# The Impact of Conditional Cash Transfers and Public Works Programs on Household Welfare in Rural Tanzania

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## Abstract

Both Public Works (PWs) and Conditional Cash Transfers (CCTs) programs have been implemented to support poor households in enhancing food security, protecting physical assets, and boosting resilience against shocks. However, ownership of valuable assets like improved housing, durables and livestock remains low among rural households in Tanzania. Evidence shows; that households without assets experience a decline in welfare and are at risk of falling into lower economic status. This study aims to assess the impact of integrated CCTs and PWs on asset holdings among households. The asset index was calculated using Principal Component Analysis (PCA) on cross-sectional data collected from 357 households (both treated and control) to determine household socioeconomic status and the Propensity Score Matching (PSM) technique was employed for impact evaluation. The results indicated that integrated CCTs and PWs contributed to improve asset accumulation by households. About 52% beneficiaries lives under improved iron roofed houses, owning 2 more goats and 3 more chicken compared to non-beneficiaries. Additionally, spending habits economics activities played a significant role in asset accumulation. The policy implications are to consider other cash transfer programs in other areas that have the potential to reduce poverty by providing direct financial assistance to vulnerable populations, leading to improved well-being and economic stability.

**Key words:** CCTs and PWs program; Asset index; PSM; Poor households

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## 1. Introduction

Both Public Works (PWs) and Conditional Cash transfers (CCTs) are social protection programs designed to help households smoothen consumption and safeguard their assets from economic risks (Fiszbein and Schady, 2009; Mussa, Agegnehu and Nashakira-Rukundo, 2022; Abay *et al.*, 2023; Zimmermann, 2023). Recently, analysts have emphasized the importance and benefits of assisting poor households in accumulating assets and protecting their current assets (Hidrobo *et al.*, 2018; Belghith, Karamba and De Bolsseson, 2020; Tadesse and Gebremedhin Zeleke, 2022; Yuliani, 2022). Argued that promoting long-term welfare through consumption or income-based assistance programs is challenging and can lead to undesired outcomes. However, asset accumulation serves a dual purpose, not only as a source of retirement, but also as a buffer against unforeseen emergencies (Modigliani and Brumberg, 1954; Liu and Hu, 2013). Furthermore, asset ownership is a reflection of household wealth status (Booysen*et al.*, 2008; Sherraden, 2016; Lawson, Ado-Kofie and Hulme, 2017).

However, despite the importance of assets ownership (Gamble and Prabhakar, 2005), poor household in rural areas owns few and or low value assets such as, house holdings (including, utensils, bench, local mats, and others) and some have few livestock (chicken, duck, pigs, sheep, and goat). Cash transfer programs have been extensively studied for their impact on asset ownership among rural households. However, findings on their effectiveness vary across different countries and programs. Some findings revealed significant while others yielded insignificant results (Daidone*et al.*, 2019; Knippenberg and Hoddinott, 2019; Tadesse and Gebremedhin Zeleke, 2022; Yuliani, 2022). These discrepancies underscore the need for a nuanced understanding of program impacts, particularly as most research has focused on CCTs rather than PWs programs. While CCTs provide periodic cash payments (Ivaschenko*et al.*, 2018), PWs offer lump-sum payments for participating in public works projects (NBS, 2016; Gehrke and Hartwig, 2018). The differing payment structures may influence how funds are utilized and impact asset accumulation differently. Thus, while valuable lessons can be drawn from existing research, generalizing program impacts across countries and contexts may not be feasible.

In Tanzania, the Productive Social Safety Net (PSSN) program, operating under TASAF since 2013, combines CCTs and PWs to support extremely low-income households and safeguard physical assets. PWs beneficiaries receive TZS 37,500 for 15 days per month in periods, totaling TZS 150,000 annually, while CCTs beneficiaries receive TZS 38,000 monthly, amounting to TZS 456,000 annually. Combined, beneficiaries could receive up to TZS 606,000 per year (NBS, 2016). Despite efforts, ownership of valuable assets like improved housing, durables and livestock remains low among rural households, highlighting persistent challenges in asset accumulation (Belghith, Karamba and De Bolsseson, 2020; World Bank, 2020a). This study examines whether the implementation of integrated PWs and CCTs programs in Tanzania's poor households resulted in greater asset ownership compared to non-participants, evaluating the impact of cash earned from both programs on asset accumulation levels at the household level. This study contributes to the knowledge by answering the three questions; (i) What is the comparative impact of integrated PWs and CCTs programs on asset ownership between beneficiary households and non-beneficiary households in Tanzania? (ii) How does the cash earned from PWs and CCTs programs influence the types and level of asset accumulation at the household level in Tanzania? (iii) What are the key socio-economic factors that influence asset ownership among households participating in integrated PWs and CCTs programs, and how can these factors inform effective strategies for reducing vulnerability to extreme poverty in Tanzania? The study is organized as follows; section 2 presents literature review, section 3 presents methodology, section 4 stands for results and discussion, and section 5 stands for conclusion and policy implications.

## 2.Literature review

The life cycle theory, as proposed by Modigliani and Brumberg in 1954, posits a significant relationship between the accumulation of assets and the consumption patterns of individuals over their lifetimes. It suggests that as individuals progress through different life stages, such as early working years, they tend to build up assets while simultaneously adjusting their consumption patterns based on available resources. Modigliani highlighted the importance of this theory in understanding how uncertainty influences individuals' decisions to save as a precautionary measure, thereby emphasizing the dual purpose of asset accumulation for both retirement planning and as a safeguard against unexpected financial emergencies. This theory underscores the crucial link between asset accumulation and consumption behavior, with assets serving as buffers to smooth consumption levels over the course of one's life(Modigliani and Brumberg, 1954; Bazzi, Sumarto and Suryahadi, 2015).The life cycle theory highlights the link between asset accumulation, consumption behaviors, and the role of assets in providing financial stability. Welfare programs like PWs and CCTs aim to support households, potentially impacting their asset accumulation and consumption stability (Jappelli, 2012; Liu and Hu, 2013). Understanding this connection can guide policymakers in designing effective social welfare strategies to alleviate poverty and enhance economic well-being.

The empirical review highlights various studies focusing on household welfare and physical asset accumulation resulting from Cash transfer programs (Andrews, Hsiao and Raiston, 2018; Daidone *et al.*, 2019; Aikaeli, Garcés-Urzainqui and Mdadila, 2021; Nirere, 2022; Tadesse and Gebremedhin Zeleke, 2022). For instance, in Zambia and Ethiopia, led to significant increases in operated land. Conversely, in Ghana, land use decreased. Notably, asset ownership varied across programs, with some emphasizing specific assets regardless of their overall impact on household welfare. For example, ownership of assets like sickles, scotch carts, and troughs increased in certain countries but may not significantly alleviate poverty alone. In Indonesia, CCTs had no significant impacts of durable assets (Yuliani, 2022). However, programs in sub-Saharan Africa demonstrated significant impacts on household consumption, savings, agricultural assets, and livestock keeping (Hidrobo *et al.*, 2018). Moreover, in Malawi, there was a substantial increase of 52% in productive assets such as goats (Bastagli *et al.*, 2019). As well, CCTs in Tanzania revealed notable impacts on bicycle and livestock ownership among beneficiaries compared to non-recipients. However, ownership of items like sewing machines, radios, mobile phones, stoves, and land showed no significant differences (Evans and Kosec, 2014).

CCTs programs have been extensively evaluated for their potential to alleviate poverty and improve household welfare (Kabeer and Waddington, 2015; Millán*et al.*, 2019). They demonstrate positive effects on children's outcomes, such as health, growth, and cognitive development, while also reducing child labor, increasing household consumption and investment, and improving schooling (Barca *et al.*, 2013; Daidone*et al.*, 2018, 2019). Similarly, PWs programs implemented in various countries have shown significant impacts on household welfare, enhancing productivity, income, coping mechanisms during shocks, and asset accumulation (Das and Mocan, 2016;

Perova*et al.*, 2021; Zimmermann, 2023). Combining CCTs with PWs programs has revealed diverse impacts, such as reducing school dropout rates and crime rates, as seen in Tanzania and El Salvador respectively (Acosta and Monsalve Montiel, 2018; De Hoop *et al.*, 2020). Mexico's PROGRESA/ Oportunidades program exhibited lasting positive effects on schooling and work patterns, emphasizing the sustainability and effectiveness of integrating cash transfers with work requirements (Abay*et al.*, 2023). Moreover, assessments utilizing Propensity Score Matching (PSM) and Difference-in-Differences (DID) methods have shown increases in household investments in productive assets and activities among CCT beneficiaries (Milla, 2020; Cirillo and Giovannetti, 2018). The existing literature extensively documents the individual impacts of CCTs programs and PWs initiatives on household welfare, yet there's a notable gap in understanding the combined effects of integrating both approaches. While studies demonstrate the effectiveness of CCTs and PWs separately in improving income, education, and reducing crime, there's limited research exploring their synergistic impacts on poverty alleviation and household asset ownership. Therefore, there's a need for further investigation into the combined effects of CCTs and PWs programs to comprehensively understand their potential in lifting households out of poverty and enhancing long-term economic prospects.

## 3. Methodology

### 3.1 Research Design, Data type and Data collection

This is a quasi-experimental study where econometric techniques were applied to create a better counterfactual by removing pre-existing significant differences in key variables. The propensity score matching (PSM) methods as described by Rosenbaum (1983) were used to create the two groups of households (treatment and control). The study was conducted in Itilima, Misungwi, and Ngara districts in Simiyu, Mwanza and Kagera region respectively. These districts implemented integrated CCTs and PWs of PSSN programs under TASAF between 2015 and 2020.The study employed a cross-sectional research design where quantitative data were collected from a sample of 357 households (175 treatment and 182 control) by a structured questionnaire with guidance from the World Bank's Living Standards Measurement Study Household Surveys (Grosh and Glewwe, 1998) and the variables used in the Proxy Means Test (PMT) when identifying program beneficiaries (URT, 2013).

### 3.2 Impact evaluation technique

To estimate the impact of the programs, the study used PSM technique. PSM focuses on comparing treated and control units at a single point in time. PSM uses a linear combination of covariates to form a composite that can be used to balance the treatment and comparison groups by constructing propensity scores, denoted as P(x). Propensity scores derived from a logit model were utilized to match the treated and control groups. The strength of PSM allows a researcher to obtain a credible counterfactual when random assignment is not possible (Imbens, 2003; Caliendo and Kopeinig, 2008; Gertler *et al.*, 2016; Granger *et al.*, 2020). Furthermore, study intend to evaluated also one - time asset variables including, number of livestock, durables, savings and extra earning including harvests that were not recorded at baseline. To measure the impact, the Average Treatment on Treated (ATT) is estimated as described below:

$$P(X_i) = P_r\,(T_i = 1 |\, X_i) \qquad (1)$$

where, $P_r$ is the probability of household i being Treated, takes dummy values; $T_i$ represents treatment status of household i (1= treated or 0 = Not treated); $X_i$ represents a set of observed variables (vector of covariates) for household i. Having the P(x) scores, PSM estimates the ATT as the mean difference in outcome of interest over the common support,

$$ATT = E_{P(x)|T=1}\{E[Y(1)|T = 1, P(x)] - E[Y(0)|T = 1, (P(x)]\} \quad (2)$$

Where, Y(1) stands for the outcome of the Treated group, and Y(0) stands for the outcome of the control group. The PSM estimator could be obtained after matching the propensity scores using different matching algorithms. The commonly used matching algorithms include nearest neighbor, Radius or caliper, Kernel and Stratified matching algorithms (Khandker, Koolwal and Samad, 2010). Different studies have utilized either all algorithms and discussed the results based on least biased algorithm (Mdadila, 2017) while others have opted for one of them, with Nearest Neighbour (NN) being widely used (Mahmoud and Thiele, 2013; Granger *et al.*, 2020). Granger et al (2020) argued that the propensity score model must be correctly specified to avoid residual confounding bias (Zhang *et al.*, 2019). Different approaches need to be considered to ensure a good fit of the model. In this study, Conditional Identification Assumption (CIA) for covariate balancing, t-value and P - values to check for statistically significance differences in covariate means between both groups (Khandker, Koolwal and Samad, 2010).

**3.3 Assessment of socioeconomic status**

The econometric evidence suggests using the asset index as a proxy for socioeconomic status to predict welfare (Filmer and Pritchett, 2001; Sherraden, 2016). The asset index is particularly effective at categorizing the wealthiest and poorest quintiles (Prakongsai, 2006; Booysen *et al.*, 2008). Assets with high scoring factors such as computers, bicycles, radios, televisions, refrigerators, mobile phones, and subwoofers should be included in the asset index construction due to their significant socioeconomic differentiation capacity. (Sahn and Stifel, 2000) and Filmer and Pritchett (2001) have classified the assets into household durables (eg. bicycle, radio, furniture) and household living environment (e.g., number of rooms, toilet facilities, housing materials, light and cooking energy). However, in this study, some assets such as Computers, televisions, refrigerators are rarely owned by poor rural households and were not used.

Asset accumulation is measured by the asset index (Ai) which is derived from Principal Component Analysis (PCA). The PCA approach is utilized to weigh the variables of assets and generate the asset index (Prakongsai, 2006; Hepelwa, 2012). To establish the asset index for each household in the survey, several procedures involve summing all owned assets multiplied by their respective weights as explained in equation 3. Therefore, PCA was applied to reduce the dimension of asset variables into a given number of Principal Components (PCs). Mathematically, for n numbers of variables, the $k^{th}$ component is expressed as shown in equation 3.

$$PC_k = \sum_{i=1}^{n} W_{ki} X_i \quad (3)$$

$PC_k$ represents the $k^{th}$ principal component, $W_{ki}$ denotes the weight assigned to the variable $X_i$ in the $k^{th}$ principal component, and $X_i$ is the variable utilized in calculation of principal components.

After conducting the PCA, we assessed the sampling adequacy using the Kaiser-Meyer-Olin (KOM) statistic to determine the relevance and adequacy of the variables utilized in PCA. The acceptability of the KMO value, that should exceed 0.5, guided our conclusions (Kaiser, 1974). To calculate the asset index score for individual households (Chartfield and Collins, 1980), we summed the product of the score factor and standard value of each asset owned by the household (Equation 4).

$$A_i = \sum_{k=1}^{n} Ps_a\, x\, (a_k - \bar{a}_k)/\delta_k \tag{4}$$

Where $A_i$ is the Household i asset index; $Ps_a$ is the score factor of asset k obtained from the principal component with largest variance; $a_k$ is the $k^{th}$ asset owned by the household; $\bar{a}_k$ is the mean value of $k^{th}$ asset considering all households, $\delta_k$ is the standard deviation of the $k^{th}$ asset.

## 4. Results and discussion

### 4.1 Descriptive statistics

In 2015, significant differences in household assets were observed between the treated and control groups. While the treated group showed lower ownership of certain housing materials like burnt brick walls and iron roofs, they had higher rates of improved toilet facilities and health insurance coverage. Notably, the treated group had more households per room on average (Table 1). These findings highlight initial disparities in asset ownership and access to amenities, suggesting areas where interventions could be targeted for improvement.

**Table 1: Descriptive statistics of the baseline variables**

| Household Assets 2015 | Treated mean | Control mean | Overall mean | Mean difference |
|---|---|---|---|---|
| **Household own house 2015 (%)** | 80 | 82 | 81 | -2 |
| **Walls burnt bricks/blocks 2015 (%)** | 6.3 | 9.9 | 8.1 | -3.6 |
| **Iron roofed 2015 (%)** | 27.4 | 42.3 | 35.0 | -14.9*** |
| **Cement/ tiles floor 2015 (%)** | 3.4 | 6.0 | 4.8 | -2.6 |
| **Improved toilet facility 2015 (%)** | 84 | 76.4 | 80.1 | 7.6* |
| **Improved cooking 2015 (%)** | 2.8 | 1.1 | 2.0 | 1.7 |
| **Improved lighting energy 2015 (%)** | 4.5 | 21.4 | 13.2 | -16.8*** |
| **Improved water source 2015 (%)** | 40 | 33.5 | 36.7 | 6.5 |
| **Households per room 2015** | 3.426 | 2.763 | 3.088 | 0.663*** |
| **Household health insured 2015(%)** | 2.9 | 12.6 | 7.8 | -9.8*** |
| **Observations** | 175 | 182 | 357 | |

Authors' findings: (using t-test; levels of significance ranges: * P<0.1 **P<0.05 ***P<0.001)

### 4.2 Model description and performance results

The model included 26 variables related to proxies of household welfare (Table 2). The Measure of Sampling Adequacy (MSA) for each variable is above 0.5 and KMO value is 0.73 indicating that the variables have adequate observations and permit the PCA to produce reliable results (Appendix I). These results indicate that the model fit is good making the results adequate and reliable for further analysis, such as the estimation of the asset index, which is the central aim of performing PCA in this study.

**Table 2: PCA results: Varimax rotation factor matrix**

| S/N | Variable (X) | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | Own house | | | | | | | 0.723 | | |
| **2** | Improved wall | | | | | | 0.656 | | | |
| **3** | Improved roof | | | | | | | | | 0.704 |
| **4** | Improved floor | | | | | | 0.424 | | | |
| **5** | Crowding | | | | | | | 0.227 | | |
| **6** | Improved Toilet | | | | | | | 0.484 | | |
| **7** | Improved water | | | | | 0.588 | | | | |
| **8** | Lighting energy | | 0.33 | | | | | | | |
| **9** | Cooking energy | | | | | 0.373 | | | | |
| **10** | Own land | | | | | 0.563 | | | | |
| **11** | Own hoe | | | 0.535 | | | | | | |
| **12** | Panga | | | 0.328 | | | | | | |
| **13** | Insurance | 0.283 | | | | | | | | |
| **14** | Chicken | | 0.357 | | | | | | | |
| **15** | Number-chickens | | 0.383 | | | | | | | |
| **16** | Goat | 0.509 | | | | | | | | |
| **17** | Number-goats | 0.458 | | | | | | | | |
| **18** | Cow | | | | | | | | 0.698 | |
| **19** | Chairs | | | 0.330 | | | | | | |
| **20** | Battery | | | | 0.692 | | | | | |
| **21** | Bicycle | | 0.467 | | | | | | | |
| **22** | Solar | | | | 0.503 | | | | | |
| **23** | Phone | | 0.262 | | | | | | | |
| **24** | Radio | | | | 0.2 | | | | | |
| **25** | Group Savings | 0.327 | | | | | | | | |
| **26** | Crop harvest | | | | | | | 0.304 | | |
| **Percent of variance (61.14%)** | | **16.02** | **9.83** | **7** | **6.14** | **5.23** | **4.65** | **4.44** | **3.94** | **3.88** |

Source: Survey results, 2020

In principle there are thus 26 components that can be associated with variables for the analysis. Following the Kaiser rule of retaining the PCs with eigenvalues above 1, the nine (9) principal components explaining variance by 61.1% were retained (Table 2) and all used to estimate the household asset index. The scree plot (Appendix II) indicated 9 PCs above an eigenvalue of 1, highlining the closeness of the coefficients. The application of more than the first principal component (PC1) is likely, which contradicts the concept given previous scholars.

Table 2 also shows the variances explained by the retained principal components. The first principal component, PC1, explained 16% of the variance, the second principal component, PC2, explained 9.8%, and the other respective PCs up to PC9 explained 3.8%, with all nine PCs giving an accumulated explained variance totaling 61.1%. Therefore, retaining only the first PC as a measure of asset index as suggested by other scholars (Sahn and Stifel, 2000; Filmer and Pritchett, 2001), may not provide strong conclusive results for the model (Hepelwa, 2012). The variables in principal components (PCs) other than PC1 have significant weights that can influence the index construction. This suggests that a methodology allowing for the inclusion of variable weights from other components is important to enhance the index's ability to represent household welfare differences in the study area.

### 4.3 Estimation of the Asset index with PCA

The components with the largest percentages of variance and eigenvalue are considered to comprise the reasonable weights of variables that explain household welfare in the study (Sahn and Stifel, 2000; Filmer and Pritchett, 2001). The 9 components were retained, ensuring that the large proportion of variance (61.1%) explained by the variables was incorporated in the analysis. Therefore, the asset index was constructed using equation 4, utilizing the weights of the components derived from the asset variables and the PC scores retained for each household from table 4 as described in equation 5.

$$A_i = \frac{16}{61.1}xPC_1 + \frac{9.8}{61.1}xPC_2 + \frac{7}{61.1}xPC_3 + \frac{6.1}{61.1}xPC_4 + \frac{5.2}{61.1}xPC_5 + \frac{4.6}{61.1}xPC_6 + \frac{4.4}{61.1}xPC_7 + \frac{3.9}{61.1}xPC_8 + \frac{3.8}{61.1}xPC_9 \qquad (5)$$

### 4.4Household asset index scores and their distribution

The results reveal significant differences in asset index scores between households that received program treatment and those in the control group, with notable variations in the volume of assets across categories. In the lower category (Figure 1), indicating extreme poverty, 91% of control group households possess fewer assets, compared to 45% of households under the CCTs and PWs programs. Moving to the middle category, where households show some improvement, 29% of control group households exhibit enhanced asset ownership, contrasting with 6% of program beneficiary households. Finally, in the upper category representing relatively better-off households, 26% of program beneficiaries own a higher volume of assets, compared to only 3% of control group households. These findings underscore the positive impact of the programs on household welfare, particularly in terms of asset accumulation. However, it's important to note that the analysis did not address baseline similarities between the two groups, warranting further assessments to ascertain the true effect of the programs.

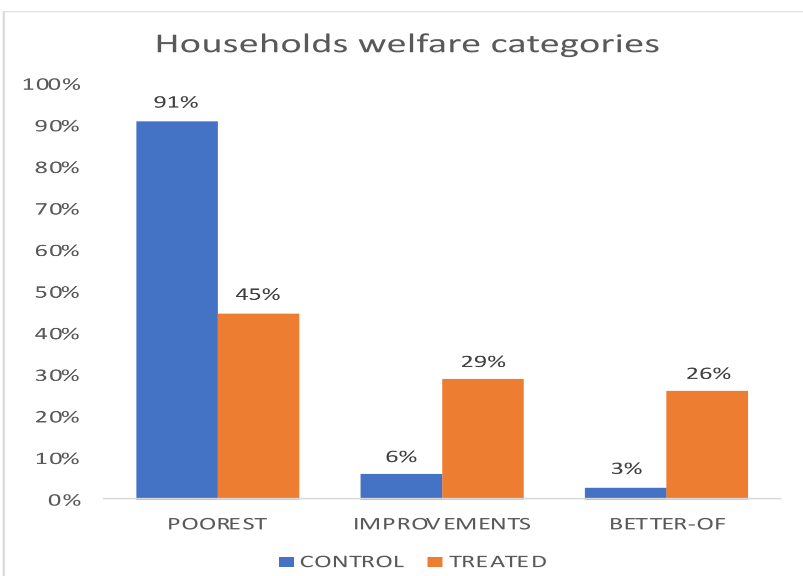


**Figure 1: Asset index categories**

### 4.5 Econometric results using PSM approach

In addressing potential biases when evaluating the impact of a social protection program on household welfare, PSM was employed. Initial tests highlighted significant differences in observable characteristics between treatment and control groups, suggesting potential bias. Through PSM, a propensity score model was developed to estimate the likelihood of treatment assignment based on observed covariates, ensuring balance between groups. This approach, outlined in studies such as (Abadie and Imbens, 2016; Zhang *et al.*, 2019; Granger *et al.*, 2020), facilitated the estimation of treatment effects while controlling for selection biases, thereby enhancing the reliability of impact assessments.

#### 4.5.1 Propensity scores using logistic regression analysis

Table 3 shows the regression coefficients derived from the logistic model. Significant results up to 10% are observed on baseline covariates including; iron roofed house, improved lighting energy, health insurance, female headed household, household aged above 35years and also household aged above 60years. Therefore, the differences observed at baseline level gives the need for the use of matching technique to create the balanced comparison groups.

**Table 3: Logistic Model for matching variables between treatment and control groups**

| Baseline Variables | Coefficient |
|---|---|
| Treated household | |
| Size of household | 0.032 |
| Household own house 2015 | -0.035 |
| Wall made of burnt bricks/ blocks 2015 =1 | -0.059 |
| Iron roofed 2015 =1 | -0.422*** |
| Cement flooring 2015=1 | 0.183 |
| Members per room 2015 | 0.018 |
| Improved toilet 2015 =1 | 0.284 |
| Improve cooking technology 2015 =1 | 0.788 |
| Improved light energy 2015 =1 | -1.32*** |
| Improved water sources 2015 =1 | 0.08 |
| Access to health insurance 2015=1 | -0.616* |
| Gender of head =1 | 0.291* |
| Head not educated =1 | -0.029 |
| Head below 18yrs =1 | 0.045 |
| Head above 35yrs but below 60yrs =1 | -0.528** |
| Head aged above 60yrs =1 | -0.924*** |
| Constant | 0.241 |

*Authors' findings, Note: * P<0.1 **P<0.05 ***P<0.001*

#### 4.5.2 The impact results using PSM approach

The research question was whether the integrated CCTs and PWs programs could significantly increase the asset ownership among poor households. Nearest Neighbor (NN) matching algorithm was applied to estimate the ATT (Austin, 2014; Nirere, 2022). Basing on the findings (Table 4), the treated households have accumulated more assets with high asset index score. Additionally, asset index was constructed from a combination of different assets; 29% of houses were improved while 52% of the houses are Iron roofed among households under the programs compared to non-beneficiaries. Households under the program were able to improve living environment like toilets such that, 13% of households have well-built toilet facility, while 10.8% households used of improved cooking stove and 18.3% have access to solar and electricity as the lighting energy. Furthermore, households under the programs owned more other assets such as Radio, Mobile phone, Solar, Bicycle and Furniture (Table 4). Also, the programs impacted significantly on the productive assets, 13% households under the programs have owned more land, 2 more goats, 3more chickens, more 25 panga, and 66% households increased their saving through groups compared to non-beneficiaries. These results are consistent with the results obtained from the low and middle-income countries (Andrews, Hsiao and Raiston, 2018; Hidrobo*et al.*, 2018; Bastagli*et al.*, 2019; Daidone*et al.*, 2019; Nirere, 2022). Although, these results are contrary with study of PSNP program in Southern Ethiopia, where assets accumulation was insignificant (Tadesse and Gebremedhin Zeleke, 2022). This discrepancy in results could be due the variables and models used for analysis.

**Table 4: PSM results**

| **Assets** | **ATT** |
|---|---|
| Asset Index | 1.86*** |
| House improved | 29%*** |
| House ownership | -13.8 |
| Wall-Bricks | -14% |
| Iron roofed | 52%*** |
| Cement flooring | 4.9 |
| Improved Toilet | 13** |
| Improved Lighting energy | 18.3** |
| Access to clean and safe Water | -6.8 |
| Improved Cooking energy | 10.8** |
| Radio | 22*** |
| Mobile phone | 34%*** |
| Solar | 21.1%*** |
| Bicycle | 16%*** |
| Battery | 6% |
| Furniture | 31%*** |
| Land ownership | 13%* |
| Hoe | -1.5 |
| Panga | 24.9*** |
| Number of Goat/sheep/pigs | 2*** |
| Number of Cows | 0 |
| Number chicken/ duck | 3*** |
| Savings | 66%*** |

*Authors' findings; analyzed with the nearest neighbor matching (*P<0.1 **P<0.05 ***P<0.001)*

### 4.6 Determinants of the asset ownership for poor households in the study area

An econometric model was developed to investigate the factors influencing the asset index of rural households, with the index categorized into three groups (seen in section 4.4). These categories served as the dependent variable in an ordered logit regression equation applied to households participating in CCTs and PWs programs. The analysis focused on identifying determinants of household asset accumulation, recognizing that households with greater asset ownership are typically associated with improved welfare outcomes (Sherraden, 2016).

Household spending habits, influenced by earnings from PWs and CCTs, play a crucial role in asset accumulation and welfare enhancement. Table 5 indicates that directing PWs earnings towards livestock or farm inputs significantly increases the likelihood of accumulating assets and achieving higher welfare levels. Livestock ownership, including chickens, goats, and cows, proves beneficial for welfare due to their productivity and multiple uses. Similarly, investing CCT earnings in petty businesses yields positive welfare outcomes, as depicted in Table 5. Savings emerge as a key determinant of welfare, with each unit increase significantly boosting the odds of higher welfare levels. Despite challenges in saving for poorer households, economic activities such as casual labor contribute positively to welfare enhancement. Moreover, households benefitting from both CCTs and PWs witness amplified welfare improvements, suggesting a supportive effect. Overall, household spending behaviors, particularly towards productive assets and investments, significantly influence asset accumulation and welfare levels, with combined program earnings playing a crucial role in promoting economic activities and enhancing household well-being (Daidone*et al.*, 2019).

**Table 5: Ordered logit regression results**

| Welfare category | Coefficient (log odds) | Std Error | P-value |
|---|---|---|---|
| **Spending of PW on** | | | |
| Livestock | 1.947*** | 0.362 | 0.000 |
| Farm inputs | 1.216* | 0.630 | 0.054 |
| Petty business | 0.305 | 0.728 | 0.675 |
| **Spending of CCTs on** | | | |
| Farm inputs | 0.657 | 0.571 | 0.250 |
| Livestock | 0.672 | 0.888 | 0.449 |
| Petty business | 0.820* | 0.488 | 0.093 |
| **Economic activities** | | | |
| Crop Farming | 0.594 | 0.419 | 0.156 |
| Petty Business | 1.407*** | 0.505 | 0.005 |
| Casual labour | 0.765* | 0.389 | 0.049 |
| Savings | 6.531*** | 1.547 | 0.000 |
| Remittances | 1.147 | 2.397 | 0.632 |
| **Income per month** | 0.542* | 0.274 | 0.048 |

Number of observations 175

LR Chi2 (13) = 253.08; Prob (chi2) = 0.000; Pseudo R2 = 0.7602

*Authors' findings; analyzed with the ordered logit model (*P<0.1 **P<0.05 ***P<0.001)*

## 5. Conclusion

The implementation of both CCTs and PWs in Tanzania, integrated together, aims to safeguard households' assets and enhance welfare. Households owning variety of assets such as an improved house, mobile phone, bicycle, chairs, chickens, goats, cows, land, trees, farm products among others, tend to have a better economic status (World Bank, 2020b).The integration of CCTs and PWs programs in Tanzania has shown positive effects on household asset protection and accumulation. Participating households exhibited greater asset ownership, indicating improved economic resilience and surplus spending beyond basic needs. Redirecting funds from both CCTs and PWs towards livestock and farming inputs correlates positively with household welfare. Engaging in non-farm activities contributes to increased asset accumulation and higher welfare levels. These findings underscore the importance of safety net programs in fostering economic empowerment and advocate for their continued integration and expansion to alleviate poverty sustainably. The policy implications are to consider other cash transfer programs in other areas that have the potential to reduce poverty by providing direct financial assistance to vulnerable populations, leading to improved well-being and economic stability. Future research should delve deeper into the intersection of these activities with social protection programs to advance poverty alleviation efforts further.

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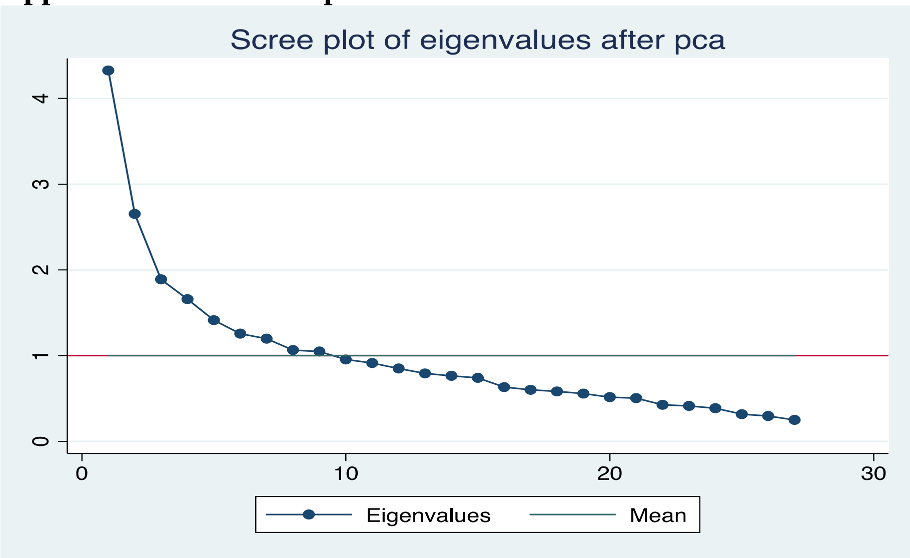
**Appendix I: Measure of Sampling Adequacy (MSA) for welfare indicators**

| Variable | Observations | MSA | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| **Ownhouse** | 357 | 0.71 | 0.2745098 | 0.4468933 | 0 | 1 |
| **Water** | 357 | 0.51 | 0.4117647 | 0.4928437 | 0 | 1 |
| **Lighting** | 357 | 0.64 | 0.4089636 | 0.4923325 | 0 | 1 |
| **Cooking** | 357 | 0.7 | 0.0868347 | 0.2819879 | 0 | 1 |
| **Toilet** | 357 | 0.75 | 0.8263305 | 0.3793567 | 0 | 1 |
| **Crowding** | 357 | 0.65 | 2.248133 | 1.52866 | 0.25 | 12 |
| **Floor** | 357 | 0.7 | 0.1148459 | 0.3192834 | 0 | 1 |
| **Wall** | 357 | 0.59 | 0.1372549 | 0.3445992 | 0 | 1 |
| **Roof** | 357 | 0.58 | 0.7815126 | 0.4137998 | 0 | 1 |
| **Cropharvest** | 357 | 0.7 | 0.859944 | 0.3475322 | 0 | 1 |
| **Insurance** | 357 | 0.79 | 0.232493 | 0.4230145 | 0 | 1 |
| **Save_group** | 357 | 0.78 | 0.3753501 | 0.4848928 | 0 | 1 |
| **Land** | 357 | 0.63 | 0.2577031 | 0.4379835 | 0 | 1 |
| **Panga** | 357 | 0.84 | 0.4145658 | 0.4933384 | 0 | 1 |
| **Hoe** | 357 | 0.79 | 0.7787115 | 0.4156969 | 0 | 1 |
| **n_chickens** | 357 | 0.75 | 2.52381 | 4.3243 | 0 | 34 |
| **Chickens** | 357 | 0.78 | 0.4481793 | 0.4980053 | 0 | 1 |
| **n_goats** | 357 | 0.7 | 1.378151 | 2.803464 | 0 | 27 |
| **Goats** | 357 | 0.73 | 0.3473389 | 0.4767928 | 0 | 1 |
| **Cow** | 357 | 0.61 | 0.0672269 | 0.250766 | 0 | 1 |
| **Chairs** | 357 | 0.83 | 0.5014006 | 0.5006998 | 0 | 1 |
| **Battery** | 357 | 0.68 | 0.0364146 | 0.1875823 | 0 | 1 |
| **Bicycle** | 357 | 0.74 | 0.1904762 | 0.3932279 | 0 | 1 |
| **Solar** | 357 | 0.68 | 0.1344538 | 0.341618 | 0 | 1 |
| **Phone** | 357 | 0.84 | 0.4061625 | 0.4918049 | 0 | 1 |
| **Radio** | 357 | 0.85 | 0.1652661 | 0.3719418 | 0 | 1 |
| **KMO** | | 0.73 | | | | |

*Author's findings*

**Appendix II: The scree plot**




*Author's findings*

**Appendix III: PSSN benefit scheme**

| PSSN program | Type of payment | Respondents / beneficiary | Basic amount (TSH) | Maximum amount /month (TSH) | Annual amount: Maximum (TSH) |
|---|---|---|---|---|---|
| CCT | Fixed | Extreme poverty | 10000 | 10000 | 120,000 |
| | Fixed | Children >18years | 4000 | 4000 | 48,000 |
| | Variable | Infant 0-5 years | 4000 | 4000 | 48,000 |
| | Variable | Child-Pupils | 2000 | 8000 | 96,000 |
| | Variable | Children; lower secondary | 4000 | | |
| | Variable | Children; upper secondary | 6000 | 12000 | 144,000 |
| PW | Variable | PW benefits | 2500 | 37500 | 150,000 |

Source: baseline survey (NBS, 2016)