a higher number of linkages. Second, we find that only GBI (and RCI to some extent) is negatively significant across the qualitative indicators, meaning that networks tied mostly towards non-resident women reduce the gains in terms of welfare for the household.

Other control variables such as the logarithm of the household size expressed in adult equivalents, the logarithm of the household head age or the highest year of education are unambiguously strong predictors of the three dimensions of consumption introduced in our analysis. In particular, larger households are – ceteris paribus - less likely to consume more, either food or non-food items while households headed by older members are more likely to consume more, in particular non-food items.

< INSERT TABLE 5 HERE >

CGP program and relative network potential may affect households' behavior in terms of expenditure decisions in different ways. A higher budget availability, due to a flat lump sum transfer, can influence households' expenditures pattern, that may change within or across food/non-food items. It is interesting to note that while average household food consumption for the different groups increases overtime (see Figure 2), the share of budget devoted to food experiences a decline.

In literature, this food-first budget allocation phenomenon is better known as Engel's Law. The intuition behind is that households must devote at least a minimum portion of income to meet their food basic needs. Therefore, for any income increase "households may allocate some of that additional income on food, but will spend proportionately more than before on other non-food items" (Regmi and Meade, 2013). Using disaggregated shares of food and non-food consumption we proceed to analyze in depth the effect of the program on the budget share (Table 6). The budget allocation of households living in treated areas follows our prediction: the treatment is negative and statistically significant for 2 out of 3 food subgroups (cereals, and vegetables). This contraction in food expenditure is largely outweighed by an expansion in the budget shares devoted to non–food subgroups. Thus, CGP transfers have an impact on expenditure choices in treated villages. Treated households, that have a lower income with respect to ITV, shift their expenditure from food to non-food items by increasing their budget allocation for education and services – which is in line with the program's objectives. For the ineligibles in treated villages, reported in Table 6, we show on the contrary that the program generates a positive spill-over effect stimulating their food expenditure, promoting an increase in the share of budget devoted to cereals and vegetables at a slight expense of education. One plausible explanation could be that reducing the cash injection in food markets has an influence on both food market prices and thus on the expenditures of ITV: prices may shift down due to the CGP-induced lower demand for food items of treated household, and so positively influence ITVs budget allocation towards food items.

For what concerns social network attributes, the relationship closeness and the index of location proximity are weakly significant (at 10%) for the share of budget devoted to vegetables and cereals, respectively. The relationship between the number of linkages and the budget shares has overall a negative effect on the percentage of budget devoted to food consumption. A possible interpretation for this result brings up the significance of inter-households transfers[8] analyzed in Table 4. It is clear that since households primarily and efficiently exchange food, the higher the number the linkages the lower the budget devoted to buy food items. This is true at least for the main staple foods. Though, the registered effect changes when it comes to the budget share devoted to buy fruit, which is positive and statistically significant. Conversely, the number of linkages amplifies the share of budget allocated to non-food items.

These results show that the food exchanges operated through the families' social networks have the positive effect of expanding and diversifying consumption towards different goods or food items, by relaxing the households' budget constraint. As the CGP increases these exchanges, it is clear that positive effect of the transfer goes beyond its immediate beneficiaries.

<center>**< INSERT TABLE 6 HERE >**</center>

Finally, in Table 7, we report the results relative to the probability of occurrence for the set of qualitative food insecurity access variables. We consider only the households giving answers to each of the questions, leaving out non-respondents. This resulted in a lower number of observations available for the estimate. We introduce indicators for adults (columns 1-3), children (columns 4-6) and for the whole households (columns 7-10). The CGP program yields relatively good results for all but one (number of food shortage) of our dependent variables related to adults and children: in both cases when

---

[8] See Figure A2 in Appendix

the program is in place the probability of eating smaller or fewer meals and going to sleep hungry is reduced. Liquidity injection in the system is thus essential in improving life's quality of all household members of any age. When looking at household's food security indicators we find that the program exerts a negative effect on the probability of not having enough food to meet the basic needs as well as the probability of extreme food shortage. At the same time it increases the average number of months with sufficient food. Results thus confirm our expectations. The coefficients for ineligible households show the expected signs (i.e. ineligibles probability to eat smaller/fewer meals is decreasing with respect to eligibles), while the spill-over effect of the program on ITV links with the findings in table 6: consumption variation is negative with respect to eligibles, and this has an effect on food security, ITV's adults and children probability to reduce the size of meals increases, and so does the risk of food shortage and to meet their basic needs.

Finally, we find that the effect of network deepness on food security is positive: it reduces the probability of going to sleep hungry, both for adults and for children (significant at 1%), with a coefficient which is higher for children. The results of the network quality indicators confirm that the network system is overall an important coping mechanism for households to face food insecurity. Looser social relations s (*i.e.* higher value of RCI) increase the probability for adults to go to sleep hungry and for children to be more food insecure. By contrast, households who have stronger linkages with family rather than non-kin members report an increase in months with sufficient food and fewer months with food shortage. The predominance of ties with women contributors management makes households more food insecure as it would have for ties with men counterparts, decreasing the months with sufficient food, while increasing the number of severe food shortages. However, it has no effect on individual food insecurity, hinting at the possible explanation that women are more likely to face problems related to production and accumulation of food. Finally, geographical proximity of linkages does not seem to play a role on food security of households.

<center>**< INSERT TABLE 7 HERE >**</center>

6.3. Heterogeneous impact of the social networks on welfare and food security

As the last point, we examine the heterogeneous impacts of the program on ITV pooling the risk with networks. We replicate the specifications reported in the previous section including the interaction term between the ITV variable and the social network variables. Tables 8 and 9 report respectively the models for total/food/non-food consumption and the share of budgets devoted to food/non-food items, while Table 10 presents the results for the food security access indicators.

The heterogeneity pattern is informative in terms of the theoretical predictions previously discussed. Starting from Table 8, we do find statistically significant results for our interactions terms. First of all, a negative and statistically significant ($p<0.1$) association exists between the logarithm of consumption and the ITV*GBI interaction term. A plausible motivation to this gender bias could be identified in both social and cultural attitudes and the way in which these norms operate in this context. As in many developing countries, female socio-cultural marginalization is often transmitted to the economic level, with negative consequences on their bargaining power. Additionally, women contributors, having less access and control over assets may devote a lower share of their resources to their peers. Therefore, establishing a linkage with female contributors may finally result in an efficiency loss in the overall network performance. Consistent with this finding is the relation with non-food consumption per capita which decreases when households are linked with a larger share of women peers.

For what concerns the RCI, the results show that extended ties (i.e. with neighbours rather than other family members) seem to increase the consumption levels for ITVs: we observe a positive spill-over

effect of the program on ITVs' for food consumption, provided that households engage in networks relationship with a higher share of non-kin partners. This could be the result of hidden bargaining skills of ITV households that drive the choice of engaging with a 'further' economically rational node, instead of strengthening the exchanges with closer family members. On the other side, households lacking these negotiating or trading abilities might be more likely to pool their risk with family members simply because they are easily available and may solve problems more smoothly.

< INSERT TABLE 8 HERE >

In table 9 we report the heterogeneity analysis for the budget shares. Only the interaction term between ITV and RCI has a statistically significant effect: we observe a significant spill-over effect that decreases the budget share devoted to education, for household with looser social ties. This result points towards the hypothesis that non-kin social interactions are mainly devoted to economic and productive activities.

< INSERT TABLE 9 HERE >

We next analyse whether the program has spill-over effects for ITV with respect to the different food security dimensions, depending on the quality of their social networks. For this, we interact the program with the set of network indicators previously introduced and we report the results in Table 10. A positive and statistically significant association ($p<0.1$) is registered for the ITV*GBI interaction with respect to the adults' probability of going to sleep hungry and food scarcity for basic needs: in line with the results shown in Table 6, ITV households with a higher share of linkages with women counterparts are worse off. A weak negative relationship ($p<0.1$) is reported in column 8, when running a Poisson regression for the number of months in which households have sufficient food. The network deepness as well as the RCI interactions have a significant impact in few of our outcome variables. Surprisingly, the indirect effect of the program on households with a higher number of linkages is negative in terms of food insecurity perceptions. This effect is weakly evident in the meal dimensions for both adults and children as well as in the number of months' households experience food shortage. This result gives a clear indication of how networks' quality is much more relevant than density for ITVs. It is worth noting the inverse relationship between the RCI interaction and the number of months in which the household has sufficient food. Again, ITVs establishing networks of blood and kin are more protected against food insecurity.

Result for the GPI interaction go in the same direction, where positive spill-over effects are found for geographically closer linkages: the program influences positively ITV households whose linkages are in place in the same village. The coefficients - which are positive - show that the farther the two nodes are located, the higher the probability that adults go to sleep hungry. This finding confirms the idea that connections within villages where program's beneficiaries are located are crucial to improve ITV's standards of living. Ineligible households living in villages where the program is in action gain much more advantages from establishing links with eligible households with respect to ineligible households living in non-treated villages. This larger indirect exposure to the treatment could lead to an improvement of the relations within these extended families which will trigger an internal exchange of items, that in turn amplifies the effect of the program on food security insurance. The effect of proximity is particularly evident when it comes to indicators of children's food security (columns 4-6): three out of three GPI variables are positive and statistically significant, showing that the program has important spill-over effects for ITVs building their network of relationships in their own villages. Networks have thus a catalysing role for the program, in particular for other linked village members.

To check for the robustness of our results we disaggregate the GPI in two dummy variables, with the first one (*d_nwk_village*) assuming value equal to 1 if the household is predominantly linked with households located in the same village, and the second one (*d_nwk_neighvillage*) being equal to 1 if the share of household's linkages with households residing in neighbour villages is higher. In Table 11 we report pooled Logit and Poisson regressions for this new specification. Statistically significant results are found for the specifications reported in columns 4, 5 and 9, for the dependent variables "children eat small meals", "children eat fewer meals" and the number of months of "some food shortage" respectively. Village networks appear to decrease the probability of occurrence of such events for ITV, while no significant effects are apparent in specifications 4 and 9 for what concerns the interaction of ITV with neighbour villages, while we still observe a decrease in the probability of a child eating fewer meals.

< INSERT TABLES 10 and 11 HERE >

6. Conclusions

We investigated the presence of spillover effects of the Lesotho CGP program on the welfare and food security of households living in treated villages but not targeted by the transfer (ineligibles in treated villages, ITV). We postulated that the presence of a well-established quantitative and qualitative network architecture could have improved ITV livelihoods, following the hypothesis that in developing countries, social networks may often substitute for formal institutions: they can provide insurance, facilitate transactions and support the exchange of goods and services, which are roles commonly assumed to be fulfilled by markets. The network architecture of Lesotho's villages has low density, it is highly disconnected and shows a predominance of dyadic relationships. The network deepness is a strong predictor of consumption, with households who manage a higher number of connections being usually better-off. It also increases food security, reducing the probability of going to sleep hungry, especially for children.

Our findings suggest that the link between social networks and the Child Grant Program are successful in generating positive spillover effects for households living in treated villages but not benefiting of the transfers. For instance, positive spill-over effects on food security are found for ITV households whose linkages are geographically closer. Proximity, both geographical and relational, seems to be strongly tied to positive spillover on food security and access to food: ITV household that have the higher share of their network within the same villages, show a lower probability of food insecurity, both at child and household level. Our results also suggest that the program does not generate positive spill-over when the networks are tied mostly to women, which points towards a problem of social inclusion and cultural norms that should be addressed by further research.

To conclude, our findings highlight that ignoring the presence and characteristics of the extended family and social ties can lead to an incomplete understanding of the forces driving the behavioral responses of households to large scale policy interventions in developing country settings. In terms of their concrete relevance, albeit non definitive, the evidence highlighted in this work advises that program objectives aimed at increasing adults and in particular children livelihoods in environments largely suffering from resource constraints, should neatly combine social network theories into their agendas, and combine key opinion and informational leaders as agents of change. Indeed, our findings provide justification for the further development of a social network approach to food security promotion.

7. References

Adams, A. M., Madhavan, S., & Simon, D. (2002). Women's social networks and child survival in Mali. Social science & medicine, 54(2), 165-178.

Angelucci, M., De Giorgi, G. (2009). Indirect effects of an aid program: how do cash transfers affect ineligibles' consumption?. The American Economic Review, 486-508.

Angelucci, M., De Giorgi, G., Rangel, M. A., & Rasul, I. (2010). Family networks and school enrolment: Evidence from a randomized social experiment. Journal of Public Economics, 94(3), 197-221.

Angelucci, M., De Giorgi G., Rasul I. (2014). Resource pooling within family networks: Insurance and investment. Unpublished Manuscript

Akresh, R. (2005). "Risk, network quality, and family structure: Child fostering decisions in Burkina Faso."Discussion paper No. 902. Economic Growth Center, Yale University.

Asfaw, S., Covarrubias, K., Davis, B., Dewbre, J., Djebbari, H., Romeo, A. and Winters, P. (2012). Analytical Framework for Evaluating the Productive Impact of Cash Transfer Programmes on Household Behaviour: Methodological Guidelines for the From Protection to Production 15 Project. Paper prepared for the From Protection to Production project. Rome, UN Food and Agriculture Organization.

Attanasio, O., Pellerano, L., Reyes, S. P. (2009). Building Trust? Conditional Cash Transfer Programmes and Social Capital. *Fiscal Studies, 30 (2)*, 139–177

Baird, T. D., & Gray, C. L. (2014). Livelihood diversification and shifting social networks of exchange: a social network transition?. *World Development*, *60*, 14-30.

Baland, J. M., Platteau, J. P. (2000). Halting Degradation of Natural Resources: Is there a Role for Rural Communities? Oxford Univ. Press, Oxford.

Barca, V., Brook, S., Holland, J., Otulana, M., and Pozarny, P. (2014). Qualitative research and analyses of the economic impact of cash transfer programmes in Sub-Saharan Africa: Synthesis Report. PtoP project report, FAO, Rome

Beegle, K., Galasso, E., and Goldberg, J. (2015). Direct and indirect effects of Malawi's public works program on food security. S Public Works Program on Food Security (December 2, 2015). World Bank Policy Research Working Paper, (7505).

Caudell, M., Rotolo, T., & Grima, M. (2015). Informal lending networks in rural Ethiopia. Social Networks, 40, 34-42.

Coates, J., Swindale A., and Bilinsky P. (2007). Household Food Insecurity Access Scale (HFIAS) for Measurement of Household Food Access: Indicator Guide (v. 3). Washington, D.C.: Food and Nutrition Technical Assistance Project, Academy for Educational Development, August 2007.

Cox, D., & Fafchamps, M. (2007). Extended family and kinship networks: economic insights and evolutionary directions. Handbook of development economics, 4, 3711-3784.

Daidone, S., Davis, B., Dewbre, J., Covarrubias, K., (2014). Lesotho's Child Grant Programme: 24-month impact report on productive activities and labour allocation. FAO PtoP Report, FAO, Rome.

Daidone, S., Handa, S., Davis, B., Park, M., Osei, R.D. and Osei-Akoto, I. (2015). Social Networks and Risk Management in Ghana's Livelihood Empowerment Against Poverty Programme, Innocenti Working Paper No.2015-06, UNICEF Office of Research, Florence.

Ellsworth, L. (1989). "Mutual insurance and non-market transactions among farmers in Burkina Faso." Unpublished PhD thesis. University of Wisconsin, Madison, WI.

Fafchamps, M. (2003). Rural Poverty, Risk and Development. Edward Elgar Publishing, Cheltenham, UK.

Fafchamps, M., & Lund, S. (2003). Risk-sharing networks in rural Philippines. Journal of development Economics, 71(2), 261-287.

Fafchamps M. and Gubert F. (2007). The formation of risk sharing networks. Journal of Development Economics, 83, 326-350.

Fawcett, J. T. (1989). Networks, linkages, and migration systems. International migration review, 23(3), 671-680.

FAO (2015). The state of food and agriculture social protection and agriculture: breaking the cycle of rural poverty. Food and Agriculture Organization of the United Nations, Rome.

FAO, ILO, UNICEF (2019). Local Economy Impacts and Cost-Benefit Analysis of Social Protection and Agricultural Interventions in Malawi. Food and Agriculture Organization of the United Nations, Rome.

Filipski, M. J., Taylor, J. E., Thome, K. E., & Davis, B. (2015). Effects of treatment beyond the treated: a general equilibrium impact evaluation of Lesotho's cash grants program. Agricultural Economics, 46(2), 227-243.

Fischer, C., (1982). To Dwell Among Friends. University of California Press, Berkeley.

Goldtein M. (2002). Chop Time, No Friends: Intrahousehold and individual insurance mechanisms in Southern Ghana. Manuscript. London, UK: London School of Economics.

Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. American journal of sociology, 481-510.

Hanneman, R.A., Riddle, M., 2005. Introduction to Social Network Methods. University of California, Riverside. Published in digital form at http://faculty.ucr.edu/~hanneman/.

Hoddinott, J., Dercon, S., & Krishnan, P. (2009). Networks and informal mutual support in 15 Ethiopian villages. International Food Policy Research Institute (IFPRI).

Huber (1967). The behavior of maximum likelihood estimates under non-standard conditions. In Proceedings of the fifth Berkeley symposium on mathematical statistics and probability. Vol 1 Berkeley: University of California Press, pp. 221–33.

Kezdi (2004). Robust standard error estimation in fixed-effects panel models. Hungarian Statistical Review. Special(9):96–116.

Ligon, E., Thomas, Jonathan P., Worrall, Tim, (2000). Mutual insurance, individual savings, and limited commitment. Review of Economic Dynamics 3 (2), 216–246.

Ligon, E., Thomas, Jonathan P., Worrall, Tim, (2001). Informal insurance arrangements in village economies. Review of Economic Studies 69 (1), 209–244.

Lucas, R.E., Stark, O. (1985). "Motivations to remit: Evidence from Botswana". Journal of Political Economy 93, 901–918

Lund, S. (1996). "Credit and risk-sharing networks in the rural Philippines." Unpublished PhD thesis. Food Research Institute, Stanford University, Stanford, CA.

Moore, G., 1990. Structural determinants of men's and women's personal networks. American Sociological Review 55, 726–735

Moulton (1990) "An illustration of a pitfall in estimating the effects of aggregate variables on micro units." The Review of Economics and Statistics. 72(2):334–338.

Krishnan, P., Sciubba, E. (2004). "Endogenous network formation and informal institutions in village economies." Working paper in economics No. 462. University of Cambridge, UK.

Ksoll, C. (2007). Family networks and orphan caretaking in Tanzania. Mimeo. Economic Growth Center, Yale University, New Haven.

Kumar, N., Raghunathan, K., Arrieta, A., Jilani, A., Chakrabarti, S., Menon, P., & Quisumbing, A. R. (2019). Social networks, mobility, and political participation: The potential for women's self-help groups to improve access and use of public entitlement schemes in India. *World Development*, *114*, 28-41.

MacAuslan, I., Riemenschneider, N. (2011) "Richer but Resented: What do Cash Transfers do to Social Relations?" *IDS Bulletin, 42, (6)*, Special Issue: Social Protection for Social Justice, 60-66.

Manchin, M., & Orazbayev, S. (2018). Social networks and the intention to migrate. *World Development*, *109*, 360-374.

Oxford Policy Management (2014). Child Grants Programme Impact Evaluation. Follow-up Report. Oxford.

Palloni, A., Massey, D. S., Ceballos, M., Espinosa, K., & Spittel, M. (2001). Social capital and international migration: A test using information on family networks. *American Journal of Sociology*, *106*(5), 1262-1298.

Pellerano, L., Moratti, M., Jakobsen, M., Bajgar, M. and Barca, V. (2014). "Child Grants Programme Impact Evaluation: Follow-up Impact Report", Commissioned by UNICEF/FAO for the Government of Lesotho, Oxford Policy Management, March 2014

Prifti, E., Daidone, S., & Davis, B. (2019). Causal pathways of the productive impacts of cash transfers: Experimental evidence from Lesotho. *World Development*, 115, 258-268.

Regmi, A., Meade, B. (2013). "Demand side drivers of global food security", *Global Food Security* 2 (3), 166-171, ISSN 2211-9124.

Rosenzweig, M. R. and Oded S. (1989) "Consumption Smoothing, Migration, and Marriage: Evidence from Rural India, *Journal of Political Economy* 97(4): 905-926.

Strupat, C., & Klohn, F. (2018). Crowding out of solidarity? Public health insurance versus informal transfer networks in Ghana. *World Development*, *104*, 212-221.

Taylor, J. E. (2013). A Methodology for Local Economywide Impact Evaluation (LEWIE) of Cash Transfers, From Protection to Production Project Report, Rome: FAO

Thome, K., Filipski, M., Kagin, J., Taylor, J. E., Davis, B. (2013). Agricultural Spillover Effects of Cash Transfers: What Does LEWIE Have to Say? *American Journal of Agricultural Economics, 95 (5),* 1338–1344, https://doi.org/10.1093/ajae/aat039

Tiwari, S., Daidone, S., Ruvalcaba, M. A., Prifti, E., Handa, S., Davis, B., Niang, O., Pellerano, L., van Ufford, P. Q., Seidenfeld, D. (2016). Impact of cash transfer programs on food security and nutrition in sub-Saharan Africa: A cross-country analysis. *Global Food Security*, 11, 72–83

Townsend, R. M., (1994). Risk and insurance in village India. *Econometrica* 62 (3), 539–591.

Valli, E., Peterman, A., Hidrobo, M. (2018) "Economic Transfer and Social Cohesion and a Refugee-hosting Setting" Innocenti Working Paper WP-2018-10, UNICEF Office of Research Innocenti.

Tables and Figures

Table 1 – Baseline and follow-up sample sizes, by population group

	Baseline		
	Treatment	Control	Total
Eligible for CGP	747	739	1,486
Non Eligible for CGP	779	789	1,568
Total	1,526	1,528	3,054
	Follow-up		
	Treatment	Control	Total
Eligible for CGP	732	674	1,406
Non Eligible for CGP	401	405	806
Total	1,133	1,079	2,212

Table 2 – Variable list and descriptive Statistics.

	2011					2013				
Variables	N	mean	sd	min	max	N	mean	sd	min	max
HH Size (Adult Equivalents)	2142	3.88	1.88	0.5	12	2146	3.82	1.88	0.6	12
Head of HH age	2151	53.66	15.79	18	105	2151	54.65	15.84	13	99
Highest yrs of education in HH	2151	7.80	2.69	0	14	2151	8.09	2.60	0	14
Female headed HH	2151	0.45	0.50	0	1	2151	0.45	0.50	0	1
HH members <=5 yrs old	2151	0.76	0.89	0	6	2151	0.72	0.85	0	5
# Orphans living in HH	2151	1.06	1.33	0	7	2151	1.46	1.54	0	8
Per capita nominal consumption	2146	197.94	159.00	5.5	2238	2150	244.01	181.65	19.6	2291
Per capita nominal food consumption	2146	125.90	99.16	4.3	1044	2147	151.22	107.68	15.2	1124
Per capita nominal non food consumption	2146	72.04	81.65	0	1658	2147	92.91	101.78	0	1257
Share of food on total consumption	2151	0.65	0.15	0	1	2151	0.64	0.16	0	1
Cereals (% Exp)	2151	27.82	14.14	0	94	2151	29.42	14.61	0	100
Fruit (% Exp)	2151	0.62	2.04	0	31	2151	0.82	2.36	0	27
Vegetables (% Exp)	2151	13.41	11.56	0	77	2151	10.45	8.61	0	62
Share of non food cons. on total consumption	2151	0.35	0.15	0	1	2151	0.36	0.15	0	1
Health Care (% Exp)	2151	6.78	5.14	0	67	2151	6.99	4.95	0	37
Services (% Exp)	2151	0.36	1.74	0	30	2151	0.24	1.53	0	25
Education (% Exp)	2151	3.59	5.86	0	52	2151	5.93	8.08	0	57
FS: Adult eats small meals	2147	0.75	0.43	0	1	2147	0.73	0.44	0	1
FS: Adult eats fewer meals	2147	0.74	0.44	0	1	2147	0.72	0.45	0	1
FS: Adult sleeps hungry	2146	0.41	0.49	0	1	2147	0.38	0.49	0	1
FS: Child eats small meals	2001	0.64	0.48	0	1	1982	0.64	0.48	0	1
FS: Child eats fewer meal	2001	0.62	0.49	0	1	1982	0.60	0.49	0	1
FS: Child sleeps hungry	2000	0.30	0.46	0	1	1981	0.31	0.46	0	1
FS: HH Not enough food to meet needs	2149	0.82	0.39	0	1	2151	0.81	0.39	0	1
FS: # months HH sufficient food	2136	4.08	4.60	0	12	2151	3.53	4.66	0	12
FS: # some food shortage	2136	3.95	3.68	0	12	2151	4.27	4.03	0	12
FS: # extreme food shortage	2136	3.97	3.90	0	12	2151	4.19	4.22	0	12
Relationship Closeness Index (RCI)	2151	1.94	0.71	0	3	2151	2.06	0.74	0	3
Gender Balance Index (GBI)	2151	1.62	0.35	0	2	2151	1.65	0.36	0	2
Geographic Proximity Index (GPI)	2151	1.37	0.63	0	6	2151	1.37	0.76	0	6
Network deepness	2151	4.61	2.72	1	17	2151	3.93	2.41	1	18

Table 3 – Household Food Insecurity Access Scale (HFIAS) questions.

1. During the **last 3 months**, did you or any <u>adult</u> household member have to eat a <u>smaller meal</u> than you felt you needed because there was not enough food?
2. During the **last 3 months**, did you or any <u>adult</u> household member have to eat <u>fewer meals</u> in a day because there was not enough food?
3. During the **last 3 months**, did you or any <u>adult</u> household member go to sleep at night <u>hungry</u> because there was not enough food?
4. During the **last 3 months**, did any <u>child (0-17)</u> have to eat a <u>smaller meal</u> than s/he felt you needed because there was not enough food?
5. During the **last 3 months**, did any <u>child (0-17)</u> have to eat <u>fewer meals</u> in a day because there was not enough food?
6. During the **last 3 months**, did any <u>child (0-17)</u> go to sleep at night <u>hungry</u> because there was not enough food?
7. In the **last 12 months**, were there months in which you did not have enough food to meet your household's needs?
8. How was food availability in your household during each of the **last 12 months**? Was it sufficient, in some shortage, or in extreme shortage?

Table 4 – Impact of CGP program on non-eligibles – Social Networks (% of Households receiving food, labour, agricultural inputs)

	Food		Food *wv*		Labour	
	b/se	BL	b/se	BL	b/se	BL
DiD	0.163***	0.685***	0.179***	0.656***	-0.033	0.148
	[0.06]		[0.06]		[0.04]	
N	1594		1594		1594	

	Labour *wv*		Agricultural Input		Agricultural Input *wv*	
	b/se	BL	b/se	BL	b/se	BL
DiD	-0.029	0.144	0.061	0.381	0.056	0.375
	[0.05]		[0.06]		[0.06]	
N	1594		1594		1594	

***, **, * indicate respectively significance at p<0.01, <0.05, <0.1 levels, while *wv* is the acronym for *within village*.
Estimations use difference-in-difference modelling among panel households. B refers to baseline mean value of indicator shown in the preceding column. All estimations control for household demographic composition, head of household characteristics, district dummies and vectors of prices, wages and shock variables. Robust standard errors clustered at the community level are recorded in parentheses. Full estimates are available on request.

Table 5 – Spillover effects of CGP on total, food and non-food consumption

Variables:	Ln Consumption (per capita)	Ln Food Consumption (per capita)	Ln Non Food Consumption (per capita)
	CRE	CRE	CRE
Sample:	(1)	(2)	(3)
Ineligibles in Treated Villages (ITV)	-0.195***	-0.126**	-0.281***
	[-4.69]	[-2.72]	[-4.68]
Treatment Areas	0.052*	0.010	0.169***
	[2.15]	[0.39]	[4.82]
Ineligibles	0.242***	0.185***	0.389***
	[9.35]	[6.71]	[10.42]
Network deepness	0.054***	0.043***	0.076***
	[11.23]	[8.00]	[10.91]
RCI	-0.035[+]	-0.023	-0.026
	[-1.78]	[-1.06]	[-0.90]
GBI	-0.081*	-0.083*	-0.050
	[-2.21]	[-2.05]	[-0.94]
GPI	-0.014	-0.010	0.017
	[-0.72]	[-0.48]	[0.61]
Ln HH Size (Adult Equivalents)	-0.460***	-0.405***	-0.450***
	[-12.58]	[-9.98]	[-8.54]
Ln Age HH head	0.221*	0.265**	0.139
	[2.51]	[2.72]	[1.09]
highest yrs of education in hh	0.024**	0.013	0.049***
	[2.86]	[1.42]	[4.08]
female headed hh	-0.057	-0.039	-0.093
	[-0.99]	[-0.60]	[-1.12]
hh members <=5 yrs old	-0.031	-0.018	-0.057[+]
	[-1.52]	[-0.80]	[-1.93]
# orphans living in hhld	0.003	0.003	-0.004
	[0.47]	[0.35]	[-0.34]
Price Controls	[Yes]	[Yes]	[Yes]
Wage Controls	[Yes]	[Yes]	[Yes]
Shocks Controls	[Yes]	[Yes]	[Yes]
Year	[Yes]	[Yes]	[Yes]
Observations	4302	4302	4302
R^2	0.366	0.278	0.333
rho	0.100	0.064	0.100

***, **, *, + indicate respectively significance at p<0.001, <0.01, <0.05, <0.1 levels, t statistics in parenthesis.
All estimations control for household demographic composition, head of household characteristics, vectors of prices, wages and shock variables.
Robust standard errors clustered at the community level are used for the analysis, t-statistics are included in parentheses. Full estimates are available on request.

Table 6 – Spillover effects of CGP on food and non-food budget shares

Variables:	Food				Non Food			
	share of food on total consumption	Cereals (% Exp)	Fruit (% Exp)	Vegetables (% Exp)	share of non food on total consumption	Health Care (% Exp)	Services (% Exp)	Education (% Exp)
	CRE	**CRE**	**CRE**	**CRE**	**CRE**	**CRE**	**CRE**	**CRE**
Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ineligibles in Treated Villages (ITV)	0.033**	3.557***	-0.125	3.093***	-0.033**	-0.253	-0.136	-1.782***
	[2.95]	[3.32]	[-0.70]	[3.82]	[-2.99]	[-0.65]	[-1.03]	[-3.55]
Treatment Areas	-0.032***	-1.646**	-0.010	-1.057*	0.031***	0.114	0.153*	0.757*
	[-4.99]	[-2.71]	[-0.11]	[-2.40]	[4.87]	[0.53]	[2.10]	[2.41]
Ineligibles	-0.035***	-4.081***	0.223*	-1.545***	0.039***	-0.295	0.099	0.252
	[-5.10]	[-6.33]	[2.20]	[-3.30]	[5.75]	[-1.28]	[1.29]	[0.76]
Network deepness	-0.005***	-0.473***	0.083***	-0.572***	0.006***	-0.064	0.018	-0.040
	[-4.18]	[-3.81]	[4.00]	[-6.10]	[4.43]	[-1.41]	[1.18]	[-0.68]
RCI	0.002	-0.741	0.010	0.765*	0.000	-0.302	-0.033	0.131
	[0.35]	[-1.46]	[0.12]	[2.00]	[0.05]	[-1.63]	[-0.52]	[0.55]
GBI	-0.003	1.477	0.158	0.002	0.005	-0.217	0.033	0.274
	[-0.32]	[1.56]	[1.00]	[0.00]	[0.52]	[-0.63]	[0.29]	[0.62]
GPI	-0.006	-1.009*	0.021	-0.458	0.004	0.123	0.006	-0.235
	[-1.17]	[-2.06]	[0.26]	[-1.24]	[0.82]	[0.69]	[0.10]	[-1.02]
Ln HH Size (Adult Equivalents)	0.026**	2.329*	0.047	0.866	0.007	-0.361	0.069	0.716
	[2.58]	[2.47]	[0.30]	[1.22]	[0.69]	[-1.05]	[0.60]	[1.63]
Ln Age HH head	0.026	-1.388	1.007**	-2.176	-0.032	-0.660	-0.125	0.208
	[1.09]	[-0.61]	[2.67]	[-1.27]	[-1.34]	[-0.80]	[-0.45]	[0.20]
highest yrs of education in hh	-0.007**	-0.278	0.048	-0.395*	0.005*	0.207**	0.001	0.356***
	[-2.89]	[-1.28]	[1.33]	[-2.42]	[2.42]	[2.62]	[0.06]	[3.52]
female headed hh	0.012	0.498	-0.242	0.608	-0.006	-0.082	0.227	-0.375
	[0.74]	[0.33]	[-0.98]	[0.54]	[-0.42]	[-0.15]	[1.24]	[-0.54]
hh members <=5 yrs old	0.006	0.287	0.015	-0.228	-0.009+	-0.116	-0.066	0.084
	[1.09]	[0.54]	[0.17]	[-0.57]	[-1.69]	[-0.61]	[-1.02]	[0.34]
# orphans living in hhld	0.001	-0.110	0.039	0.237+	-0.001	0.070	0.029	-0.116
	[0.41]	[-0.60]	[1.29]	[1.72]	[-0.54]	[1.05]	[1.29]	[-1.36]
Price Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Wage Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Shocks Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Year	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Observations	4302	4302	4302	4302	4302	4302	4302	4302
r2_o	0.162	0.154	0.060	0.095	0.164	0.104	0.041	0.163
rho	0.067	0.067	0.011	0.030	0.070	0.050	0.044	0.167

***, **, *, + indicate respectively significance at p<0.001, <0.01, <0.05, <0.1 levels, t statistics in parenthesis.
All estimations control for household demographic composition, head of household characteristics, vectors of prices, wages and shock variables.
Robust standard errors clustered at the community level are used for the analysis, t-statistics are included in parentheses. Full estimates are available on request.

Table 7 - Spillover effects of CGP on food security dimensions

Variables:	Adults			Children			Households			
	Adults eat small meals	Adults eat fewer meals	Adults sleeps hungry	Child eat small meals	Child eat fewer meal	Child sleeps hungry	HH Not enough food to meet needs	# months HH sufficient food	# some food shortage	# extreme food shortage
	Pooled logit	Pooled logit	Pooled logit	Pooled logit	Pooled logit	Pooled logit	Pooled logit	Poisson	Poisson	Poisson
Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ineligibles in Treated Villages (ITV)	0.697***	0.764***	0.883***	0.586***	0.745***	0.706***	0.801***	-0.212***	0.053	0.231***
	[4.10]	[4.44]	[4.85]	[3.46]	[4.41]	[3.47]	[4.08]	[-6.35]	[1.57]	[6.40]
Treatment Areas	-0.525***	-0.536***	-0.456***	-0.418***	-0.546***	-0.411***	-0.502***	0.127***	-0.009	-0.115***
	[-5.03]	[-5.01]	[-4.31]	[-4.43]	[-5.80]	[-3.94]	[-4.02]	[6.70]	[-0.49]	[-6.56]
Ineligibles	-1.027***	-1.185***	-1.042***	-0.869***	-0.929***	-0.792***	-1.256***	0.466***	-0.137***	-0.378***
	[-9.57]	[-10.66]	[-8.90]	[-8.56]	[-9.17]	[-6.58]	[-9.78]	[25.17]	[-7.09]	[-18.55]
Network deepness	0.023	0.011	-0.088***	-0.007	-0.028+	-0.122***	0.010	0.009**	0.023***	-0.034***
	[1.31]	[0.64]	[-5.03]	[-0.45]	[-1.77]	[-6.49]	[0.48]	[3.04]	[7.66]	[-10.35]
RCI	0.105+	0.090	0.126*	0.141*	0.132*	0.060	0.058	-0.063***	0.039***	0.019
	[1.65]	[1.39]	[1.98]	[2.37]	[2.23]	[0.93]	[0.78]	[-5.34]	[3.40]	[1.64]
GBI	0.115	0.117	0.172	0.078	0.046	0.172	0.052	-0.057*	-0.084***	0.132***
	[0.96]	[0.96]	[1.41]	[0.69]	[0.41]	[1.38]	[0.36]	[-2.56]	[-3.82]	[5.96]
GPI	-0.094	-0.109+	0.017	-0.082	-0.109+	0.023	-0.048	0.001	-0.008	0.007
	[-1.54]	[-1.74]	[0.27]	[-1.40]	[-1.86]	[0.36]	[-0.67]	[0.08]	[-0.66]	[0.62]
Ln HH Size (Adult Equivalents)	0.508***	0.447***	0.363***	0.516***	0.502***	0.455***	0.513***	-0.203***	0.029	0.175***
	[5.51]	[4.74]	[3.69]	[5.40]	[5.30]	[4.13]	[4.78]	[-12.28]	[1.69]	[9.93]
Ln Age HH head	-0.518***	-0.611***	-0.692***	-0.462***	-0.535***	-0.631***	-0.372*	0.129***	-0.008	-0.141***
	[-3.51]	[-4.02]	[-4.56]	[-3.37]	[-3.92]	[-4.13]	[-2.12]	[4.89]	[-0.33]	[-5.52]
highest yrs of education in hh	0.125***	0.119***	0.145***	0.117***	0.099***	0.121***	0.154***	0.067***	0.001	-0.069***
	[-7.10]	[-6.62]	[-7.74]	[-6.86]	[-5.84]	[-6.23]	[-7.42]	[21.35]	[0.29]	[-21.75]
female headed hh	0.536***	0.521***	0.246*	0.567***	0.574***	0.332***	0.587***	-0.244***	0.115***	0.117***
	[5.50]	[5.23]	[2.49]	[6.29]	[6.43]	[3.36]	[5.00]	[-13.80]	[6.98]	[7.03]
hh members <=5 yrs old	0.087	0.084	0.146**	-0.003	-0.022	-0.097+	0.143*	-0.049***	0.023*	0.015
	[1.52]	[1.43]	[2.64]	[-0.06]	[-0.45]	[-1.77]	[2.04]	[-4.61]	[2.45]	[1.57]
# orphans living in hhld	0.024	0.050	0.020	0.051+	0.060*	0.030	0.047	-0.002	-0.004	0.005
	[0.72]	[1.47]	[0.66]	[1.75]	[2.06]	[0.97]	[1.16]	[-0.36]	[-0.60]	[0.93]
Price Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Wage Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Shocks Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Year	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Observations	4294	4294	4293	3983	3983	3981	4300	4287	4287	4287
rho	0.188	0.224	0.317	0.148	0.152	0.220	0.271	0.148	0.113	0.153

***, **, *, + indicate respectively significance at p<0.001, <0.01, <0.05, <0.1 levels, t statistics in parenthesis.
All estimations control for household demographic composition, head of household characteristics, vectors of prices, wages and shock variables.
Robust standard errors clustered at the community level are used for the analysis, t-statistics are included in parentheses. Full estimates are available on request.

Table 8 – Heterogeneity analysis – Consumption

Variables:	Ln Consumption (per capita)	Ln Food Consumption (per capita)	Ln Non Food Consumption (per capita)
	CRE	CRE	CRE
Sample:	(1)	(2)	(3)
Ineligibles in Treated Villages (ITV)	-0.171	-0.108	-0.014
	[-0.77]	[-0.44]	[-0.04]
Treatment Areas	0.053*	0.011	0.171***
	[2.19]	[0.43]	[4.85]
Ineligibles	0.242***	0.186***	0.389***
	[9.38]	[6.73]	[10.42]
Network deepness	0.050***	0.039***	0.070***
	[9.87]	[7.04]	[9.66]
RCI	-0.037	-0.028	-0.022
	[-1.81]	[-1.23]	[-0.74]
GBI	-0.036	-0.043	0.009
	[-0.92]	[-1.01]	[0.16]
GPI	-0.022	-0.016	0.011
	[-1.07]	[-0.73]	[0.38]
ITV * GBI	-0.182+	-0.183	-0.271+
	[-1.72]	[-1.58]	[-1.79]
ITV * GPI	0.059	0.045	0.038
	[1.12]	[0.77]	[0.51]
ITV * RCI	0.104+	0.110+	0.059
	[1.92]	[1.84]	[0.75]
ITV * Network deepness	0.014	0.014	0.023
	[0.88]	[0.80]	[1.00]
Ln HH Size (Adult Equivalents)	-0.464***	-0.406***	-0.455***
	[-12.54]	[-9.97]	[-8.56]
Ln Age HH head	0.252**	0.290**	0.176
	[2.84]	[2.97]	[1.38]
highest yrs of education in hh	0.028**	0.016+	0.054***
	[3.28]	[1.76]	[4.42]
female headed hh	-0.066	-0.046	-0.102
	[-1.13]	[-0.71]	[-1.21]
hh members <=5 yrs old	-0.037+	-0.022	-0.063*
	[-1.79]	[-0.98]	[-2.13]
# orphans living in hhld	0.009	0.007	0.003
	[1.24]	[0.89]	[0.26]
Price Controls	[Yes]	[Yes]	[Yes]
Wage Controls	[Yes]	[Yes]	[Yes]
Shocks Controls	[Yes]	[Yes]	[Yes]
Year	[Yes]	[Yes]	[Yes]
Observations	4302	4302	4302
R^2	0.363	0.278	0.330
Rho	0.089	0.058	0.094

***, **, *, + indicate respectively significance at p<0.001, <0.01, <0.05, <0.1 levels, t statistics in parenthesis.
All estimations control for household demographic composition, head of household characteristics, vectors of prices, wages and shock variables. Robust standard errors clustered at the community level are used for the analysis, t-statistics are included in parentheses. Full estimates are available on request.

Table 9 – Heterogeneity Analysis - Budget Share

Variables:	share of food on total cons.	Cereals (% Exp)	Fruit (% Exp)	Vegetables (% Exp)	share of non food on total cons.	Health Care (% Exp)	Services (% Exp)	Education (% Exp)
	CRE	CRE	CRE	CRE	CRE	CRE	CRE	CRE
Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ineligibles in Treated Villages (ITV)	0.002	5.455	-0.340	1.646	-0.005	2.828	0.379	0.281
	[0.03]	[0.96]	[-0.36]	[0.38]	[-0.09]	[1.37]	[0.54]	[0.11]
Treatment Areas	-0.032***	-1.664**	-0.011	-1.051*	0.031***	0.109	0.152*	0.755*
	[-5.00]	[-2.74]	[-0.12]	[-2.38]	[4.87]	[0.50]	[2.09]	[2.41]
Ineligibles	-0.035***	-4.086***	0.223*	-1.543***	0.039***	-0.296	0.099	0.252
	[-5.10]	[-6.34]	[2.20]	[-3.29]	[5.75]	[-1.28]	[1.28]	[0.76]
Network deepness	-0.005***	-0.527***	0.088***	-0.543***	0.005***	-0.069	0.022	-0.080
	[-3.68]	[-4.07]	[4.10]	[-5.54]	[3.96]	[-1.47]	[1.38]	[-1.32]
RCI	-0.000	-0.616	-0.007	0.753$^+$	0.002	-0.261	-0.049	0.356
	[-0.04]	[-1.17]	[-0.08]	[1.89]	[0.41]	[-1.36]	[-0.76]	[1.44]
GBI	-0.005	1.699$^+$	0.159	-0.379	0.007	-0.051	0.046	0.345
	[-0.51]	[1.71]	[0.96]	[-0.50]	[0.64]	[-0.14]	[0.37]	[0.74]
GPI	-0.006	-0.878$^+$	-0.007	-0.585	0.004	0.170	0.020	-0.153
	[-1.14]	[-1.71]	[-0.08]	[-1.50]	[0.80]	[0.91]	[0.32]	[-0.63]
ITV * GBI	0.002	0.018	-0.129	0.293	-0.001	-1.156	-0.351	1.238
	[0.06]	[0.01]	[-0.29]	[0.14]	[-0.03]	[-1.18]	[-1.06]	[0.98]
ITV * GPI	0.002	-1.144	0.237	1.199	-0.001	-0.447	-0.123	-0.724
	[0.11]	[-0.85]	[1.06]	[1.18]	[-0.08]	[-0.92]	[-0.75]	[-1.15]
ITV * RCI	0.013	-0.341	0.103	-1.044	-0.013	-0.290	0.057	-1.360*
	[0.89]	[-0.25]	[0.45]	[-0.99]	[-0.92]	[-0.57]	[0.33]	[-2.09]
ITV * Network deepness	-0.002	0.281	-0.041	0.080	0.002	0.031	0.005	0.104
	[-0.38]	[0.70]	[-0.62]	[0.26]	[0.39]	[0.21]	[0.11]	[0.55]
Ln HH Size (Adult Equivalents)	0.026**	2.330*	0.042	0.849	0.006	-0.363	0.079	0.673
	[2.63]	[2.47]	[0.27]	[1.19]	[0.62]	[-1.06]	[0.68]	[1.52]
Ln Age HH head	0.023	-0.985	0.970*	-2.709	-0.029	-0.599	-0.162	0.566
	[0.96]	[-0.43]	[2.57]	[-1.58]	[-1.25]	[-0.73]	[-0.58]	[0.53]
highest yrs of education in hh	-0.007**	-0.248	0.047	-0.444**	0.006*	0.215**	-0.001	0.379***
	[-2.99]	[-1.14]	[1.29]	[-2.70]	[2.49]	[2.72]	[-0.03]	[3.72]
female headed hh	0.012	0.424	-0.237	0.766	-0.007	-0.098	0.231	-0.420
	[0.76]	[0.28]	[-0.96]	[0.68]	[-0.43]	[-0.18]	[1.26]	[-0.60]
hh members <=5 yrs old	0.007	0.208	0.022	-0.124	-0.010$^+$	-0.121	-0.057	0.011
	[1.19]	[0.39]	[0.25]	[-0.31]	[-1.76]	[-0.63]	[-0.88]	[0.04]
# orphans living in hhld	0.000	-0.055	0.036	0.154	-0.001	0.078	0.023	-0.063
	[0.18]	[-0.30]	[1.18]	[1.12]	[-0.36]	[1.18]	[1.01]	[-0.74]
Price Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Wage Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Shocks Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Year	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Observations	4302	4302	4302	4302	4302	4302	4302	4302
r2_o	0.161	0.154	0.062	0.091	0.164	0.105	0.041	0.160
Rho	0.065	0.066	0.009	0.025	0.069	0.050	0.043	0.161

***, **, *, + indicate respectively significance at p<0.001, <0.01, <0.05, <0.1 levels, t statistics in parenthesis.
All estimations control for household demographic composition, head of household characteristics, vectors of prices, wages and shock variables.
Robust standard errors clustered at the community level are used for the analysis, t-statistics are included in parentheses. Full estimates are available on request.

Table 10 – Heterogeneity Analysis – Food Security

Variables:	Adults			Children			Households			
	Adult eats small meals	Adult eats fewer meals	Adult sleeps hungry	Child eats small meals	Child eats fewer meal	Child sleeps hungry	HH Not enough food to meet needs	# months HH sufficient food	# some food shortage	# extreme food shortage
	Pooled logit	**Pooled logit**	**Pooled logit**	**Pooled logit**	**Pooled logit**	**Pooled logit**	**Pooled logit**	**Poisson**	**Poisson**	**Poisson**
Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ineligibles in Treated Villages	-0.214	0.038	-1.047	-0.665	-0.812	-1.531	-0.350	0.010	-0.095	0.090
	[-0.28]	[0.05]	[-1.17]	[-0.84]	[-1.03]	[-1.48]	[-0.40]	[0.07]	[-0.60]	[0.54]
Treatment Areas	-0.497***	-0.502***	-0.422***	-0.396***	-0.510***	-0.389***	-0.489***	0.135***	-0.019	-0.113***
	[-4.80]	[-4.77]	[-4.04]	[-4.24]	[-5.50]	[-3.76]	[-3.97]	[7.25]	[-1.07]	[-6.44]
Ineligibles	-1.001***	-1.149***	-1.003***	-0.841***	-0.887***	-0.769***	-1.241***	0.471***	-0.146***	-0.375***
	[-9.41]	[-10.52]	[-8.69]	[-8.38]	[-8.88]	[-6.44]	[-9.78]	[25.65]	[-7.62]	[-18.47]
Network deepness	0.015	0.007	-0.080***	-0.013	-0.026	-0.116***	0.011	0.013***	0.022***	-0.036***
	[0.82]	[0.41]	[-4.48]	[-0.77]	[-1.62]	[-6.03]	[0.54]	[4.07]	[6.90]	[-10.54]
RCI	0.117+	0.103	0.106	0.138*	0.117+	0.021	0.063	-0.074***	0.045***	0.021
	[1.74]	[1.51]	[1.61]	[2.23]	[1.91]	[0.32]	[0.79]	[-5.92]	[3.76]	[1.79]
GBI	0.084	0.062	0.083	0.059	-0.007	0.125	-0.043	-0.045+	-0.088***	0.124***
	[0.65]	[0.48]	[0.65]	[0.50]	[-0.06]	[0.97]	[-0.29]	[-1.89]	[-3.79]	[5.36]
LPI	-0.133*	-0.124+	-0.027	-0.140*	-0.163**	-0.028	-0.059	0.008	-0.016	0.007
	[-2.05]	[-1.88]	[-0.40]	[-2.24]	[-2.62]	[-0.40]	[-0.78]	[0.66]	[-1.23]	[0.61]
ITV * GBI	0.159	0.311	0.755+	0.130	0.404	0.508	0.696+	-0.117+	0.103	0.059
	[0.44]	[0.85]	[1.84]	[0.35]	[1.09]	[1.09]	[1.68]	[-1.67]	[1.39]	[0.75]
ITV * GPI	0.324+	0.139	0.396*	0.513**	0.473*	0.519*	0.100	-0.062+	0.063+	-0.001
	[1.74]	[0.77]	[2.01]	[2.69]	[2.56]	[2.42]	[0.49]	[-1.72]	[1.78]	[-0.02]
ITV * RCI	-0.152	-0.182	0.060	-0.075	-0.030	0.348	-0.061	0.075*	-0.036	-0.041
	[-0.79]	[-0.94]	[0.29]	[-0.39]	[-0.15]	[1.45]	[-0.28]	[2.08]	[-0.93]	[-1.01]
ITV * Network deepness	0.106+	0.072	-0.030	0.096+	0.040	-0.033	-0.007	-0.031**	0.001	0.030*
	[1.85]	[1.26]	[-0.48]	[1.73]	[0.73]	[-0.46]	[-0.11]	[-2.89]	[0.09]	[2.52]
Ln HH Size (Adult Equivalents)	0.509***	0.450***	0.375***	0.516***	0.509***	0.466***	0.521***	-0.200***	0.025	0.176***
	[5.50]	[4.78]	[3.83]	[5.41]	[5.39]	[4.23]	[4.85]	[-12.07]	[1.46]	[9.93]
Ln Age HH head	-0.529***	-0.620***	-0.707***	-0.476***	-0.551***	-0.641***	-0.384*	0.129***	-0.007	-0.140***
	[-3.58]	[-4.09]	[-4.69]	[-3.48]	[-4.06]	[-4.20]	[-2.19]	[4.87]	[-0.28]	[-5.50]
highest yrs of education in hh	-0.127***	-0.121***	-0.147***	-0.119***	-0.101***	-0.122***	-0.155***	0.066***	0.002	-0.069***
	[-7.18]	[-6.74]	[-7.88]	[-6.95]	[-5.99]	[-6.32]	[-7.47]	[21.23]	[0.65]	[-21.89]
female headed hh	0.542***	0.522***	0.249*	0.572***	0.575***	0.333***	0.587***	-0.244***	0.115***	0.117***
hh members <=5 yrs old	0.091	0.087	0.150**	0.000	-0.018	-0.094+	0.144*	-0.048***	0.022*	0.015
	[1.58]	[1.50]	[2.72]	[0.00]	[-0.36]	[-1.72]	[2.06]	[-4.51]	[2.35]	[1.56]
# orphans living in hhld	0.016	0.040	0.011	0.045	0.049+	0.026	0.044	-0.004	-0.001	0.004
	[0.47]	[1.20]	[0.38]	[1.53]	[1.72]	[0.85]	[1.10]	[-0.58]	[-0.15]	[0.75]
Price Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Wage Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Shocks Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Year	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Observations	4294	4294	4293	3983	3983	3981	4300	4287	4287	4287
rho	0.190	0.219	0.310	0.145	0.146	0.216	0.209			

***, **, *, + indicate respectively significance at p<0.001, <0.01, <0.05, <0.1 levels, t statistics in parenthesis.
All estimations control for household demographic composition, head of household characteristics, vectors of prices, wages and shock variables.
Robust standard errors clustered at the community level are used for the analysis, t-statistics are included in parentheses. Full estimates are available on request.

Table 11 – Heterogeneous impact of disaggregated GPI

Variables:	Adults			Children			Households			
	Adult eat small meals	Adult eat fewer meals	Adult sleeps hungry	Child eat small meals	Child eat fewer meal	Child sleeps hungry	HH Not enough food to meet needs	# months HH sufficient food	# some food shortage	# extreme food shortage
	Pooled logit	**Pooled logit**	**Pooled logit**	**Pooled logit**	**Pooled logit**	**Pooled logit**	**Pooled logit**	**Poisson**	**Poisson**	**Poisson**
Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ITV * d_nwkvillage	-0.426	-0.190	-0.414	-0.889*	-0.912*	-0.584	0.213	0.180[+]	-0.249*	0.037
	[-1.14]	[-0.52]	[-1.13]	[-2.26]	[-2.34]	[-1.39]	[0.54]	[1.74]	[-2.24]	[0.31]
ITV * d_nwkneighvill	-0.357	-0.225	-0.215	-0.705	-1.057*	-0.701	0.448	0.036	-0.203[+]	0.164
	[-0.81]	[-0.52]	[-0.50]	[-1.50]	[-2.28]	[-1.34]	[0.91]	[0.30]	[-1.67]	[1.26]
Household Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Price Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Wage Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Shocks Controls	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Year	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]	[Yes]
Observations	4294	4294	4293	3983	3983	3981	4300	4287	4287	4287

***, **, *, + indicate respectively significance at p<0.001, <0.01, <0.05, <0.1 levels, t statistics in parenthesis.
All estimations control for household demographic composition, head of household characteristics, vectors of prices, wages and shock variables. Robust standard errors clustered at the community level are used for the analysis, t-statistics are included in parentheses. Full estimates are available on request.

Figure 1 – Measure of importance of eligible/ineligible households among treated and control: in-degree centrality.
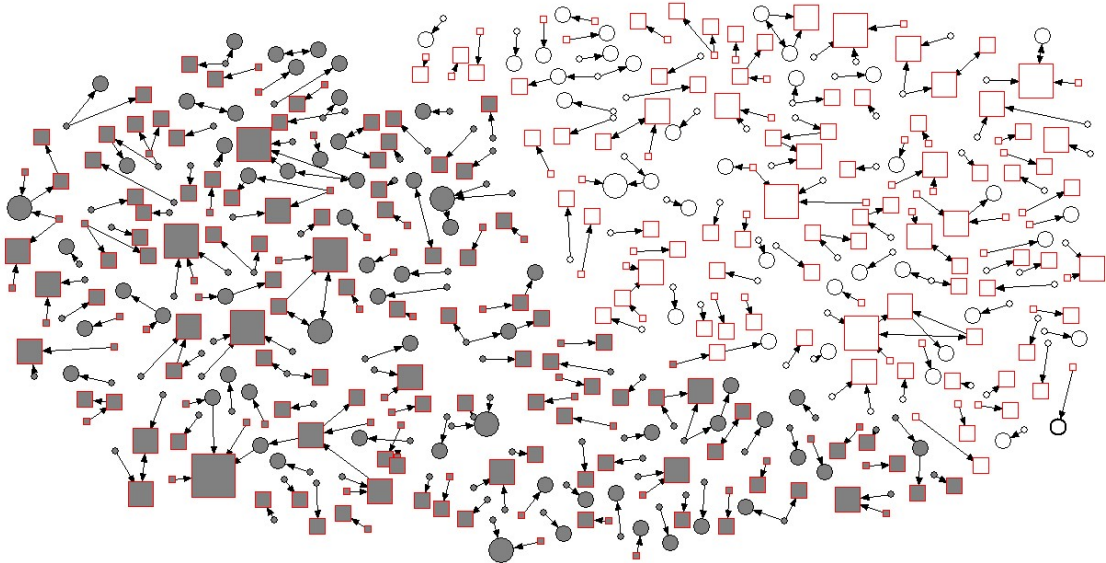
Note: Grey nodes represent treated households while white nodes represent control households. Squares and circles denote ineligible and eligible households respectively. Node size provides a measure of importance of eligible/ineligible households among treated and control (in-degree centrality).

Figure 2 – Expenditure and consumption variation (2011-2013), by treatment status.

EXPENDITURE AND CONSUMPTION VARIATION (2011-2013)
BY TREATMENT STATUS

■ Δ Overall   ■ Δ ineligibles   ■ Δ Eligibles   ◣ Δ Eligibles C   ▨ Δ Eligibles T
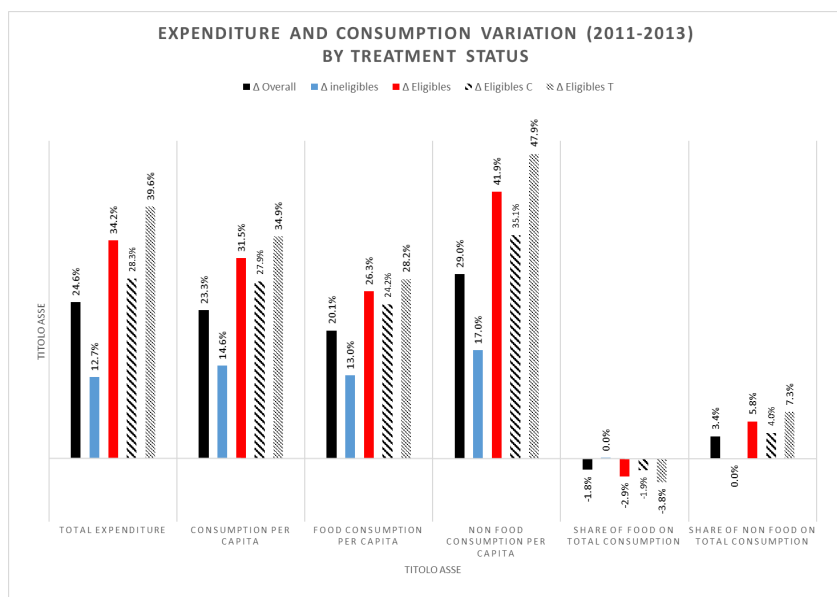
Annex A

A.1. Network characteristics

When describing networks, studies like Fafchamps and Lund (2003) or Hoddinott *et al.* (2009) have been largely reliant on egocentric data, which provide information on only those individuals/households establishing a direct tie to individuals/households responding to the questionnaire. In this paper we consider a different framework, where the respondents are directly and/or indirectly tied with each other. This helps providing much more reliable data on individuals' connectedness and at the same time a much more complete explanation of their integration within a particular network (Granovetter, 1985). Based on the social network theory, the primary aim of this section is to provide a qualitative characterization of the different types of connections among the households populating of our sample. Figure 1 displays the Lesotho CGP networks map, consisting of 535 nodes and 333 ties. We plot only households with available information on eligibility and treatment status, while connections involving households without any information associated and relative nodes have been suppressed. The network map gives a snapshot of the network architecture of households involved in money transfers at baseline[9]. Treated households consisted of 312 nodes and 195 arcs, while control households consisted of 224 nodes and 138 arcs. We focused on the single large component and we coded nodes by the individual treatment status, eligibility and in-degree network. Grey nodes represent treated households while white nodes represent control households. As a result of the randomization process, defined at community level, it is fairly evident that treated and control households are perfectly divided in two groups that do not communicate between each other. Squares and circles denote ineligible and eligible households respectively. Node size provides a measure of importance of eligible/ineligible households among treated and control (in-degree centrality). It is weighted by the number of in-degree connections: the bigger the node, the larger the number of ties directed towards it. Aggregate properties of the network like the degree distribution (in-degree and out-degree centrality) are relevant to study the network robustness. In both sub-samples (treatment and control) the majority of households show low degree centrality (positively skewed degree distribution) meaning that they contribute little to network connectivity (see Figure A1). The highest number of nodes shows a null or 1-degree connection, and only 1.6-1.8% of nodes receives more than two ties. Among them the vast majority is associated to ineligible households for both treated and control villages. This low in-degree centrality is confirmed by the index of network density reported in table 1. Neither treated nor control villages show a dense network. Density, which is defined as the sum of the values of all ties divided by the number of possible (not actual) ties, is very low in both groups. This means that there is a large proportion of isolated and dyadic connected agents. Being *A* and *B* two nodes representing two different agents within a certain network, there are four possible dyadic relationships: *A* and *B* are not linked (null), *A* sends to *B*, *A* sends to *B* (asymmetric) or *A* and *B* send to each other (reciprocal) (Hanneman and Riddle, 2005). A network showing a prevalence of null or reciprocated ties over asymmetric relations can be a more stable network with respect to one with a predominance of asymmetric connections. We see that of all pairs of actors showing any connection, around 5% of the pairs have a reciprocated connection, which represents a very low degree of horizontal connection. We also provide a rough measure of the average degree of separation among pairs by calculating the average shortest path (geodesic distance), which helps to capture how cohesive and connected the network is (Wasserman and Faust, 1995)[10]. The geodesic distance is higher for the control sub-sample (17.4) than for the treatment one (10.6), showing a higher cohesion for the former.

---

[10] It is worth noting that this measurement would have highly benefited of a clustering at village level, which would have yielded more precise estimates

Table A1 – Network characteristics

	Treatment	**Control**	**Total**
Summary:			
Nodes	312	224	535
Arcs	195	138	333
Density	0.002	0.003	0.001
Dyads:			
Mutual	9	7	16
Asymmetric	177	126	303
Null	48330	24843	142525
Reciprocity	0.051	0.053	0.052
Geodesic Distance:			
Number of Paths	90	30	90
Diameter	5	4	5
Avg Shortest Path	10.6	17.4	16.4

Note: These values refer to the plotted network which entails only actors with available associated information.

Figure A1 – Degree Distribution for treatment and control groups.
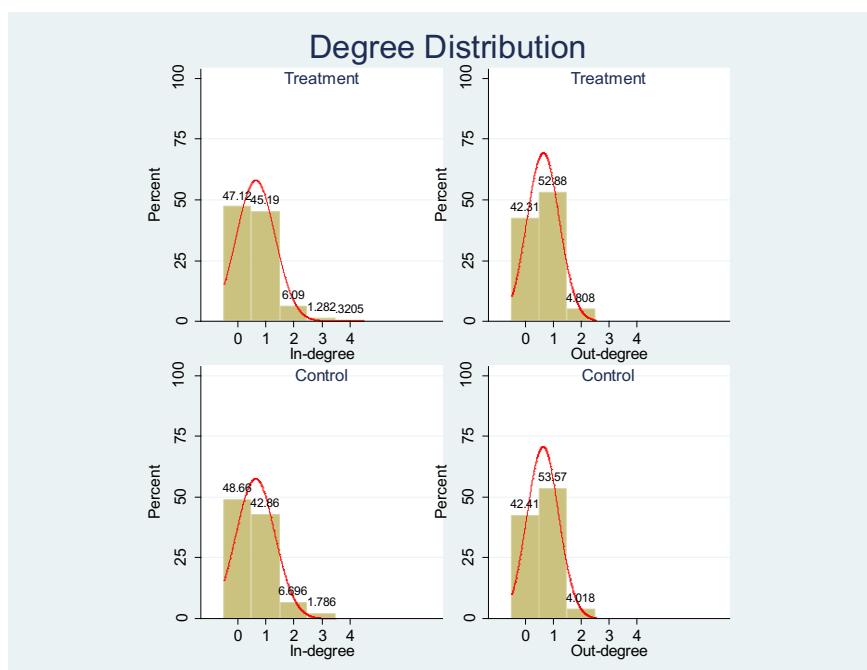

Figure A2 – Received and given transfers (food, labour, agricultural inputs).

TRANSFERS