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Impact of Cash Transfer on Poverty Reduction in Lindi District, Tanzania

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Abstract: Cash Transfers (CT) as a strategy for poverty reduction acquired prominence in Latin America but spread later to the rest of the developing world including Tanzania. Government through its umbrella institution, Tanzania Social Action Fund (TASAF) introduced what has become the largest CT for poor households in the country since 2010 to date. Although there is growing evidence on the impact of CT on poverty reduction, results are contextual. Thus, the paper examined the causal effect of CT on poverty reduction in Lindi District, Tanzania. Specifically, the study assessed the impact of CT on households' overall wealth, housing conditions, use of basic services, productive and non-productive assets. The study employed Propensity Score Matching (PSM) to estimate the effects of CT on households by matching recipients and non-recipients' households using Nearest Neighbor, Radius caliper and Mahalanobis matching techniques. Sample size constituted 398 respondents, split into equal number of recipients and non-recipients' households. Five Focus Group Discussions (FGDs) and 13 Key Informants Interviews (KIIs) were conducted. Qualitative data was analysed using content analysis. Findings indicated that CT to poor households by itself is not enough to significantly reduce extreme poverty. However, the results indicated significant effect of CT on five poverty indicators which are type of floor, sanitation facilities, livestock, mobile phone and chair. The study recommends to government adoption of multi-intervention programs directed on key living standard indicators such as productive assets to transform the quality of low-income households.

Keywords: Cash transfer (CT); Poverty; Propensity Score Matching; Lindi; Tanzania.

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Introduction

The majority of the world's poorest people live in Sub Sahara Africa and they struggle to make ends meet, particularly in light of challenges such as climate change, declining cash crop prices, decreased access to land and declining employment opportunities (Hajdu *et al.*, 2020). Various development efforts, ranging from agricultural development interventions and microfinance initiatives to private investment promotion, have frequently failed to foster sustainable livelihoods in impoverished rural areas (Magombeyi & Odhiambo, 2016; Nagarajan, 2021). For many years, poverty alleviation programs have focused on providing goods or services, constructing infrastructure, providing training, or more recently, financial services such as microloans (Page & Pande, 2018). Conventional wisdom held that these programs were superior to handing out cash.

However, beginning in the early 2000s, developing countries began experimenting giving poor people cash grants in exchange for them to use the money in a specific way or following through on a commitment such as sending their children to school (Davis *et al.*, n.d.). Cash Transfers (CTs) are direct payments made to eligible groups of people, usually by governments with the objective of increasing poor and vulnerable households' real income.

There are two types of CTs: Unconditional Cash Transfers (UCTs) which are made without any conditions for the recipient and Conditional Cash Transfers (CCTs) which are made on the condition that the recipient meets certain criteria, such as school attendance or vaccinations. CTs are a continuation of the social protection program outlined in the 2030 Sustainable Development Goal 1.3, which calls for the abolition of all forms of poverty through the implementation of nationally appropriate social protection systems (Cluver *et al.*, 2016). Their popularity grew globally due to their relative simplicity and ability to reach a large number of recipients when compared to other social safety net programs. Today, such CT programs exist in over 120 countries, with over $200 million in cash distributed daily (Martin & Rawlings, 2018). The obvious question is how much a small and predictable sum of money paid monthly could lead to poverty reduction?

The decision to distribute cash via targeted transfers is a complicated one. Some arguments are fundamentally ethical, arguing that society should protect the vulnerable and provide them with additional assistance (Hagen-Zanker, Ulrichs & Holmes, 2018). As a result, CT should enable recipients to afford basic services and improved living conditions. Other arguments, however, are economic in nature, claiming that transfers should have a transformative impact on household income and reduce poverty. Poor households' investment in productive assets helps them to create sustainable sources of income. This is supported by Stoeffler, Mills and Premand (2020) who suggest that small regular CTs combined with enhanced saving mechanisms can generate asset accumulation among the extreme poor. Still others make arguments based on the intergenerational transmission of poverty, viewing transfers as a mechanism to help increase investments in child health and education (Manley & Slavchevska, 2019). This argument is supported by those who are for conditional CT.

Tanzania launched a national CT program in 2013 as part of the third phase of the Tanzania Social Action Fund (UNICEF, 2018). The program targets households living in extreme poverty in the country. 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). Until 2018, Tanzania pro-poor CT had benefited 1 million households and 4.9 million people, reaching 15% of extremely poor households, 14% of poor households and 8% of non-poor ones (World Bank, 2022b). The program intends to reduce households' poverty by improving consumption of poor households. Although positive progress has been reported, significant proportion of the recipients remains vulnerable to falling into poverty and number of poor people in Tanzania is increasing, up to 14 million in 2018 from 12.3 million in 2012 (World Bank, 2019). The fact that cash alone is rarely sufficient to mitigate all risks and vulnerabilities facing poor households pose question on what can and what cannot be achieved by CT programs in reducing poverty at the households' level.

Evans, Hausladen, Kosec and Reese (2016) investigated the impact of CT in various aspect of household's development in Tanzania. He concluded that CT had impact on purchase of livestock assets. Mzingula (2020) found that CT had impact on livestock and food security. However, both studies focused on conditional CT only. The fact that at the time Evans, Hausladen, Kosec & Reese (2016) conducted the study, the largest CT program targeting poor households in the country was conditional, the justification was clear. As an attempt to overcome pitfalls of conditional CT such as lack of choice on use of money by recipients and high exclusion rate, TASAF introduced unconditional CT to poor households in the year 2015 (UNICEF, 2018). This created the need to understand how the combined bimonthly (conditional and unconditional CT) CT programs improve the previous reported pitfalls of conditional CT. Thus, this study investigated the impact of these bimonthly CT programs on poverty reduction in their combined form in Tanzania.

The study will add to a stock of knowledge and literatures on the relationship between CT and poverty of poor households. The need to understand the impact of CT on poverty is especially pressing given the world leaders' commitment to eliminate extreme poverty by 2030 as part of sustainable development goals. Moreover, information about the relationship between CT programs and households' poverty level is major input to the improvement of the CT program design. Therefore, this study is timely and is significant as the findings will provide considerable information on modeling the impact of CT in Tanzania and providing the useful feedback to policymakers, program managers and other development stakeholders on terms of program evaluation, design and implementation.

Hypothesis Development and Theoretical Framework

The Concept of Poverty

Poverty can be viewed from absolute or relative point of view. Absolute term refers to a single standard such as poverty line while relative poverty is defined on reference to the comparative members of the particular community (Decerf, 2021). The most common example of poverty definition in absolute terms is the poverty line established by the World Bank. The bank defines extreme poverty as living on less than US$ 2.15 per day and moderate poverty as less than $3.10 a day (World Bank, 2022a). On this view, poverty is a lack of sufficient income to meet basic needs. However, due to challenges of capturing income such as possibility of underreporting and short fluctuation, economists prefer to use expenditure per capital as the proxy of income (Ali, Radzi, Kosnin, Hassan & Saidin, 2021; Ramadan, 2021). Even if income and expenditure are perfectly measured, none of these measures objectively show well-being. Major developments and research in this area indicate that traditional one-dimensional measures of poverty, based primarily on income or calorie consumption, are severely flawed (Coudouel, Hentschel & Wodon n.d.). This is because poverty frequently entails being deprived on multiple fronts, which do not always correlate well with income.

Thus, to understand poverty beyond monetary deprivation Multidimensional Poverty Index (MPI) was introduced by UNDP and Oxford University (UNDP, 2020). The MPI addresses poverty on multiple levels and investigates how these levels interact. This is why target 1.2 of the Sustainable Development Goals (SDGs) states, "to reduce at least half the proportion of men, women and children of all ages living in poverty in all its dimensions, according to national definitions, by 2030". The MPI is both universal and sensitive to the national complexities of each country (OPHI, 2018). Many countries are using either global or national MPI to assess their achievement of SGD indicator 1.2.2 (MPPN, n.d). These countries include India, Bangladesh, Chile and Colombia. A universal or global MPI is internationally comparable and can incorporate agreed-upon poverty dimensions. It captures the various types of deprivation that each poor person faces in ten indicators across three dimensions – education, health, and living standards. The ability of MPI to show many different aspects of poverty that poor people experience at the same time can inform more integrated policy and provide incentives to reduce many aspects of poverty concurrently, breaking down the silos of poverty-reduction programs. Thus, this study views poverty as a multidimensional concept and as dependent on social context, which means that poverty is relative.

Hypothesis Development

Evidence from the first wave of Latin America CT programs suggested that these interventions might have helped reduce poverty among participants. After two years, The Nicaraguan CT program reduced the proportion of participating households below the poverty line by five percentage points, while the Colombian CT program reduced the percentage of poor people by three over four years (Saavedra, 2016). Evidence from programs in Mexico and Honduras suggests that there is no discernible impact on the poverty rate among participants (Boo & Creamer, 2019; Martínez-Martínez, Coronado-García & Orta-Alemán (2020).Thus, there is consensus among scholars that CT has no negative impact on households' poverty reduction. However, the difference in rates of CT impact on poverty from one country to another suggests that the extent on which these programs can reduce poverty may be contextual. Therefore, the paper hypothesizes that CT has a significant impact on households' poverty reduction.

Guiding Theory

There are two main competing theories explaining the causes of poverty. First, is the cultural theory which was propounded by the anthropologist Oscar Lewis in his 1959 book, Five Families: Mexican Case Studies in the Culture of Poverty. The theory suggests that individuals create, sustain and transmit to future generations a culture that reinforces the various social and behavioral deficiencies (Lamichhane, 2021**)**. This means that the poor household choices are mirrored in their behaviour lenses which reflect their cultural background. Reflecting culture theories, Burney (2018); Bergolo and Galyan (2018) used the individual level data sets to study poor households' behavioural responses to CTs.

The study adopted the theory because the primary casual pathway through which CT impact poverty is through individual improvement of behaviours (Owusu-Addo, Renzaho & Smith 2019). Thus, the theory is relevant in understanding factors guiding the choices of poor households in using the CTs. The fact that low levels of the economy and the likelihood of poverty experienced by the people of the coastal villages is caused by the lack of proper lifestyle of the coastal village community itself (Rukin, Rahman, Toha & Gianawati, 2018) underpins the relevance of the theory in providing the roadmap for impact analysis in the context of Lindi District. In the views of cultural theory, its household's behavior which determines CT influence on household's poverty level. Criticism of this theory is based on its overemphasis on the individual deficiencies and that the poor are to blame for the situation.This leaves out other macro-economic actors who directly or indirectly might influence the lives of poor households.

Therefore, to address theoretical limitations described above, the study adopted the structural theory of poverty. The theory is traced back from the ideas presented by John Keynes in 1939 the book, "the Great Theory of Economy, Interest and Money." The theory presents a contrary argument to the idea that individual behaviours are the cause of poverty. Structural theorists contend that poverty is the outcome of macro and meso-level demographic and economic factors (Brady, 2019). Bradshaw (2006) argued that structural contexts cause problematic behaviours, which cause poverty. Additionally, structure directly causes poverty. For instance, Sharkey (2013) applied the theory to demonstrate that growing up in segregated and concentrated poor neighbourhoods exposes children to stress. Likewise, Husz, Kopasz and Medgyesi (2022) used the theory to explain how multiple disadvantages are concentrated on poorest municipalities. Thus, constraints facing poor households in making economic choices differ from those of wealthier people.

The presumptions that human behaviour responds to structural reforms, rather than cultural changes justifies government intervention such as CT to easy the economic burden of poor households in the context of missing or malfunctioning markets. From this perspective, CT to poor households is an effort by the government to break structural barriers that socially exclude poor people and can be a powerful driver of sustainable poverty escape. So, the theory provides theoretical ground for explaining the structural characteristics propelling or impeding a CT program. Critics of this theory argue that poverty is merely the deprivation or shortfall of basic capabilities. Hence, it is difficult to change this common structural reality with just a simple CT, no matter how big it is. In this case, cultural and structural theories complement one another.

Methodology

Description of the Study Area

Lindi District, 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). With 14.8 percent of households enrolled in CT programs, is also the district with the highest percentage of recipients enrolled in the program (URT, 2018). As a result, the chosen district is a suitable area to investigate Tanzania's CT program's influence on household poverty.

Population and Sampling

Since the number of households in Lindi district is known, finite population formula proposed by Yamane (1967) is 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 (National Bureau of Statistics, 2019), e is a precision level which was 0.05. As a result, the proposed minimum sample unit was 398 households. To empirically estimate casual impact of intervention when randomization is not feasible, quasi-experimental design is recommended (Weber, Uhlmann, Schönenberger & Kieser, 2019). Thus, this study adopted the quasi experimental design since assignment to intervention (cash transfer) was by means of administrator selection rather than random. The design identifies two comparable groups (treatment and control) so that researchers can look into disparities in outcomes of these groups. Therefore, 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 yields highest statistical power. Thus, the ratio of 1:1 was used in selection of recipient and non-recipient 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, the 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 the representative sample size. A size-proportional formula was employed. White and Sabarwal (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 characteristics, assets and other households' indicators of living standard. CT recipients and non-recipients' received a total of 398 questionnaire forms. 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 recipients were included in the FGD because they are the ones who can best describe the link between CTs and household poverty. The number of FGDs to be undertaken was determined using the theoretical saturation principle. Thirteen KIIs were chosen based on their previous expertise, nine of them are village executive officers and four of whom are TASAF coordinators.

Analytical Model

Furthermore, to estimate the impact of CTs on household poverty, the study used the Propensity Score Matching (PSM). It calculated the average treatment effect of cash program participation on the outcome of interest. The study specifically compared poverty indicators of households participating in CT programs with those not participating, after matching both groups based on their characteristics. The difference in poverty levels is then attributed to household participation in the CT program. Participation in the CT program was represented by a dummy variable Pj, equals to one for participating households j and zero for non-participating households. Let Vij_1 and Vij_0 represent variables indicating the poverty indicators in commodity i for household j in the presence and absence of a CT program. As a result, the intervention effect of CT on relevant outcome indicators can be calculated as:

$$\pi_j = E\left[V_{j1} \middle| P_j\right] - E\left[V_{j0} \middle| P = 1\right] \qquad (1)$$

where π_j is the average treatment effect on CT program participation (average difference on poverty levels of CT recipients and non-recipients). This study does not track the particular household over two different time periods. Therefore, the study can estimate $E(V_{j1}/Pj=1)$ and $E(V_{j0}/Pj=0)$ but it cannot estimate the counterfactuals $E(V_{j1}/Pj=0)$ and $E(V_{j0}/Pj=1)$.

Selecting the covariates to be used in the model is the first stage in applying the PSM. It is vital to incorporate variables related to self-selection and traits present at the beginning of the intervention (Harris & Horst, 2016). The study looked at the variables that influenced households' participation in the program. The study used age, gender, household size, marital status, years in school, production land size, home land size and occupation variables. The choice of the variables was influenced by indicators used in selection of CT recipients in Tanzania as indicated by Evans, Holtemeyer, Kosec (2018).

The estimation of propensity score was the second stage. Given the model's set of variables, the propensity score is the likelihood that the household will receive CT. Expression S(X) = S(Pj=1/X) represent the propensity score, which is the probability of being assigned to treatment. The goal of developing a propensity score was to allow for a more balanced distribution of characteristics between recipients and non-recipients. On the basis of observable factors, the comparison between households getting CT and those not receiving CT implies that unobservable features have no effect on participation in CT programs. PSM expects that the outcomes of interest are unaffected by CT participation status when a set of X characteristics is assumed. The conditional independence assumption is the name given to this assumption. Only factors that are unaffected by participation in the CT program should be included in the model, according to this assumption. The condition presupposes those unobservable factors will not cause selection bias. It can be expressed as:

$$(V_{j0}, V_{j1}) \perp P_j \ / X_j \text{.....................} \ (2)$$

Where ⊥ denotes independence. In addition, the overlap assumption states that each household with matching characteristics has positive probability of receiving the CT (Dehejia and Wahba, 2018). The assumption is expressed as:

$$0 < (P_j{=}1/X_i) < 1 \text{..........................} \ (3)$$

Equations (2) and (3) confirm that households are randomly exposed to treatment, hence treated and control households should be examined similarly. As a result, counterfactual estimation is shown as:

$$E(V_{j0}/P{=}1, V_j) = \mathrm{E}\,(V_{jo}/P_j = 0, X_j) \text{.......} \ (4)$$

Finally, for household j, the PSM average treatment effect on the treated (ATT) is expressed as

$$\pi_j = \mathrm{E}\,(V_{j1}/P = 1, \mathrm{S}\,(X_j) - \mathrm{E}\,(V_{j0}/P_j = 0, \mathrm{S}\,(X_j) \text{........................} \ (5)$$

A number of techniques have been proposed for matching recipients and non-recipients. Nearest Neighbor Matching (NNM), Kernel Matching (KM), Radius Calliper Matching and Mahalanobis Distance are the most prominent approaches (Lane, To, Shelley & Henson, 2012). In terms of the trade-off between quantity and quality of outcomes, each of the matching technique described has pros and cons. As a result, they are frequently used in conjunction with others. NNM, Radius Calliper and Mahalanobis were used in this study to match recipients and non-recipients because they provided adequate covariate balance.

The ATT calculated with PSM was based on the premise that unobserved variables had no influence. However, a hidden bias may exist and the matching results may no longer be robust if unobserved variables that affect impoverished households' participation to CT program exist. The study employed the Rosenbaum's proposed sensitivity parameter gamma coefficient (*Γ*) to assess the presence of a hidden bias in the model (Becker & Caliendo, 2007). When the reported confounders have been dealt with using matching methods, which generate matched pairs of exposed and unexposed households, who are similar on the observed variables, this method is most commonly utilized. The core premise of the Rosenbaum technique is to employ Γ to measure the effects of hidden bias on processing estimations (Nannicini, 2013). The value cannot be calculated directly since the unobserved variables cannot be determined; hence, the value representing hidden bias is assumed before calculating the significance of the estimated changes on treatment effects. As the value of Γ increases, so does the level of significance. This is performed with various values of to determine the value at which the upper-bound p-value becomes non-significant. (e.g., p>0.05). A higher value of Γ is desired to make the upper-bound p-value non-significant as it shows that the odds ratio of the association between the outcome and the exposure is more resilient to unobserved bias. The assumed maximum gamma is referred as Rosenbaum boundary. There is no specific criteria for determining the value of Γ; however other studies (Ji, Jin, Wang & Ye, 2019; Krishnamoorthy & Rehman, 2021) in the social sciences, used Γ between 1 and 2 to indicate that a hidden bias does not exist.

Poverty variables were adopted from living standard measures proposed in Global Multidimensional Poverty Index (MPI) as recommended by World Food Program (2017) and Demographic and Health

Survey (DHS) wealth index (Hjelm, Mathiassen, Miller & Wadhwa, n.d.; Pirani, 2014) .The index was chosen because it measures the simultaneous occurrence of multiple deprivations in an individual or household. The use of multidimensional poverty measures in the evaluation of the CT program raises the bar for the program success because, in order to be effective, the transfer must address multiple deprivations, not only by reducing each deprivation individually, but also by lowering the likelihood of them occurring simultaneously. They do not cover all aspects of human welfare, but they do capture a critical component of any assessment of low-income country living standards. The study used seventeen indicators to measure five dimensions of deprivation (Appendix 1). Four dimensions proposed are housing dimensions (SDG 11: Sustainable Cities and Communities), use of basic services (SDG 6: Clean Water and Sanitation, SDG 7: Affordable clean energy), productive and non-productive assets (SDG 1: No poverty). The choice of variables was guided by their indication of the longer-term economic status of household rather than short-term economic changes. Indicators are defined as binary variables, taking value 1 if the individual is deprived, 0 otherwise. Appendix 1 shows the definition of deprivation for each indicator used in this analysis.

Factor analysis was used to calculate the overall wealth index. The Kaiser-Meyer-Olkin (KMO), a Measure of Sampling Adequacy (MSA), was used to detect multicollinearity in the data and determine whether or not to conduct a factor analysis. KMO has a maximum value of 1.0, but any value above 0.6 is acceptable (Krishnan, n.d.). For this data it was 0.743, indicating that a factor analysis of the variables can proceed. The Bartlett's (1950) Test of Sphericity was used to assess the strength of the relationship between variables. The null hypothesis that the variables in the population correlation matrix are uncorrelated is tested using Bartlett's Test of Sphericity. Analysis revealed a significance level of 0.00, which is small enough to rule out the hypothesis (the probability should be less than 0.05 to reject the null). It can be concluded that the relationship between variables is strong, or that the correlation matrix is not an identity matrix, as required by factor analysis.

Table 1: Results of PCA: Varimax Rotation Matrix

Indicator	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Livestock						0.707	
Hoe	0.801						
Panga	0.732						
Crowding			0.813				
Type of wall		0.642					
Type of roofing		0.739					
Type of floor		0.659					
Lighting					0.597		
Drinking water					0.793		
Toilet				0.736			
Axe	0.601						
Slasher							0.771
Chair					0.601		
Bed	0.616						
Cupboard							0.579
Mobile phone	0.464						
Cooking fuel						0.774	
Eugen Value	2.543	1.915	1.381	1.261	1.201	1.086	1.051
% of variance	14.129	10.636	7.665	7.004	6.675	6.036	5.839

Appendix 1 contains the PCA results using varimax rotation. The number of extracted factors can be defined by the user, and there are techniques available in SPSS to assist in determining the number of factors. Kaiser's criterion, also known as the eigenvalue rule, is a popular technique. Only factors with an eigenvalue (the variances extracted by the factors) of 1.0 or greater are retained under this rule (Yeoman & Golder, 1982). Using this criterion, seven factors were retained.

The seven factors accounted for 57.984% of the total variation. As a result, the importance of the factors in measuring overall socioeconomic condition differs. A Non-standardized Index (NSI) was created for each household by using the proportion of these percentages as weights on the factor score coefficients. On a linear scale, this index compares the socioeconomic status of one DA to another. The index's value can be positive or negative, making interpretation difficult. As a result, a Standardized Index (SI) was created, with a value ranging from 0 to 100.

Results and Discussion

This section presents results on the CT impact on overall poverty levels and on selected dimensions of poverty.

CT Impact on Households' Poverty Level

Impact Analysis on Overall Wealth

Using the wealth index created previously, the study estimated the impact of CT on living standard of poor households by using PSM. The PSM estimated results using NNM (1), Radius caliper (0.05) and Mahalanobis techniques which are presented on Table 2. T-statistics by NNM (1), Radius caliper and Mahalanobis were 1.64, 1.51 and 1.72 respectively. Although the effect of CT on overall household's wealth using all three PSM matching estimators was positive, findings did not indicate significant impact on the same. These findings are in line with the study by Saeed, Kashif, Azmat, Saeed, M & Hayat, 2020) in Pakistan and Sumarto (2021) in Indonesia who both found that CT has no significant impact in the overall wealth of poor households.

Table 2: PSM estimation of overall wealth index

	Matching Estimators	Recipients (ATT)	Non-recipients (ATT)	Mean diff.	Standard errors	t-stat
Wealth Index	NNM(1)	43.92	39.91	4.01	2.45	1.64
	Radius (0.05)	42.45	39.90	2.55	1.69	1.51
	Mahalanobis	42.53	38.99	4.49	2.61	1.72

Table 3: Estimation of impact of CT on housing conditions

Outcome Indicators	Matching Estimators	Recipients (ATT)	Non-recipients (ATT)	Mean Diff.	Standard. Error	t-stat
Crowding	NNM(1)	0.0057	0.0088	-0.0031	0.0087	-0.36
	Radius(0.05)	0.0066	0.0132	-0.0066	0.011	-0.58
	Mahalanobis	0.0057	0.0114	-0.0057	0.0128	-0.45
Type of wall	NNM(1)	0.3198	0.2733	0.0465	0.0606	0.77
	Radius(0.05)	0.3223	0.2961	0.0263	0.0532	0.49
	Mahalanobis	0.3829	0.3200	0.0629	0.0664	0.95
Roof material	NNM(1)	0.6047	0.5872	0.0174	0.0663	0.26
	Radius(0.05)	0.6053	0.5724	0.0329	0.0566	0.58
	Mahalanobis	0.6239	0.5943	0.0296	0.0492	0.60
Type of floor	NNM(1)	0.1991	0.1086	0.0905	0.0367	2.47
	Radius(0.05)	0.2039	0.1052	0.0987	0.0412	2.39
	Mahalanobis	0.2457	0.1086	0.1371	0.0539	2.54

Findings do not support the alternative hypothesis that CTs have impact on households' poverty reduction. This was confirmed by consensus from the FGD that: "...We know no one whose life has really been transformed because of CT. We are all still struggling to make our ends meet" (Lindi District, 24 January 2020). This indicates that CTs alone are generally not sufficient on their own to lift the poorest households out of poverty permanently. However, to further understand the impact of CT on each specific indicator of the index, impact analysis for each item was carried out.

Impact of CT on Housing Conditions

With reference to MPI which was developed by UNDP (2020), one of the indicators of deprivation is the housing conditions. Therefore, the study sought to establish the impact of CT on housing conditions by using Propensity Score Matching (PSM). Housing conditions analyzed comprise of crowding, type of wall, roofing materials and type of floor. PSM results using three matching techniques, NNM, Radius caliper (0.05) and Mahalanobis are presented in Table 3.

Findings indicate that mean scores for recipients are higher than that of non-recipients in type of wall, roofing materials and type of floor. This suggests that it is likely that CT is contributing positively to housing conditions. Furthermore, CT was found to have statistically significant impact on type of floor only. For type of floor the t-statistic was 2.47, 2.39 and 2.54 for NNM, Radius caliper (0.5) and Mahalanobis matching techniques respectively. This means that in comparison to non-recipients' houses, most of recipients' houses had cement floor.

Findings are consistent with the study by Habimana, Haughton Nkurunziza & Haughton (2021) in Rwanda and Pettifor, Wamoyi, Balvanz, Gichan & Maman, (2019) which concluded that CT has impact on type of floor. The probable reason is that it's easier and cheaper to renovate house floor than other house properties. This was confirmed by consensus from FGD that "... We wish we could be able to improve our houses, but you know, we lack money to do so, some of us have only been able to improve the floors of our homes. ...." (Lindi District, 20 January, 2020).

The above statement means that improvement of floor is a cheaper option compared to other options which they have thought about. The poor have to make their decisions under severe resource conditions which influence the way they choose. While improvements of other house structures such as wall and roof may necessitate the households to shift to another house during construction, changing or improving the floor can be done while household's members still live in the house. This implies that households' choice on how to spend the CT is also guided by convenience.

Impact of CT on Basic Services

CT can address financial barriers to basic services. Thus, the impact of CT on household's source of lighting energy, cooking fuel, source of drinking water and type of sanitation facility is estimated. PSM results on estimation of the CT impact on basic services are presented in Table 4. Mean score difference on cooking fuel, source of drinking water and type of sanitation facility is positive, indicating that CT may positively contribute to the improvement of the basic services. Nevertheless, its impact is statistically significant on households' sanitation facility only.

Table 4: PSM Estimation of CT Impact on Basic Services

Outcome Indicators	Matching Estimators	Recipients (ATT)	Non-recipients (ATT)	Mean Diff.	Standard. Error	t-stat
Lighting	NNM(1)	0.7558	0.8256	-0.0698	0.054	-1.28
	Radius(0.05)	0.7697	0.8092	-0.0395	0.047	-0.84
	Mahalanobis	0.7486	0.8343	-0.0857	0.058	-1.48
Cooking fuel	NNM(1)	0.6452	0.5623	0.0829	0.0911	0.91
	Radius(0.05)	0.6310	0.6200	0.1100	0.1211	0.92
	Mahalanobis	0.6221	0.6124	0.0097	0.0132	0.73
Drinking water	NNM(1)	0.4069	0.3547	0.0523	0.6610	0.79
	Radius(0.05)	0.4211	0.4013	0.0197	0.0566	0.35
	Mahalanobis	0.4057	0.3829	0.0229	0.0683	0.33
Sanitation facility	NNM(1)	0.9543	0.9292	0.0251	0.0122	2.05
	Radius(0.05)	0.9474	0.9211	0.0263	0.0090	2.92
	Mahalanobis	0.9543	0.9486	0.0057	0.0026	2.18

T-statistics results for sanitation facility are 2.05, 2.92 and 2.18 by using NNM, radius caliper (0.5) and Mahalanobis matching techniques respectively. Data from Nepal suggest that households receiving CTs have better sanitation facilities than those not receiving (Renzaho *et al.*, 2018). Most households were concerned with their privacy in using facilities. Thus, CT was useful in addressing lack of privacy which was associated with lack of money. Although the main concerns of policy makers in using unimproved sanitation facilities are health, respondents were less concerned with health issues. The feeling that they were inferior to other households because of poor toilets and bathroom guided them to this choice.

Impact of CT on Productive Assets

To get insight on how low-income households create wealth, the study analyzed the impact of CT on households' productive assets. Four agricultural assets which mostly explain productive capabilities of rural Tanzanians were chosen (Bjornlund, Bjornlund & van Rooyen, 2020). PSM estimation on the livestock, hoe and panga are presented on Table

5. Furthermore, findings indicate that assets accumulation for recipients in all four items is more than for non-recipients; however, only increase in livestock is robust. T-statistics for livestock was 2.58, 3.11 and 2.56 for NNM, Radius (0.05) and Mahalanobis respectively.

Although most of recipients argued that the money received was not enough to cause significant impact on productive assets, the indirect effect of CT on livestock was noticed. The probable pathway through which livestock assets were increased is through reduced depletion as the results of increased economic resilience. These findings are consistent with the study by Daidone, Davis, Handa & Winters, 2019) which concluded that CT in Malawi has significant impacts on livestock. This is the indication that in long run, CT can have transformative impact in livestock accumulation of low-income households.

Impact of CT on Non-productive Assets

The study sought to establish the impact of CT on non-productive assets. Non-productive assets such as household durables represent households' wellbeing and may determine households' consumption. Six assets which are axe, mobile phone, cupboard, bed, chair and slasher were analyzed and the findings are presented in Table 6.

Table 5: PSM estimation on productive assets

Outcome Indicators	Matching Estimators	Recipients (ATT)	Non-recipients (ATT)	Mean Diff.	Standard. Error	t-stat
Livestock	NNM(1)	0.8895	0.7733	0.1163	0.0451	2.58
	Radius(0.05)	0.8800	0.8171	0.0629	0.0202	3.11
	Mahalanobis	0.8571	0.8389	0.0182	0.0071	2.56
Hoe	NNM (1)	0.2500	0.2034	0.0465	0.0577	0.81
	Radius(0.05)	0.2571	0.2457	0.0114	0.0593	0.19
	Mahalanobis	0.2566	0.2434	0.0132	0.0498	0.26
Panga	NNM(1)	0.7849	0.7558	0.0291	0.0538	0.54
	Radius(0.05)	0.7965	0.7771	0.0193	0.0412	0.47
	Mahalanobis	0.8026	0.7961	0.0066	0.0461	0.41

Table 6: PSM estimation on non-productive assets

Outcome Indicators	Matching Estimators	Recipients (ATT)	Non-recipients (ATT)	Mean Diff.	Standard. error	t-stat
Axe	NNM(1)	0.4417	0.4400	0.0017	0.0503	0.03
	Radius(0.05)	0.4823	0.4474	0.0349	0.0504	0.69
	Mahalanobis	0.4710	0.4581	0.0129	0.024	0.53
Mobile phone	NNM(1)	0.3982	0.2920	0.1062	0.048	2.21
	Radius(0.05)	0.3965	0.2134	0.1831	0.063	2.90
	Mahalanobis	0.3872	0.3469	0.0403	0.017	2.42
Cupboard	NNM(1)	0.1046	0.0639	0.0406	0.037	1.09
	Radius(0.05)	0.1157	0.0601	0.0556	0.057	0.98
	Mahalanobis	0.1103	0.0782	0.0321	0.026	1.23
Bed	NNM(1)	0.7151	0.7093	0.0058	0.059	0.10
	Radius(0.05)	0.6977	0.6812	0.0165	0.034	0.49
	Mahalanobis	0.7045	0.7131	-0.0086	0.066	-0.13
Chair	NNM(1)	0.2478	0.1611	0.0867	0.041	2.15
	Radius(0.05)	0.2500	0.1710	0.0789	0.029	2.70
	Mahalanobis	0.2629	0.1693	0.0936	0.034	2.76
Slasher	NNM(1)	0.0291	0.0233	0.0058	0.0166	0.35
	Radius(0.05)	0.0197	0.0066	0.0132	0.0131	1.01
	Mahalanobis	0.0265	0.0214	0.0051	0.001	0.91

PSM estimation indicated that in all six assets, there is positive mean difference between recipients and non-recipients' households. This implies that recipients were more likely to own non-productive assets than non-recipients' households. However, the CT had significant impact on mobile phone and chair with t-statistics above 1.96 in all matching techniques.

T-statistics for mobile phone were 2.21, 2.90 and 2.42 for NNM, Radius caliper (0.05) and Mahalanobis matching techniques respectively. For chair, the T-statistics were 2.15, 2.70 and 2.76 for NNM, Radius caliper (0.05) and Mahalanobis matching techniques respectively. This might imply that recipients used the money received from the CT program to buy mobile phones and chairs. While the purchase of mobile phones might be instigated by the need for social participation, the chair improves social and economic prestige. These findings are supported by Bursztyn and Jensen (2017) and Fershtman and Segal (2018) that human is inherently social, and his craving for social participation effect his economic choices. This means interaction between decision makers affect their preferences. CT improves social inclusion by improving the terms of participation n in a society.

Sensitivity Analysis

PSM results presented previously relied heavily on the assumption of unfoundedness or conditional independence. That is, all the variables affecting both the treatment and the outcome variable are observed and can be controlled for. However, hidden bias may arise by exclusion of variables that may have impact on participation in the CT program and poverty indicators. Thus, this study adopted the Rosenbaum bounds approach to determine how strongly unobserved confounders relate with the participation in the CT program.

Table 7: CT participation sensitivity analysis

Gamma	Hodges-Lehmann point estimate (ATT)		Wilcoxon's signed rank (p-value)	
(Γ)	Lower bound	Upper bound	Lower bound	Upper bound
1	0.4206	0.4206	0	0
1.1	0.4160	0.4252	0	0
1.2	0.4119	0.4293	0	0
1.3	0.4081	0.4329	0	0
1.4	0.4046	0.4366	0	0
1.5	0.4010	0.4398	0	0
1.6	0.3979	0.4429	0	0
1.7	0.3951	0.4458	0	0
1.8	0.3923	0.4484	0	0
1.9	0.3897	0.4509	0	0
2.0	0.3872	0.4533	0	0

Table 7 presents the Rosenbaum bounds sensitivity analysis using the Hodges-Lehmann point estimate of the treatment effect and Wilcoxon's signed rank statistic. The Hodges-Lehmann test gives the median range of ATT for every value of gamma while the Wilcoxon provides their corresponding ranges of significance levels for each ATT generated from gamma values.

Results indicate that for each variation of gama (Γ) by 0.1 from 1 to 2, Wilcoxon's sign rank was significant with $p<0.0001$. This implies that there is a significant relationship between unobserved confounder and participation in the CT program. This renders the association between poverty indicators and unobserved bias to become non-significant and no unobserved variables that affect households' participation in CT program.

Conclusions and Recommendations

The study concludes that to eliminate extreme poverty in Tanzania, small, regular CT program by itself is not enough. While CT has positive influence on reducing poverty levels of low-income households, the impact on overall poverty level is not significant.

CT has impact on type of floor, livestock, sanitation facilities, mobile phone and chairs. Thus, the unit increase of income for low-income households improves some households' living standard indicators. Nevertheless, the number of indicators impacted and the extent of impact were not enough to significantly influence the overall wealth. Therefore, the extent to which additional unit of income influence poverty reduction levels is contextual.

The fact that CT has significant impact in some poverty indicators confirms that structural changes in rural areas might improves the living standards of poor households. The fact that the choice of poor households to use monies from CTs on improvement of their house floor was the results of convenience signals the existence of structural constraints facing poor households in making economic decisions. Additionally, significant impact of CT on livestock assets as the result of increased resilience signifies the ability of CTs to loosen up some structural constraints. Thus, CT impact on poverty reduction is limited in a context where other structural factors strain recipients' ability to excel.

Furthermore, the findings are consistent with the cultural theory of poverty which states that CTs can alleviate harsh conditions of poverty if they will result into changes in households' behavior. Impact of CTs on use of basic services, productive, and non-productive assets is explained by the need for privacy, social participation and social prestige. The study contributes to the cultural theory by specifying behaviors which incentivize the use of CT.

To address multiple aspects of households' poverty, the study recommends TASAF to adopt multi-intervention programs which can directly impact key poverty indicators. One program fits for all, results into unbalanced program outcomes. Thus, understanding the needs of low-income households and how selected intervention affect poverty indicators is useful in tailoring programs for specific context. To increase the impact of CT programs on specific indicators, additional supportive initiatives are needed to address resource multiplication constraints facing low-income households.

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Appendix 1

Operationalization of Variables

Variable	Indicator	Wealthier	Poorer
Housing conditions	Crowding	1=1 or fewer than 5 in a room	0= 6 or more people per room
	Type of wall	1= baked bricks, sundries brick	0=Mud, timber, branches
	Roof material	1= Iron sheet	0= Grass or leaves
	Type of floor	1= Cement/Tiles	0= Sand/Earth
Use of basic services	Source of lighting energy	1= Solar and Electricity	0=Kerosene
	Cooking fuel	1=Electricity/Gas, charcoal, kerosene/Purchased wood	0= Collected Wood and dung
	Source of drinking water	1=Improved sources	0=Unimproved sources
	Sanitation facility	1=Improved facility	0=Unimproved facility
Productive assets	Had a livestock	1=Yes	0=No
	Had a hoe	1=Yes	0=No
	Had a panga	1=Yes	0=No
Non-productive assets	Had an axe	1=Yes	0=No
	Had a mobile phone	1=Yes	0=No
	Had a cupboard	1=Yes	0=No
	Had a bed	1=Yes	0=No
	Had a chair	1=Yes	0=No
	Had a slasher	1=Yes	0=No