East African Journal of Management and Business Studies
EAJMBS July– September 2022, Vol. 2, No. 3, pp. 12-.26
ISSN: 2799-2276 (Online). Published by G-Card
DOI: https://doi.org/10.46606/eajmbs2022v02i03.0010.

Effect of Cash Transfer on Food Demand in Lindi District, Tanzania

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Abstract*:* This study assessed the Cash Transfer (CT) effect on food demand and its implications on food security in Lindi District using Almost Ideal Demand Framework. The study employed the Instrumental Variable (IV) technique. To gather households' information, a questionnaire was administered to 398 households, apportioned to two groups of beneficiaries and non-beneficiaries' households using the ratio of 1:1. Five Focus Group Discussions (FGDs) and 14 Key Informants Interviews (KIIs) were conducted. Qualitative data were analysed using content analysis. Findings indicated that CT has effect on demand for roots and tubers, cereals and vegetables. Roots and tubers and cereals are staple foods in Lindi district, implying that, as the income rises, poor households demand for staple food together with its side dishes tend to increase. This increase on demand had no significant effect on reduction of food insecurity. Therefore, to further increase food demand and ultimately reduce food insecurity, the study recommends TASAF to increase the amount of money given to poor households and introduce food schemes that directly focused on tackling food insecurity.

Keywords: Cash Transfer (CT); Food demand; Instrumental Variable (IV); Lindi district.

How to cite: Njuga, G. O., Kazuzuru, B.B., and Warsanga, W. B. (2022). Effect of Cash Transfer on Food Demand in Lindi District, Tanzania. East African Journal of Management and Business Studies *2(3),* 12-26. Doi: https://doi.org/10.46606/eajmbs2022v02i03.0010.

Introduction

Tanzania has made considerable advancements in food production during the past ten years, supported by consistent economic growth. In the year 2021/2022, food surplus increased to 3.8 tonnes from 1.4 tonnes in the year 2010/2011 (URT, 2022). Despite this increase, poorest and most marginalized households have limited access to it. Lack of food (inability to afford or access a healthy diet) is a public health emergency, manifesting as a short-term dilemma of accessing food alongside longer-term effects of relying on poor nutritional quality foods to satiate hunger and worrying about food running out because of lack of money. As of 2022, 5.3 million people in Tanzania lacked sufficient food for consumption

(Kamer, 2022). This corresponds to 9.4 percent of the country's population. Having the food surplus on one hand and food insecurity on the other hand, reveals the marginalization of market economy to those who are not able to compete. This is due to the fact that food production is unequally distributed across the country (Mkonda & He, 2018). While larger producers have enough surplus to meet their demand and sell to others, poor households still produce low than what they need for consumption and lack financial muscles to purchase the food they need even if it is available in the market (Kinyondo & Maghashi, 2017).

One possible approach to eliminate food insecurity for poor households is to alleviate their financial constraints through livelihood diversification or by implementing income assistance programs based on Cash Transfers (CTs) or food credit schemes. Cash Transfers (CTs) are direct payments by government made to eligible groups of people, usually poor households for the purpose of smoothing consumption. In 2013, as part of the third phase of the Tanzania Social Action Fund (TASAF), Tanzania began a countrywide CT program (UNICEF, 2018) which aimed to help households in the nation that are extremely poor. Although there are other CT programs in the country, such as Cash Plus, TASAF program is by far the largest (Pettifor, Wamoyi, Balvanz, Gichane & Maman, 2019). The program targets 9.7 per cent of the population below the food poverty line plus an additional 5 per cent who are transient poor (Wright, Leyaro, Kisanga & Byaruhanga, 2018). The program intends to increase poor households' income and gives them the power to make their own choices about what they need each month. It is expected that, with increase of poor households' income, positive effect will be achieved on nutrition through direct or indirect mechanisms. The direct effect expected is through purchase of highly needed food to meet their household's food demand. These expectations are banked on the assumption that the recipients are rational and they will choose the best for their health.

Nevertheless, the argument over food insecurity in developing nations centers on everyone's right to obtain safe, adequate, culturally acceptable and nourishing food, rather than the food choices made by impoverished households (Bandumula, 2018; Waha *et al.,* 2018; Giller, 2020). Poor households are challenged to balance between the need for nutrients or satiation. CT program by TASAF encourage recipients to maintain the balanced diet as recommended by Tanzania Food and Nutrition Centre (TFNC) (Msuya, 2017).

Studies have documented the difficulties that low-income households experience in trying to satisfy their food needs within the constraints of limited budget (Ahmed, Ying, Bashir, Abid & Zulfiqar, 2017; Mah & Taylor, 2020). Higher food prices and availability of food particularly in rural areas have been repeatedly mentioned as factors directly influencing poor households' choices on food demand. The law of demand indicates that the consumption rate declines when the price of food rises, even when the consumer is monetarily compensated for the effect of the higher price; this is called the substitution effect (Mazurek *et al.,* 2019). As the cost of food increases, buyers tend to turn to other food categories. The reduction in total buying power caused by the price increase leads to reduction in food demand, when the increase is not substituted with increase in income (Franks & Bryant, 2017).

The effects of prices are minimized in the context that the rise is proportion to the increase in income. Thus, as the income of households rises, demand for most food products increases, shifting the demand curve higher at all possible prices (Mian, Straub & Sufi, 2021).

It has been documented by empirical studies that as the income increases, the demand for food increase at a decreasing rate (Cranfield, 2020; Ndanshau, 2018, Yu, 2018). Poor households spend a much higher share of their income on food than on other items (Arndt *et. al.,* 2020). This relationship between food consumption and income is well described by Engel curves. FAO estimates food budget share of poor households between 60 per cent and 80 percent of households' total expenditure (Rahayu, Marwanti & Antriyandarti, 2018). This implies that any policy changes which influence food demand might significantly influence the life style and choices of poor households.

However, the relationship between income and specified food category cannot be generalized. Types of food available and preferences of consumers vary greatly from one context to another. In Thailand, the increase in income had significant effect on demand for eggs and dairy

products, rice and oils and fats (Phetcharat & Chinnakum, 2022). In China, the increase of household's income had no effect on demand for grain and positive effect on all remaining food categories. Explaining this variation of food consumption demand from one context to another, Moreno and Malone (2020) argued that consumers are more willing to pay a premium for the food product which is part of their local identity than for a similar food which is not a part of their identity.

Additionally, people's judgements and decisions are frequently affected by systemic biases or heuristics and are highly dependent on the context in which they are produced; hence, even little or unanticipated changes in the environment can have a significant effect on people's choices (Reisch & Zhao, 2017). This complicates the understanding of what guides individual households' choice of appropriate food mix.

In Tanzania, a study by McCullough, Shin Arsenault & Zhen (2020) found that the poorest consumers exhibit elastic demand (with respect to their total expenditures) for poultry, eggs, red meat, wheat, nuts and seeds, fruit, dairy and fish and seafood. Expenditure elasticities of demand are lower (less than 1) for maize, pulses, vegetables, roots and tubers, cassava, fats and oils, sugar, and other foods. These outcomes are contrary to those by Cockx, Colen, De Weerdt & Paloma (2019) who found that consumption for Tanzanian households were elastic for staple foods such as maize, cereals and tubers and less elastic for fruits, seeds and fish. In both studies, there was a consensus that changes in income levels influence the food consumption demand. However, the extent and direction of changes differed on the basis of sources of income. McCullough, Shin, Arsenault & Zhen, (2020) focused on the income generated from agricultural activities while Cockx, Colen De Weerdt & Paloma (2019) focused on income from employment as the outcome of urbanization.

Thus, if the source of income may lead to variation of food demand, the need to understand how CT income can influence food spending of poor households should not be ignored. In developing countries, where a large percentage of household expenditure is allocated to food, analysis on food demand is particularly useful because they can provide information on specific subpopulation of households that are more likely to be affected by changes in commodity prices or household incomes. Furthermore, for promotion of poor households' consumption shift towards more beneficial goods (such as nutritious foods), the knowledge on their demand of different food items is needed.

Theoretical framework and Hypothesis development

Almost Ideal Demand System Framework

The study adopted the Almost Ideal Demand System (AIDS) framework proposed by Deaton and Muellbauer (1980) to estimate household budget shares for different food groups. The budget proportions of the different commodities under the AIDS framework are linearly connected to the logarithms of real total spending and relative price logarithms. This study selected this framework because it has a functional form that is consistent for use with household budget and cross-sectional data and has the majority of the desirable qualities in traditional demand analysis (Deaton & Muellbauer 1986, Deaton 1997). Furthermore, it is focused on explaining behavioral variations between households in cross-section research (Deaton & Muellbauer, 1980). Since it is typically assumed that all households have access to the same pricing, behavioral differences are only explained in terms of variations in total spending and household characteristics.

Other studies that have employed variants of the AIDS model to estimate households' food demand include Khed and Kb (2018); Ji (2019) and Lei, Zhai & Bai (2021). The limitation of AIDS framework is based on the fact that in estimating demand equations, one of the right-hand-side added explanatory variables, participating in CT program, may be endogenous in the sense that it is correlated with the equation error. Therefore, to deal with endogeneity problems, this study introduced Instrumental Variable (IV).

Hypothesis

A rise in income often encourages people to eat a variety of foods and tends to boost their intake of high-quality foods like meat, fish, milk, fresh fruit, and vegetables (Seidu, 2019; Korir, Rizov & Ruto, 2020). Additionally, when earnings rise and lifestyle changes, there is a corresponding rise in the need for energy, which effects grain demand. Mostly, Tanzanians consume cereals, with maize

as the main dietary group along with fruits, vegetables, milk, eggs and other starchy foods. Few people consume sweeteners, legumes, nuts, oil crops and animal items (Minja *et al.,* 2021). Thus, the main assumption with CT programs is that, the increased household's income will increase household food consumption in term of quantity and diversification. As income increases, households' demand for goods, including food, increases.

Research Methodology

Research Design

To empirically estimate casual effect of intervention when randomization is not feasible, quasi-experimental design is recommended (Weber, Amos, Fry, Stevens & Rinehimer, 2019). Thus, this study adopted the quasi experimental design since assignment to intervention (CT) was by means of administrator selection rather than random. The design identified two comparable groups (treatment and control) so that researchers could look into disparities in outcomes of these groups**.**

Description of the Study Area

Lindi District, which is part of the Lindi Region, a seaside town in Tanzania's southeast, was the area of study. With 38 percent of the population living below the national poverty line, Lindi is Tanzania's third poorest region (World Bank, 2019). The Lindi district has more than 14.8 percent of households enrolled in the CT program, making it the district with the highest percentage of recipients enrolled in the program (URT, 2018b). As a result, the chosen region and district, in particular, were suitable area to investigate Tanzania's CT influence on household's food demand.

Population and Sampling

The sample size for this investigation was determined in two stages. The first stage was to calculate the required minimum sample size, and since the number of households in Lindi district is known, finite population formula proposed by Yamane (1963) detailed below was used;

$$n = \frac{N}{N * (e)^2 + 1} = \frac{99{,}559}{99{,}559 * (0.05)^2 + 1} = 398\, respondents$$

Where, n is sample size, N is number of households in Lindi district (NBS, 2019), e is a precision level which was 0.05. As a result, proposed minimum sample units included 398 households. The second stage was to determine comparison groups. Using Monte Carlo simulation, White II (2018) recommended splinting 50/50 treatment and control groups since it yielded highest statistical power. Thus, the ratio of 1:1 was used in selection of beneficiary and non-beneficiary households. Each group constituted 199 households.

In Tanzania, the largest Productive Social Safety Net (PSSN) is carried out by Tanzania Social Action Fund (TASAF) since 2000 to date. TASAF's main components during data collection period were public works, conditional CTs and unconditional CTs. Thus, treatment group included only those households benefiting by both conditional and unconditional CT. Nine villages were chosen in a systematic manner and the number of CT recipients in a village was used to calculate a representative sample size using size-proportional formula. White and Subarwal (2014) argue that in order for matching estimators to decrease biasness as conventionally measured, the control group must be sampled from the same population as the treated. Non-recipients were then selected to reflect the selection of recipients. Recipients were assigned codes and then automated number generator was used to randomly select them. To select non-recipients, a snowballing technique was used, in which each respondent provided information about one other non-recipient.

Data collection Techniques and Tools

A questionnaire was used to gather data on the household characteristics and food expenditure. A total of 398 questionnaires were administered to both CT recipients and non-recipients. The questionnaires included both open and close ended questions. The use of open and close ended questions enabled the study to obtain both quantitative and qualitative data, resulting in more comprehensive results. Focus Group Discussions (FGDs) and Key Informant Interviews (KIIs) were also employed to acquire qualitative data in order to validate survey results. Each of the five focus groups had seven participants from

five villages. Only CT recipients were included in the FGD because they were the ones who could best describe the link between CTs and household food expenditures. The number of FGDs to be undertaken was determined using the theoretical saturation principle. Validation sessions with representatives from all FGDs were held to reconcile divergent viewpoints on the same subject. Fourteen KIIs were chosen based on their previous expertise, nine of them being Village Executive Officers (VEOs); four were TASAF coordinators and one was a District Nutrition Officer. Qualitative data were analysed by using content analysis as recommended by Schilling (2006). The steps included transcription of interview tapes into raw data, condensing and structuring the data, building and applying a category system, displaying data and results for concluding analyses and interpretation. Quantitative data were first analyzed using AIDS model and then supplemented by using qualitative data.

Ethical Considerations

During fieldwork, participants were informed about the purpose of the study and the possible outcomes. Each participant's consent form was obtained and participants were informed that information so extracted will be treated in a strictly confidential way and the names of individuals would not be included in the reporting of the findings. Analysis and interpretation were guided by literature review and there was no fabrication and falsification of results.

Analytical Model

The study models household food consumption behavior using an Almost Ideal Demand System. Correspondingly, the demand functions, expressed in terms of budget shares, become;

$$w_{ij} = \alpha_i + \sum_i \gamma_{ij} \log p_j + \beta_i \log\left(X/_P\right) \quad (1)$$

where i =1,2… W_{ij} is the budget share of household i in good j while α_i, β_i and γ_i are unknown parameters to be estimated. p_j is the price of good j, X is total expenditure where P is the translog price index defined by;

$$\text{P} = \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \log \sum_j \sum_k \alpha_k log\ p_k \quad (2)$$

where p_k is the aggregate price for food group k. To obtain linear demand system at the estimation stage, Deaton and Muellbauer (1986) suggests replacing equation (2) by the Stone price index P* defined as;

$$\log \text{P} = \sum_k w_k \log p_k \quad (3)$$

Approximation of the AIDS using this price index has produced empirical results similar to those obtained from the complete nonlinear system (Nuani, Gido, Ayuya & Musyoka, 2022). For the AIDS to be consistent with the properties of individual consumer demand theory, the structural parameters of Equation (1) must satisfy the homogeneity, adding-up, and Slutsky symmetry as presented below;

$$\sum_{i=1}^{n} \alpha_i = 1; \sum_{i=1}^{n} \gamma_{ij} = 0 \sum_{i=1}^{n} \beta_i = 0;\ \sum_{j=1}^{n} \gamma_{ij} = 0; \gamma_{ij} = \gamma_{ji} \quad (4)$$

Alternatively, these restrictions can be tested as behavioural hypotheses implied by the theory of consumer demand. Since one of the objectives of the study was to estimate expenditure (income) elasticities of various group of foods, the coefficients from the demand system estimated in equation (1) are inserted in the following formula;

$$e_{ij} = \left(\beta_j + w_{ij}\right)\frac{1}{w_{ij}} = \frac{\beta_j}{w_{ij}} + 1 \quad (5)$$

Where e_{ij} is the expenditure elasticity of household i in food group j. The computation of elasticities allows the study to determine if a particular food group should be categorized as luxury ($e_{ij} > 1$), necessity commodity ($e_{ij} < 1$) or it is an inferior commodity ($e_{ij} < 0$).

To estimate the effect of CT on food budget share, CT participation status dummies and households' characteristics were introduced to equation (1). It was extended and presented as;

$$w_{ij} = \alpha_i + \sum_i \gamma_{ij} \log p_j + \beta_i \log\left(X/P\right) + \beta_{2i} D_j + \beta_{3i} Z_j + \epsilon_{ij} \quad (6)$$

Where D_j is a dummy variable capturing whether the household received CT or not, z_i is the vector of household characteristics and ϵ_{ij} is the error term.

However, estimation of equation (6) is subject to endogeneity errors due to selection bias which may occur as the result of differences in characteristics between the treatment group (households receiving CTs) and the control group (households not receiving CTs) prior to the program. To address the potential endogeneity problem, this study adopted the instrumental variable (IV) approach which takes care of the issues related to unobserved variables and since it uses Ordinary Least Square (OLS) equations, coefficients β_j can be estimated. If the correlation between the explanatory variable and the error term is zero, then the OLS estimate is consistent. However, if the explanatory variable is correlated with the error term via other unobservable, then one needs an IV estimator to achieve consistency. IV improves over OLS in the sense that the effect is still biased but is consistent, while under endogeneity the effect would not only be biased but also inconsistent.

For the IV model the following equations were estimated:

$$w_{ij} = \alpha_i + \sum_i \gamma_{ij} \log p_j + \beta_i \log\left(X/P\right) + \beta_{2i} D_j + \beta_{3i} Z_j + \epsilon_{ij} \quad (6)$$

$$D_j = \alpha_i + \beta_{4i} T_i + \beta_{5i} Z_j + \pi_{ij} \quad (7)$$

Where T_i represents the vector of instrumental variables relating to D_j. The study implemented IV estimation using two-stage least squares (2SLS) in Stata 15, where equation (7) was first estimated by OLS to obtain the predicted value of the treatment variable. In the second stage, the parameters in equation (6) were estimated by replacing D_j with the predicted value. When the instrument is valid, the estimated coefficient of the treatment variable β_{2i} can be interpreted as the local average effect of the treatment on household food budget share.

Furthermore, to estimate how changes in food demand influenced poor households' food insecurity, the following Instrumental Variable (IV) models were used:

$$Y_{ij} = \alpha_i + \beta_{2i} D_j + \beta_{3i} Z_j + \epsilon_{ij} \quad (8)$$

$$D_j = \alpha_i + \beta_{4i} T_i + \beta_{5i} Z_j + \pi_{ij} \quad (9)$$

Here, the dependent variable is Y_{ij} is Household Hunger Scale (HHS). The scale is recommended by USAID (2011) and has been widely used to assess food insecurity in developing countries such as Ghana, Bangladesh and Zambia (Cooper, Brown, Azzarri & Meinzen-Dick, 2019; Nkomoki, Bavorová & Banout, 2019). The USAID (2011) recommends three household hunger categories as shown in table 1:

Table 1: HHS Categorical Indicator

Household Hunger Score (HHS)	Household Hunger Categories
0-1	Little to no hunger in the household
2-3	Moderate hunger in the household
4-6	Severe hunger in the household

Source: USAID (2011).

Food expenditure was divided into seven food groups as presented in Table 1. Categorization of the groups based on the food composition table recommended by Tanzania Food and Nutrition Centre (TFNC). On reference to TFNC (URT, 2008c), these food groups were; cereals and

cereals products, pulses, seeds and nuts, meat, poultry and fish, fruits and fruit juices, vegetables, oils and fats. The details of each group are presented in Table 2. Spending on each food item, the household reported for the earlier seven days including both food purchased and produced by the household. The price index for each food group was computed by dividing the group expenditure by the group quantity, and the aggregate price of food (in log form) was computed as a weighted sum of the index of prices for each group (in log form), where the weights were the average share of food expenditure for each group.

Table 2: Description of Food Categories

Food group	Details
Cereals	Cereals such as rice, wheat, oat, sorghum. Cereal products such as bread, biscuits, porridge, breakfast cereals. Local dishes prepared with cereals (e.g. porridges, chapatti)
Roots and tubers	Cassava (fresh and flour), cooking bananas and plantains, Irish potatoes, sweet potatoes, other roots and tubers
Pulses, nuts and seeds	Beans, peas, lentils and other pulses groundnuts, cashew nuts etc
Vegetables	Tomatoes, onions, spinach, pumpkin leaves, pumpkin, cassava leaves and other dark green leaves
Fruits	Mango, papaya, ripe banana, lemon, oranges, fruit juices etc
Meat, poultry and fish products	Chicken, fish, cow, goat, sheep milk, seafood and meats (any)
Oils and fats	Cooking oil, animal fats, butter, margarine

Source: URT (2008c)

On the assumptions of the models (Table 3 and Table 5), multicollinearity (<0.6), tolerance value of variables were >0.10, while Variance Inflation Factor (VIF) for variables were <10. The goodness of fit for the models indicated acceptability as ANOVA ($p<0.01$) and Durbin-Watson value >1 but <2. For the instrument to be valid, two key assumptions must be met. First, the instrument should have no independent effect on the food budget share, unless it is through participation in CT program. Second, variation in the instruments should cause substantial variation in the CT participation status. In this study, frequency of attending in VEO's office was used as instrument variable. Since CT recipients are required to pick their CTs at VEO's office, they are more likely to be attending VEO's office than CT non-recipients. Furthermore, attending VEO's office by itself doesn't influence expenditure elasticities of food items unless it is through CTs. To evaluate the instrument, the weak instrument test suggested by Stock and Yogo (2010) was used. For all models, the F-statistic of the weak instrument test exceeds the rule of thumb criterion of 10 or the critical value of Stock and Yogo (2010). These results suggest that there is no evidence of weak instrument and that the instrument is relevant.

Results and Discussion

CT effect on budget share of specified foods

The study sought to determine the effect of CT on budget share of seven food categories. Thus, coefficients and standard errors of variables influencing budget shares of households participating on CT program were estimated using 2SLS equations (6) and (7). The variable of interest was participation on CT program and its' results are presented on Table 3. Results for additional variables' coefficients and standard errors are shown in the appendix 1. This data is crucial in order to provide a sense of the relative importance of each food group to the overall spending of recipients' households. Findings indicate that CT resulted into positive increase on the budget share of all food items with exception of pulses, nuts and seeds and fruits. However, significant influence was noted in cereals, roots and tubers, and vegetables.

Table 3: Estimation of CT effect on households' food budget shares using IV

Variables	Cereals	Roots & tubers	Pulses, Nuts and seeds	Vegetables	Fruits	Meat, poultry & fish	Oils and fats
Part TASAF	0.102***	0.047***	-0.0531	0.0361**	-0.0091	0.0014	0.010
	(0.021)	(0.011)	(0.0423)	(0.013)	(0.026)	(0.043)	(0.091)
Constant	-0.717**	0.204**	-0.456	0.134***	-0.0835	0.0901***	-0.487
	(0.267)	(0.0781)	(0.562)	(0.035)	(0.067)	(0.004)	(0.346)
F statistic	756.66	534.78	345.68	632.56	453.01	676.11	564.42
Observations	398	398	398	398	398	398	398
R-squared	0.644	0.734	0.534	0.223	0.431	0.710	0.691

Standard error in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1

Findings show that participation in CT program, *ceteris paribus*, increases budget share of roots and tubers by 4.7 percent. Cereals are staple food in most parts of Tanzania. However, in Lindi District, the staple food are roots and tubers. These results are supported by a study by Filmer, Friedman, Kandpal & Onishi (2018) who concluded that CT had effect of staple food in Philippines. Although staple food in Philippines was rice, in context of Lindi district, ugali cooked by cassava flour was their main food. Ugali is among the high calorie food and much preferred by poor households for its ability to reduce hunger. Booth (2018) argued that eating high-calorie products reduces hunger more than eating low-calorie products. People learn to consume more energy rich foods when hungry than when sated. Cassava flour can be substituted by sorghum or maize flour since they both have characteristics similar to those of cassava flour, although their taste is different. Increase of budget share of staple food might therefore signify that households don't have enough to eat. Although 75% of the food is produced at home in rural areas in Tanzania (Sanches-Pereira *et al.,* 2017), substantial amount of the food by poor households is purchased. Thus, CT gives poor households ability to acquire the difference between what is produced and what is needed.

Furthermore, findings indicate that's CT resulted into the increase of cereals by 10.2 percent, *ceteris paribus*. These results are in line with the finding by Dietrich and Schmerzeck (2022) in Kenya and Zhou and Hendricks (2017) in Mozambique that CT increased consumption of cereals. In the context of Lindi District, cereals are their main alternative food after the staple foods. This is reflected in the report by URT (2018a) about food production in the neighboring Lindi Municipal, that their second and third most produced food crops after cassava, are maize and sorghum. Thus, the CT gives poor households the room to diversify their food consumption. A study by Mani and Azam (n.d) argued that food choice behavior is guided by two personality variables which are variety seeking and quality-consciousness. However, the latter variable is more associated with middle- and high-income households than poor households. Therefore, the most likely reason that CT recipients increased consumption of the cereals is variety seeking behaviors.

Moreover, findings indicated that participation in CT increased household consumption of vegetables by 3.61 percent, *ceteris paribus*. This is true even if the veggies that poor rural households eat are either self-produced or freely taken from the forest. This implies that an increase in vegetable consumption has a tangential relationship with CT. Ugali is typically served with veggies in Lindi district. Therefore, an increase in ugali eating is likely to result in an increase in vegetable consumption. The FGD consensus endorsed the following: "…we usually eat ugali and kisamvu (type of green vegetables) ..this is our main dish inherited from our four fathers" (Lindi District, 23 January 2020).

This claim highlights the fact that eating ugali with green vegetables is a way of life for them. This implies that developing a taste for certain foods is probably a lifelong process. Although omnivores—including humans—have the freedom to choose, their decisions are influenced by the requirement for a little amount of variation in their diets in order to receive all essential nutrients. Even though it is ingrained throughout life, this culture helps to retain the nutrients that the human body needs.

However, to establish the extent to which the increase in income has affected the quantity of food consumed in each category, the study

estimated income elasticities by substituting coefficients from Table 3 in equation (5). Income elasticity measures the responsiveness of demand to a change in consumer income and since it is independent of the main units in which demand is measured, it provides more meaningful measurement. It may be interpreted as the percentage change in quantity demanded when income changes by 1%, *ceteris paribus*. The measure enables classification of commodity as luxury, necessity or inferior. Household consumption expenditure was used as proxy of income as the data were more reliable than income data.

Table 4: Income elasticities of food categories

Food items	Cereals	Roots and tubes	Nuts and seeds	Vegetables	Fruits	Condiments and spices	Meat, poultry and fish
Income elasticities	0.453***	0.820***	0.091	0.110***	0.137	0.042	1.46

Table 5: CT effect on food insecurity using IV and descriptive statistics

	IV			Descriptive statistics	
	Coef.	SE	p-value	Mean	Std. dev
Part TASAF Beneficiaries HH	-0.108	1.9323	0.409	2.93	1.02
Constant	0.811	0.368	0.028		
R square	0.47				

F statistic=567.81

Income elasticities of demand are presented in Table 4. On average, all food categories had positive income elasticities of demand. However, the significant effect was on roots and tubers, cereals and vegetables. This infers that increase of income will result into increase of quantity demanded on all seven food categories. Thus, these results support the hypothesis that CT affects households' food demand. Elasticities of demand for roots and tubers, cereals and vegetables were less than 1 which means they were regarded as necessities. Meat, poultry and fish had more than 1 elasticities of demand. Therefore, they are classified as luxury food. However, the elasticity for roots and tubers are very close to 1, justifying the findings that as the income increase, households will seek to diversify their food consumption (Kundu *et al.,* 2021). These findings are in line with the study by Naheed and Hussain (2020) which estimated income elasticities of cereals and vegetables at 0.67 and 0.31 respectively by applying AIDS model. They found cereals and vegetables to be necessities which is similar to the results of this study. These results violate Engels' curve that as the income rise, the budget share of necessities tend to decrease

To assess whether the increase in food was significant enough to reduce food insecurity, the study estimated the effect of CT on food insecurity using 2SLS equations (8) and (9). To measure household insecurity, HHS was used. Essentially HHS is the behavior measure which captures the most extreme manifestations of insufficiency. Thus, it is appropriate measure for assessing poor households' food insecurity as this is the subpopulation mostly severely affected by any food demand-supply imbalances.

Results of 2SLS with IV estimations and descriptive statistics are presented in Table 5. Findings indicate that CT has no significant effect on reduction of food insecurity with the coefficient of -0.108 and p-value = 0.409. These results are contrary to findings by Resosudarmo, Yamazaki & Girsang (2020) who found that, lamp-sum CT program in Indonesia reduced food insecurity. This difference in results may be explained by the fact that, CT program in Tanzania is on the basis of small and regular payments rather than lump-sum.

This suggests that CT influence on food demand was not significant enough to improve food

security. According to mean score interpretation in table 1, the HHS mean of 2.93 indicates that majority of CT recipients still faced moderate hunger. They sometimes lacked enough food to eat due to lack of resources. One of Key Informants indicated that; "…Most of people here take only two meals per day which are breakfast and supper, or one meal per day often a dinner..." (Lindi District, 25 January 2020). This indicates that majority of poor households in rural areas cannot afford the luxury of three meals per day as recommended by TFNC guideline. By considering two major dimensions of food insufficiency, the amount of food taken per meal and the number of meals per day, the results obtained from household demand analysis presented in Table 3 imply that CT improved the amount of food taken per day but still CT recipients' stay long hours without any meal. Which means, though, the demand of some food items has increased, food insecurity for CT recipients persists.

Conclusions and Recommendations

This section presents the conclusions of the study and then gives the recommendations as follows:

Conclusions

The study concludes that the direction of changes in food demand as the results of the CT program is steered by household's satiation level variety seeking behaviour and hereditary eating patterns. The income generated from participating in CT programme increased poor households demand for staple food together with its substitute and side dishes. The fact that out of seven food categories, six of them were regarded as necessities indicate that the increase of income increased households' food demand at decreasing rate. The increase in food demand as the result of cash transfer had no significant impact on households' food insecurity. This indicates that the amount of money given as cash transfer are not enough to cover the difference between the food produced and food demanded by recipients' households to achieve the recommended food requirements.

Recommendations

The study recommends TASAF to increase the amount of money given to poor households if there should be improvements in food demand to the extent that the significant changes on food insecurity levels are noted. Raising the cash transfer amount will increase households' disposable income which is associated with increased food security. However, the increase should be done with caution such that negative effects of free meal are minimized. Furthermore, the study recommends to the central government of Tanzania to introduce food schemes that directly focused on tackling food insecurity rather than including food poverty issues on schemes targeting poverty in general. Programs such as provision of subsidized food for poor households or free food to most needy groups in community such as children and pregnant women will address food insecurity directly.

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Appendix 1: 2SLS estimation of CT effect on households' food budget shares.

Variables	Cereals	Roots & tubers	Pulses, Nuts and seeds	Vegetables	Fruits	Meat, poultry &fish	Oils and fats
Part –TASAF	0.102***	0.047***	-0.0531	0.0361**	-0.0091	0.0014	0.010
	(0.021)	(0.011)	(0.0423)	(0.013)	(0.026)	(0.043)	(0.091)
Marital	-0.00991	0.0012	-0.0046	-0.0014	0.0013	0.004	-0.00003
	(0.0801)	(0.00418)	(0.0067)	(0.00274)	(0.0016)	(0.0045)	(0.0036)
Sex	-0.0206	0.0049	0.0263	-0.004	0.0034	-0.007	-0.0029
	(0.0239)	(0.0124)	(0.0200)	(0.00816)	(0.00477)	(0.01351)	(0.0107)
Age	0.0013*	0.0004	-0.0011*	0.0028	0.327	-0.0006	-0.00043
	(0.0008)	(0.0004)	(0.0007)	(0.00027)	(0.00015)	(0.00043)	(0.00035)
Years_school	-0.0065	0.0053***	00.0012	0.0022*	0.00092	-0.0037	0.00065
	(0.0035)	(0.0018)	(0.0026)	(0.0012)	(0.0007)	(0.00201)	(0.00159)
Occupation	0.008***	0.0278	0.00067	0.0027**	0.0006	-0.005***	-0.0034**
	(0.0033)	(0.0017)	(0.0027)	(0.0011)	(0.00065)	(0.00184)	(0.0015)
HH_size	0.004	-0.0008	-0.0075	-0.0013	-0.0015	-0.005	0.0117***
	(0.0067)	(0.0035)	(0.0057)	(0.0023)	(0.00134)	(0.0038)	(0.00302)
Yrs_village	0.00027	0.00004	-0.00038	-0.00001	0.00003	-0.00004	0.00008
	(0.0003)	(0.00016)	(0.00026)	(0.0001)	(0.000061)	(0.00017)	(0.00014)
Homeland size	0.00061	0.016***	-0.011	0.0074	0.00075	-0.0045	0.0033
	(0.0109)	(0.0057)	(0.0092)	(0.0071)	(0.0022)	(0.0062)	(0.0049)
Land production	-0.0056	-0.004	0.067	0.0051	-0.0008	0.0029	-0.00087
	(0.0061)	(0.00317)	(0.0051)	(0.00208)	(0.0012)	(0.0034)	(0.00272)
Log P	0.019***	0.0467	0.00091	0.027**	0.0056	-0.053***	-0.0134**
	(0.033)	(0.0610)	(0.0027)	(0.013)	(0.0045)	(0.00134)	(0.0116)
Log (X/P)	-	-0.01*	0.063***	0.0093***	-0.001	0.025**	0.012**
	0.109***	(0.0058)	(0.0093)	(0.0038)	(0.0022)	(0.063)	(0.0050)
	(0.0111)						
Constant	-0.717**	0.204**	-0.456	0.134***	-0.0835	0.0901***	-0.487
	(0.267)	(0.0781)	(0.562)	(0.035)	(0.067)	(0.004)	(0.346)
Observations	398	398	398	398	398	398	398
R-squared	0.644	0.734	0.534	0.223	0.431	0.710	0.691

Standard error in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1

Appendix 2: Estimation of CT Effect on Households' Insecurity

Variables	Coefficient	Standard Error	p-value
Part-TASAF	-0.108	1.9323	0.409
Marital	2.96	2.85	0.299
Sex	2.86	1.57	0.070
Age	5.20	3.81	0.172
Years school	-2.91	2.13	0.175
Occupation	-0.41	0.24	0.082
HH-size	4.64	4.31	0.282
Yrs-village	2.08	1.61	0.198
Homeland-size	4.68	2.61	0.074
Land-production	0.59	0.63	0.346
Log P	0.147	0.0038	0.000
Log (X/P)	0.525	0.256	0.040
Constant	0.811	0.368	0.028
Observations	398		
R-squared	0.691		

Appendix 3: Description of Household Characteristics Variables

Variable	Definition and Unit of Measurement
MAR (X_1)	Marital status (1 = Married, 0 = Not married)
AGE (X_2)	Age of household head (years)
HHS (X_3)	Household size (number of household members)
HHG (X_4)	Household head sex (1=Male; 0=Female)
EDU (X_5)	Household head education Level (years of school)
OCU (X_6)	Household occupation (scores)
PAT (X_7)	TASAF Participation (1=Beneficiary; 0= Non-beneficiary)
YRS (X_8)	Years lived in a village (Number of years)
LAP (X_9)	Land for production (Number of acres)
LAH (X_{10})	Land for home (Number of acres)