Msuha, Basil; Kissoly, Luitfred D.

Article

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Impact of productive social safety net on households' vulnerability to food insecurity in Tanzania

Basil Msuha[a,b] and Luitfred D. Kissoly[b]

[a]Social Economics and Marketing Research, Tanzania Agricultural Research Institute (TARI), Dodoma, Tanzania; [b]Department of Economics and Social Studies (ESS), School of Spatial Planning and Social Sciences, Ardhi University, Dar es Salaam, Tanzania

ABSTRACT

The effectiveness of social safety nets (SSNs) as anti-poverty policy instruments is increasingly attracting attention in development discourse. Previous studies on their impacts have mainly considered outcomes other than vulnerability, leaving a gap in the knowledge and literature. We use the Tanzanian 2017–18 Household Budget Survey dataset, comprising 9,463 households, to evaluate the impact of the productive social safety net (PSSN) program on households' vulnerability to food insecurity (VFI). The VFI is evaluated using the vulnerability as expected poverty (VEP) approach, whereas the impact is estimated using the Instrumental Variable (IV) approach. We found evidence consistent with the significant impact of PSSN on the VFI. Curiously, the estimated impacts are greater for households enrolled in conditional cash transfer (CCT) and public works (PW) combined, implying that a package of CCT and PW is likely to have a greater impact on vulnerability reduction space. Overall, the results provide evidence in support of policies that encourage wider expansion of SSNs as a policy instrument for assisting extremely poor households in moving out of the chronically poor and the risk of falling or remaining food insecure in the future.

IMPACT STATEMENT

Social safety nets are widely used in sub-Saharan Africa to address persistent poverty. However, despite holding the premise of poverty and vulnerability reduction, opponents criticize them as short-term measures and wasteful use of limited public resources, with an insignificant impact on poverty reduction. Previous research has primarily concentrated on evaluating ex post evidence, with little attention given to ex ante evidence. Both types of evidence are crucial for determining the effectiveness of anti-poverty policy interventions because poverty is a dynamic phenomenon that can change over time. We drew on the Tanzanian 2017-18 Household Budget Survey dataset, comprising 9,463 households, to evaluate the impact of the productive social safety net (PSSN) program on households' vulnerability to food insecurity, considering the role of conditional cash transfer (CCT) and public works (PW) schemes in the vulnerability reduction space. The vulnerability to food insecurity is estimated using vulnerability as expected poverty, whereas the impact is estimated using the instrumental variable (IV) approach. Findings indicated that social safety nets significantly reduced households' vulnerability to food insecurity, with CCT and PW combined having more impact than CCT alone. The findings imply that social safety nets are effective in reducing poverty and vulnerability, and combining CCTs and PWs may have a significantly greater impact than when the two are separated. Consequently, it is quite shortsighted to view social safety nets as merely short-term palliatives, wasting money or squandering scarce public resources, and doing little to overcome the problems of poverty and food insecurity. The significance of this study lies in its endeavor to broaden the range of existing literature on the effectiveness of social safety nets by incorporating ex ante analysis. This knowledge and understanding are helpful in expanding or designing effective social safety nets.

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CONTACT Basil Msuha basil.msuha@gmail.com; basil.aloyce@tari.go.tz Social Economics and Marketing Research, Tanzania Agricultural Research Institute (TARI), Head Office (Makutupora), Dodoma, Tanzania

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1. Introduction

Chronic food insecurity continues to affect millions of people in sub-Saharan Africa (SSA). Illustratively, 2022 estimates show that about 342 million people were severely food insecure (FAO, 2023). In Tanzania, over four million people are food poor, whereas those who are non-food poor are also vulnerable to falling into food poverty (World Bank 2019b). At the center of this crisis, social safety nets (SSNs) have been regarded as key policy instruments that can address the problems of food insecurity and poverty, thereby minimize the vulnerability of rural and urban households (Beegle et al., 2018). Since 2000, all SSA countries have implemented at least one type of SSNs (Beegle et al., 2018), whereas Tanzania has implemented more than 20 SSN programs (Msuha et al., 2024). The prime objective of SSNs is to address food poverty and vulnerability, which are two sides of the same coin (Hoddinott & Quisumbing, 2010).

Following the implementation of SSN programs, there has been a proliferation of empirical studies testing their effectiveness in addressing the challenges of food insecurity globally and SSA in particular. Several studies have shown that SSNs have a positive and significant impact on improving current food consumption (Beegle et al., 2018; Hailu & Amare, 2022; Tadesse & Zeleke, 2022). However, there is limited evidence on their impact on future food consumption. When investigating the impact of policy interventions on addressing food insecurity, a forward-looking analysis is necessary to predict future welfare changes caused by such interventions (Lu et al., 2023). This is critical as an individual or household who is currently food secure may become food insecure in the future, and vice versa (Mahanta & Das, 2021). In addition, the existing empirical studies on the impact of SSNs on food security outcomes have primarily focused on conditional cash transfers (CCTs), with public work schemes (PWs) receiving less attention in impact evaluation studies, despite their potential to stabilize consumption during lean seasons (Beegle et al., 2018). Moreover, there is a scarcity of studies systematically comparing the impacts of CCTs and PWs interventions on food security outcomes.

The contribution of this paper is twofold. First, we focus on whether SSNs reduce the risk of a household remaining or falling into food insecurity in the future after participating in SSN programs – their impact on vulnerability to food insecurity (VFI). Existing studies on the impact of social safety nets on poverty have primarily focused on providing evidence of ex-post impacts, linking conditional cash transfers to food security or chronic poverty. Our study extends previous research by providing new insights and evidence on ex-ante impacts, thus offering a comprehensive understanding of the poverty impacts of social safety nets. Secondly, our study evaluates and compares the impacts of conditional cash transfers (CCTs) and public works (PWs) on vulnerability to food insecurity.

The remainder of this paper is structured as follows. Section 2 explores the concept of social safety nets and their relationship to vulnerability to food insecurity, while providing a comprehensive overview of the productive social safety net program in Tanzania. It delineates the conceptual framework supporting the study and discusses empirical research on the topic, highlighting the existing research gap. Section 3 delves into the data sources and analytical methods employed in the study. Sections 4 and 5 present the results and discussion respectively, whereas Section 6 presents the limitations of the study and areas for further research, while Section 7 offers conclusions and policy implications.

2. Social safety nets and vulnerability to food insecurity

Social Safety Nets (SSNs) fall within the broader typologies of "social protection," protecting and helping the poor and vulnerable (Browne, 2015). Social protection comprises (i) SSNs (noncontributory), (ii) social insurance (contributory), and (iii) labor market schemes that are contributory and noncontributory (Browne, 2015; World Bank, 2012a). The major types of SSNs are cash transfers (CTs) and public works (PWs) (Mccord, 2008, 2012; World Bank, 2018). An illustration of this is provided in Figure 1. Vulnerability is the likelihood that individual or household welfare will fall below a benchmark at a given time in the future (Chaudhuri et al., 2002; Hoddinott & Quisumbing, 2010). Correspondingly, vulnerability to food insecurity is the likelihood that a household (if currently food poor) will remain food poor or (if currently non-food poor) will fall below the food poverty line in the future.

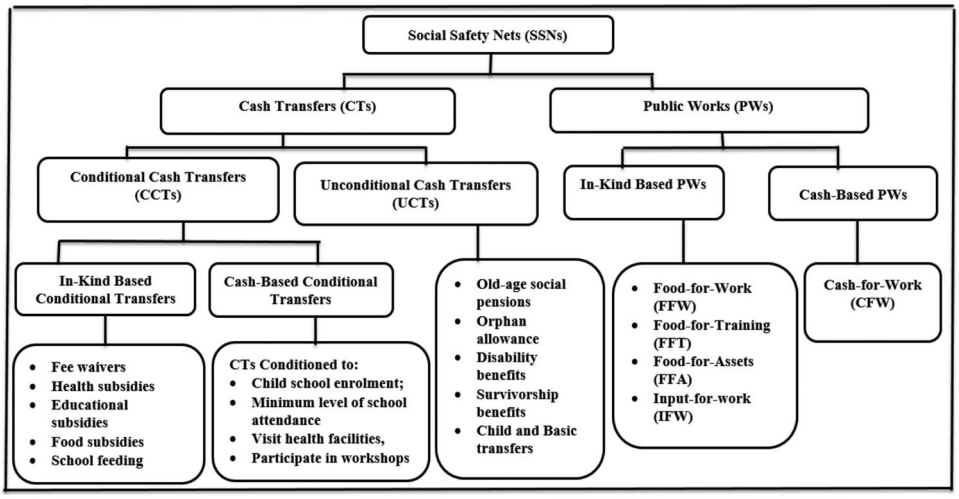

Figure 1. Typology of social safety nets.
Source: Authors' constructs from reviewed literature.

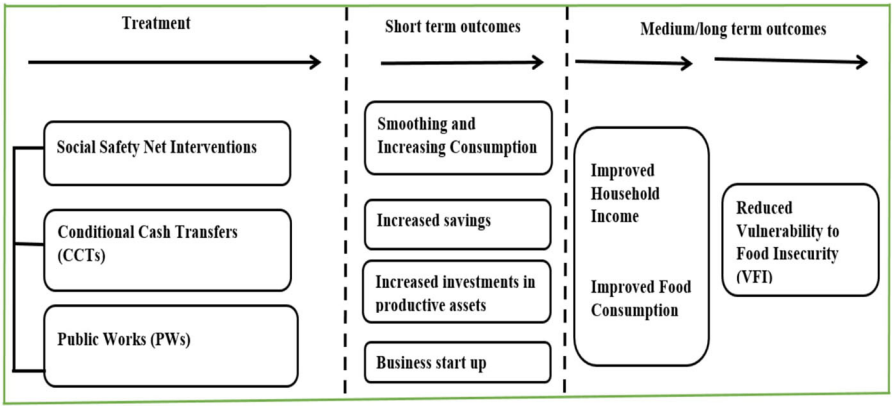

Figure 2. Conceptial framework for evaluation impact of social safety net programs on vulnerability to food insecurity.
Source: Authors' constructs from reviewed literature.

Food poverty is frequently linked to food insecurity, often resulting in the two being equated (Bartelmeß et al., 2022). To live in a state of food poverty is to lack the means to obtain an adequate amount of food necessary for a healthy life. People who are living in food poverty have an income or expenditure that is less than the amount required to consistently afford a basket of food with the minimum recommended nutritional intake. A universally accepted standard for the threshold of food poverty is 2,100 kcal per adult per day (Bellù & Liberati, 2005). The cost of this basket is referred to as the food poverty line. In Tanzania, it is estimated at TZS 33,748 (NBS, 2019). Individuals or households who fall below the food poverty line are unable to afford the cost of food needed for good health. Subsequently, vulnerability to food insecurity is an ex-ante concept (i.e. forward-looking as opposed to an ex-post concept[1]), we cannot directly observe it; rather, we can only predict it (Hoddinott & Quisumbing, 2010).

Social safety nets hold the premise of vulnerability reduction (Bastagli et al., 2019). Generally, it is hypothesized that when extremely poor and vulnerable households are enrolled in social safety net programs, they receive cash transfers that have immediate effects on increasing and smoothing consumption (Asfaw et al., 2014; Mccord, 2012), savings, starting businesses, and investing in productive assets (Tadesse & Zeleke, 2022) (see Figure 2). These short-term outcomes subsequently translate into improved household income and food consumption (World Bank, 2018) which eventually translates into reduced food poverty (Bastagli et al., 2019).

Tanzania, like many sub-Saharan Africa countries, has implemented the Productive Social Safety Nets (PSSN) program, which is one of the most extensive social safety net initiatives in Africa aimed at households that are extremely poor and food insecure. This program delivers cash transfers to over one million

households (World Bank, 2016). Apart from offering conditional cash transfers, the PSSN also features a public works component (PW), which shares similarities with other social safety net programs in sub-Saharan Africa (Hirvonen et al., 2022). The PSSN provides a CCT value of USD 6-16.3 per month, enabling households to attain a minimum level of consumption, invest in productive assets, and build resilience against shocks (World Bank, 2012b). Moreover, eligible households receive a daily rate of USD 1.35 for 15 days of paid work per month for four months during the annual lean season as part of the PW scheme. This additional source of income helps to smooth consumption and mitigate shocks (World Bank, 2019b). Therefore, the current arrangement allows eligible households to either receive "CCT only" or "CCT + PW combined".

Although it is commonly acknowledged that social safety nets contribute to reducing poverty and vulnerability across the globe, there is ongoing disagreement regarding their effectiveness (Handa & Davis, 2006; Slater, 2011). Critics argue that all forms of social safety nets, including conditional cash transfers (CCTs) and public works (PWs), serve only as short-term solutions or constitute a misuse of public financial resources (Brown & Gentilini, 2007; Gentilini & Omamo, 2009; Ravallion, 2003). To the best of our knowledge, existing poverty impact studies of social safety nets have mainly indicated impacts by linking conditional cash transfers and food security (Beegle et al., 2018; Hailu & Amare, 2022; Tadesse & Zeleke, 2022) or chronic poverty (Bastagli et al., 2019), thus limiting the findings to ex-post evidence. The existing body of research on this topic demonstrates a consistent pattern. For instance, Bastagli et al. (2016) examined the poverty impacts of 37 social safety nets in sub-Saharan Africa, 36 in Latin America, 18 in South Asia, 10 in East Asia and the Pacific, three in Europe and Central Asia, five in North America, and four in the Middle East and North Africa. This review provides robust empirical evidence of the positive and significant impact of social safety nets on food consumption and nutrition. Furthermore, Peterman et al. (2019) and Andrews et al. (2018) show that social safety nets have had a considerable impact on improving food security among participants in Africa. Other studies on similar topics include the World Bank's (2019a) study on Tanzania's Productive Social Safety Nets (PSSN) program, which revealed a positive impact on current food consumption. Overall, these studies do not offer an empirical evidence on the relationship between social safety nets and vulnerability to food insecurity, consequently providing insights on their impact on future food poverty.

Our current research expands upon previous studies by incorporating theoretical variables within the model (the ex-ante variable) - specifically, vulnerability to food insecurity (VFI). Poverty and vulnerability are two sides of the same coin (Hoddinott & Quisumbing, 2010), and it is crucial to consider both in order to gain a comprehensive understanding of the poverty impacts of social safety nets.

3. Methods and materials

3.1. Study setting and design

Tanzania is divided into 31 geographic administrative regions comprising 195 local government authorities (LGAs) in the Tanzania Mainland and Zanzibar. The PSSN program was implemented in 184 LGAs in mainland Tanzania and 11 LGAs in Zanzibar. To date, there are approximately 1.118 million PSSN beneficiary households, of which more than one million are on Tanzania's mainland. The current study covers the Tanzania Mainland only, and this follows the availability of a household budget survey (HBS) dataset that contains a specific PSSN module to measure the impact of the program.

Although the PSSN program design is built under randomized controlled trials (RCT), the HBS data generation process does not follow the RCT protocol; rather, it is a cross-sectional study design. Therefore, a quasi-experimental design was the second-best choice in this situation. Thus, the current study was framed within a quasi-experimental design to account for the lack of random assignment. The design allows the identification of a comparison group that is as similar as possible to the PSSN beneficiaries to capture what would have been the VFI if the PSSN had not been implemented (the counterfactual).

3.2. Data source

This study uses the latest Household Budget Survey (HBS) dataset (2017-18 HBS), which is the national representative data collected by the National Bureau of Statistics (NBS). The NBS is the principal agency

for data collection in Tanzania Mainland and is responsible for conducting nationally representative surveys in the country (URT Statistics Act, 2019). The 2017-18 HBS is the seventh in the series, producing estimates at the national level, Urban Areas, Rural Areas, and separate estimates for each of the 26 regions of Tanzania Mainland, whereas the first round of HBS was conducted in 1991. The HBS data series is the primary source of information for estimating poverty and its associated characteristics, and assessing the progress made in improving people's living standards (NBS, 2019).

The 2017-18 HBS consists of seven questionnaire types (forms I-VII) that collect different information. Questionnaire II (form II) contains a separate module on PSSN with a 'filter question' (22E.01) asking if a household received cash transfers (CCT) from the Tanzania Social Action Fund (TASAF), excluding cash transfers paid as wages from public works (PWs)[2]. There is also a second 'filter question' (22E.06), which asks if a household received cash transfers paid as wages for participating in the TASAF public works (PWs). We used these 'filter questions' to generate the treatment variables.

The 2017-18 HBS adopted a two-stage cluster-sampling design. The first step involved the selection of primary sampling units (PSUs) or enumeration areas from the 2012 population and housing census frame (2012 PHC). The 796 PSUs were selected through a listing exercise in which households residing in the selected PSUs were listed freshly before selection. A representative probability sample of 9,552 households was selected. The sample was designed to allow separate estimates for each of the 26 regions of Mainland Tanzania and the present urban and rural areas separately at the national level. Out of the 9,552 selected households, 9,463 were successfully interviewed, yielding a response rate of 99 per cent.

From the 2017-18 HBS dataset we use the two filter questions (22E.01 & 22E.06) to generate three treatment variables: *First*, the variable 'PSSN' is generated as an indicator equal to one if the household was enrolled in the PSSN program, receiving, either cash only (CCT) or cash and public works (PW). *Secondly*, the variable 'CCT only' is generated as an indicator equal to one if the household was enrolled in the PSSN program, receiving conditional cash transfers (CCT) only. *Third*, the variable 'CCT + PW' is generated as an indicator equal to one if the household was enrolled in PSSN program, receiving both CCT and PW. Otherwise, the household was considered the comparison group. Currently, the program does not offer public works scheme (PW) only, instead the households who receives CCT and has at least one adult aged 18-65 years who is able and willing to work qualifies to receive an additional cash through participating in the PWs scheme, hence 'CCT + PW' (World Bank, 2019b).

3.3. Estimation strategy

We followed two steps. *First*, we estimated the vulnerability to food insecurity index (VFI) of each household (PSSN participants and non-participants) using the vulnerability as expected poverty (VEP) approach. We followed the VEP procedure suggested by Chaudhuri et al. (2002), Gaiha and Imai (2008), and Günther and Harttgen (2009). Subsequently, the probability of a household falling below TZS 33,748 per adult equivalent per month (VFI) was estimated as follows:

$$\hat{\mathrm{VFI}}_{\mathrm{i}} = \hat{\Pr}\ (\ln \mathrm{C}_{\mathrm{i}} < \mathrm{TZS}\ 33,748 | \mathrm{Xi}) = \Phi\left(\frac{\ln(\mathrm{TZS}\ 33,748) - \mathrm{Xi}\hat{\beta}}{\sqrt{\mathrm{Xi}\hat{\theta}}}\right) \quad (1)$$

where:

VFI_i	=	Vulnerability to food insecurity of household 'i'
$\ln C_i$	=	Log of per capita consumption for the i-th household
TZS 33,748	=	Tanzanian official food poverty line (NBS, 2019).
*X*i	=	Set of observable household characteristics
$\Phi(.)$	=	Cumulative density of the standard normal distribution function
$\hat{\beta}$	=	Predicted per capita mean consumption (predicted 'yhat')
$\hat{\theta}$	=	Estimated variance of per capita (log) consumption

Equation (1) was estimated using a three-step feasible generalized least squares (FGLS) procedure (Amemiya, 1977). Households were considered vulnerable to food insecurity if the estimated VFI was above or equal to 0.5 (Chaudhuri et al., 2002). Appendix A presents the detailed VFI estimation procedure under the VEP approach.

In the second step, we estimated the impact of PSSN on VFI using the instrumental variable (IV) approach via Two-Stage Least Squares (2SLS) (Wooldridge, 2002, 2010). We specified the two-stage least squares method under the IV framework as follows:

Stage I

$$PSSN_i = \delta_0 + \delta_1 Z_i + \delta_2 X_i + \varepsilon_i \quad (2)$$

Stage II

$$VFI_i = \alpha_0 + \alpha_1 \hat{PSSN}_i + \alpha_2 X_i + \varepsilon_i \quad (3)$$

where:

VFI_i = Denotes vulnerability to food insecurity (outcome variable) obtained from Equation (1)

$PSSN_i$ = Dummy for treatment; equals to 1 = if household *i* is enrolled in PSSN program and 0 otherwise

Z_i = Denotes eligibility rule =1 if household *i* is eligible to PSSN program

$\hat{PSSN}_i$ = Probability of being enrolled in the PSSN program for household i which is the estimated IV generated in equation (2)

X_i = Denotes the set of covariates

ε_i = Part of VFI that is not explained by PSSN participation or by observed characteristics

The estimation procedures were conducted in STATA (version 17) using the 'ivregress' command (StataCorp., 2021). Appendix A presents the detailed estimation procedure for Equations (1–3).

4. Results

4.1. Descriptive results

A summary of the descriptive statistics is provided in Table 1. The findings show that the average age of household heads among PSSN households was 55.2 years. On average, female-headed households are older (58.3 years) than their male-headed counterparts (52.9 years). Generally, the results suggest that the PSSN program targets poor and vulnerable households, the majority of which are aged over 50 years on average. The dependency ratio is higher among PSSN households, whereas it is higher in female-headed households and households residing in rural areas. Household size is higher among PSSN households, whereas male-headed households and those residing in rural areas lead in this regard. Most households are headed by men.

Descriptive results also indicate that the dependency ratio was higher among PSSN households, whereas the ratio was higher in female-headed households and among those residing in rural areas.

Table 1. Descriptive results.

				PSSN households			PSSN households		
Variable	Pooled	PSSN	Non-PSSN	Female	Male	t/χ2 statistic	Urban	Rural	t/χ2 statistic
Panel A: Demography and social-economic characteristics									
Age of HH head (years)	47.37	55.17	46.56	58.3	52.85	−52.9(0.000)	56.4	54.8	−13.4(0.000)
Dependency ratio (ratio)	1.548	1.599	1.543	1.67	1.55	−16.1(0.000)	1.34	1.67	37.8(0.000)
Family size (adult equivalent)	4.965	5.174	4.944	4.57	5.62	68.3(0.000)	5.02	5.22	9.1(0.000)
Sex (1 = Male) †	76.0	57.7	77.9				44.4	61.5	196(0.000)
Location (1 = rural) †	68.2	77.6	67.2	70.6	82.7	195.9(0.000)			
Livestock	46.9	51.5	46.4	48.2	53.9	30.3(0.000)	16.9	61.5	1309(0.000)
Food poverty (1 = extremely poor) †	8.0	12.3	7.6	9.8	14.1	38.7(0.000)	12.4	12.2	0.03(0.7233)
Poverty (1 = poor) †	26.4	38.0	25.2	33.1	41.5	69.9(0.000)	39.9	37.4	4.5(0.000)
Occupation (1 = employee/self) †	74.6	68.3	75.3	69.1	67.7	2.03(0.000)	76.9	65.8	93.2(0.000)
Remittances (1 = received) †	10.9	13.9	10.6	16.6	11.9	42.3(0.000)	10.5	14.9	26.6(0.000)
Business (1 = own business) †	22.2	18.8	22.6	18.8	18.8	0.01(0.7694)	22.6	17.7	25.4(0.000)
PSSN (1 = yes)		9.39	90.61	42.3	57.7		22.4	77.6	
Panel B: Vulnerability status									
Vulnerability to food insecurity (VFI) index ††	0.32	0.40	0.42	0.30	0.38	81.2(0.000)	0.26	0.37	76.5(0.000)
Number of obs/Subpop.:		9,463			844			844	
Number of strata:		51			51			51	
Number of PSUs:		796			796			796	
Design df:		745			745			745	

†Variables involved in chi2 test statistic; Figures in parentheses are P-values.

††Computations of VFI for PSSN and Non-PSSN is based on the households in the poor subpopulation.

This result suggests that there are 167 dependents (0-14 and 65+) for every 100 working age adults among female-headed PSSN households. This phenomenon pressures the working age to generate income (World Bank, 2019a). Implying that every female-headed PSSN household member between 15 and 64 years of age has to generate income for themselves and an additional 1.67 persons; the male-headed PSSN households need to do so for an additional 1.55 people. This is true for every PSSN household member in rural areas.

Descriptive results further indicated that the majority of PSSN households were male-headed, whereas most of them resided in rural areas, with only 22 per cent of PSSN households living in urban areas. Most PSSN households (52 per cent) own livestock. This could probably be attributed to investment undertaken after they had received cash transfers, since the evidence suggests that social safety net beneficiaries increase ownership of productive assets in the form of livestock after some time once they are exposed to the program (World Bank, 2019a).

4.2. Econometric results for impact of PSSN on VFI

Our instrumental variables (IV) strategy combined information on eligibility rules for each household and monthly per capita consumption (Supplementary Appendix A). We argue that eligibility for the PSSN program is influenced by households' monthly per capita consumption. Households with monthly per capita consumption below the minimum threshold might become eligible; consequently, eligibility and lower monthly per capita consumption are likely to be instrumental in ensuring participation in the program, but they are not directly correlated to the outcomes of interest.

Specifically, we regressed the binary treatment variable (PSSN) on the eligibility rule and a set of covariates (Xi) using the Probit model (Wooldridge, 2010; Xu, 2021) (see Supplementary Appendix B). Then, we used the predicted probability of PSSN obtained as the instrumental variable (Z) in two-stage least square (2SLS). The probability of participation $[P(PSSN_i|Z_i, X_i)]$ as its orthogonal projection is considered the optimal IV (Wooldridge, 2010). We provide strong evidence that our instrument is statistically valid.

Subsequently, before interpreting the econometric results, we ensured a valid IV by conducting post-estimation diagnostics. Supplementary Appendix D presents the post-estimation results. The first assumption required that the instrument be correlated with the treatment, that is, participation in the program [Corr (Z, PSSN) $>$ 0]. The results of the first-stage regression statistics test indicated that the *F*-statistics were significant at the 1 pe.r cent level, and that the first-stage *F*-statistic values for each treatment level exceeded 10 (Stock et al., 2002) (see Supplementary Appendix D). Therefore, the null hypothesis of weak instruments was rejected, indicating that the instrument was strongly correlated with treatments (PSSN, CCT, and PW). Subsequently, we tested whether the instrument was uncorrelated with the error term [Corr (Z, ε) $=$ 0]. Sargan's (1958) and Basmann's (1960) χ^2 tests indicated that the instrument was uncorrelated with the error term, suggesting that it was valid, and the model was correctly specified.

The econometric results for the impact of PSSN on VFI are presented in Table 2 (see the complete IV regression results in Supplementary Appendix C). The impact results in Table 2 are presented in Panels A, B and C, respectively. In panel A, PSSN is an indicator equal to one if the household was enrolled in

Table 2. Impact of PSSN on vulnerability to food insecurity (VFI).

Outcome: VP	Instrumental variable (IV) (ATT)
Panel A: Overall impact	
PSSN	−0.267***
	(0.0443)
Panel B: Conditional cash transfers	
CCTs Only	−0.278***
	(0.0466)
Panel C: Conditional cash transfers and public works	
CCT + PW	−0.773***
	(0.1982)

The figures in parentheses are standard errors; ***P $<$ 0.01; **P $<$ 0.05; *P $<$ 0.1.
The analysis was adjusted for age, age squared, sex, adult equivalent, adult equivalent squared, dependence ratio, marital status, location, livestock, employment, remittances, income sources, food assistance, health subsidies, and business ownership. The complete IV regression results are presented in Appendices B and C.

the PSSN program and received either CCT only or CCT + PWs. In panel B, CCT only equal one if the household received CCT only, and CCT + PW is equal to one if the household receives additional transfer in the form of PW.

The results in Table 2 indicate that the average VFI was reduced by 0.27 point when extremely poor households were enrolled in the PSSN program, relative to the case when they had not been enrolled in the PSSN program (ATT= -0.267, $P < 0.001$)[3]. The results present evidence that supports the alternative hypothesis that CCT and PWs reduce vulnerability to food insecurity in extremely poor households. This result suggests that when extremely food poor households are enrolled in the PSSN program receiving either CCT only or CCT + PW, the probability that they will remain food poor or below the food poverty line in the future is reduced by 27 per cent.

Similarly, the results in Table 2 show that the average VFI was reduced by 0.28 point when extremely poor households were enrolled in CCT (ATT= -0.278, $P < 0.001$) and 0.77 point when they were enrolled in CCT + PW (ATT= -0.773, $P < 0.001$). In other words, the likelihood that extremely poor households will remain food poor or below the food poverty line in the future is reduced by 28 per cent when they are enrolled in the PSSN program receiving CCT only and 77.3 per cent when they are enrolled in the PSSN program receiving CCT + PW combined. The results present evidence that supports the alternative hypothesis, suggesting that the combined impact of CCT and PW on vulnerability to food insecurity of extremely poor households is higher than that of CCT only.

5. Discussions

Our primary objective in this study was to assess whether productive social safety net (PSSN) program are effective in reducing the vulnerability of households to food insecurity (VFI) and to evaluate the relative impact of conditional cash transfer (CCT) and public work (PW) on reducing this vulnerability. The results revealed that the likelihood of experiencing future food insecurity was significantly reduced by 0.27 points for extremely poor households who participated in the PSSN program, as compared to those who did not enroll in the program. Further analysis indicated that the estimated impacts of CCT and PW combined were higher (0.78 points) than those of CCT (0.28 points) alone.

The results suggest that when extremely poor households are enrolled in the productive social safety net program, leads to a 27 percentage point reduction in the probability of future food insecurity. Our empirical finding align with those of Bhalla et al. (2018), who observed a similar relationship in Zimbabwe while assessing the impact of the Zimbabwe Harmonized Social Cash Transfer (HSCT) on household food insecurity. They discovered that household vulnerability was closely linked to food security outcomes. These results are also consistent with Korir et al. (2021), who found a negative correlation between household vulnerability to food insecurity and the receipt of any cash transfer or assistance in Kenya.

The study indicates that the combined impact of CCT and PW on vulnerability to food insecurity (VFI) of extremely poor households is greater than that of CCT alone. This could be due to the fact that, in addition to cash transfers, PWs have three potential impact channels: wage transfers, asset creation, and skills development (Sakketa & Braun, 2019). As a result, the joint vulnerability reduction impact is likely to be higher than that of CCT alone. This trend is of interest to policy makers who want to determine whether to implement 'CCT' and 'PW' separately or to combine them as a package when designing social safety net programs. However, it should be noted that our analysis would be more comprehensive with a better understanding of the impacts of 'CCT', 'PW', and 'CCT + PW', which is not the case in this study. Further research, particularly randomized control trials (RTCs) with PW as a separate treatment arm, is needed in this area. Currently, PSSN does not offer PW as a separate treatment arm that is why we could not obtain data for that analysis. Public work (PW) schemes are also common in some Asian and sub-Saharan African countries (Filipski et al., 2017; Mccord, 2012; Zimmermann, 2012).

Taken together, our research findings align with the claim that social safety nets are effective policy instruments for reducing vulnerability (Handa & Davis, 2006; Slater, 2011). It is also in line with sustainable development goals 1.3 which promotes the implementation of nationally appropriate social protection systems to cover the poor and vulnerable (United Nations, 2017a). Consequently, the findings favor the ongoing debate regarding the effectiveness of social safety nets in the vulnerability reduction space (Bastagli et al., 2019). Our findings dispute the view that social safety nets are squandering scarce public

resources and doing little to overcome the problem of poverty and food insecurity (Hoddinott, 2008), or the view that they are short-term palliatives and a waste of money (Brown & Gentilini, 2007). In the context of PSSN, the results also dispute the notion that the transfers provided are too small to make them meaningful (Berg & Cuong, 2011; Molyneux et al., 2016) or create dependency (Baird et al., 2018; Becker, 1965). Instead, the results provide evidence to show that PSSN in Tanzania not only increases food expenditure, as indicated in the studies by the World Bank (2016, 2019a), but also reduces the vulnerability to food insecurity (the probability of households falling below the food poverty line in the future).

This leads us to hypothesize that social safety nets can substantially support the concept of graduation by assisting food poor households in moving out of the poverty and the risk of falling or remaining food poor in the future (Mahanta & Das, 2021). This is a positive move toward achieving sustainable development goals 1.1 and 2.1 (United Nations, 2017a, 2017b) which advocates the eradication of extreme poverty for all individuals, regardless of their location. This includes ending hunger and ensuring access to sufficient food on a year-round basis, with a particular focus on assisting the poor and vulnerable.

6. Limitations of the study and areas for further research

Our study is not without limitations: *first* is the limitations of data. We sought to estimate the relative impact of conditional cash transfer (CCT) and public work (PW) on households' vulnerability to food insecurity. To that end, the analysis of the relative impact of CCT and PW on households' vulnerability to food insecurity would be more complete with an understanding of the separate impacts of CCT only, PW only, and CCT + PW combined. This is not the case in our study; instead, we have shown a relative impact of CCT and CCT + PW; the PW is missing because of data limitations. The 2017-18 Household Budget Survey (HBS) dataset did not provide these variables (treatment arms) in a way that was sought. This is because, currently, the PSSN program does not offer PW as a separate treatment arm. More research, especially randomized control trials (RTCs) with PW as separate treatment arms, is needed in this area. *Second* is the limitations of the focus: We aimed to examine the effect of cash-based social safety nets, specifically CCT and PW, on the vulnerability to food insecurity. The question remains unanswered as to whether cash-based or in-kind based transfers, or a combination of both, is more effective in reducing vulnerability to food insecurity. In designing social safety net interventions, a crucial question is whether to provide cash-based or in-kind based transfers to the poor (Gadenne et al., 2023). The literature remains inconclusive on which type is superior to the other (Gentilini, 2023; Hoddinott & Hirvonen, 2021). Our analysis was limited to cash-based social safety nets. Building upon our analysis and considering the ongoing debate regarding whether to focus on cash-based, in-kind based transfers, or a combination of both when designing social safety net programs, we recommend that future impact studies address the relative impacts of these different approaches. This will provide valuable insights into which type is more effective in reducing poverty and vulnerability, thereby enhancing the overall effectiveness of social safety nets.

7. Conclusions and policy implications

The effectiveness of social safety nets as anti-poverty policy instruments is increasingly drawing the attention of researchers. Previous studies on their impacts have mainly considered outcomes other than vulnerability, leaving a gap in the knowledge and literature. This study draws on Tanzanian 2017-18 Household Budget Survey dataset, comprising 9,463 households, to evaluate the impact of the productive social safety net program on households' vulnerability to food insecurity. More importantly, the question of whether the impacts of CCT and PW are the same or different has been tested with the hope of providing insights into the design and implementation of SSNs. We found evidence consistent with the significant impact of conditional cash transfer (CCT) and public work (PW) interventions on households' vulnerability to food insecurity (VFI). We also found that the estimated impacts (i.e. the magnitude of the coefficients) of CCT + PW combined are greater than those of CCT alone.

Based on these findings, a number of policy implications are discerned. *First*, the findings suggest that social safety nets can substantially support the concept of graduation by assisting poor households in moving out of the chronically poor and the risk of falling or remaining in extreme poverty in the future. Consequently, it is quite shortsighted to view social safety nets as merely short-term palliatives,

waste money or squandering scarce public resources, and doing little to overcome the problem of poverty and food insecurity. *Second*, combining CCTs and PWs in policy efforts to support chronically poor households from the risk of falling or remaining food poor in the future may have a significantly greater impact than when the two are separated. *Third*, governments and development organizations should encourage the wider expansion of social safety nets as anti-poverty policy instruments, which is in line with sustainable development goals 1.3 which promotes the implementation of nationally appropriate social protection systems to cover the poor and vulnerable.

Notes

1. We can directly observe household food insecurity status (ex-post) at a given time of period given the threshold.
2. The Tanzania Social Action Fund (TASAF) is the principal agency established in 2000 in response to poverty reduction strategy. The agency is responsible for implementing PSSN program.
3. The impact of a PSSN program can be conceptualized as the difference between the actual outcome (VFI) and the outcome (VFI) that would have occurred in the absence of the PSSN program.

Authors' contributions

Basil Msuha: Conceptualization; writing-original draft; methodology; formal analysis; discussion and conclusion: **Luitfred D. Kissoly:** Supervision, review, and editing

Disclosure statement

The authors declare that they have no affiliations with or involvement in any organization or entity with any financial interest in the subject matter or materials discussed in this manuscript.

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About the authors

Basil Msuha is a specialist in Development Economics and a researcher at the Tanzania Agricultural Research Institute (TARI). He focuses on evaluating development policies, programs, projects, and interventions, as well as conducting poverty and vulnerability analysis. Msuha's work involves utilizing data to inform the design and implementation of development policies and programs, and evaluating their impact on individuals affected by them. He is currently pursuing a PhD in Economics at Ardhi University, Tanzania, with a specialization in Impact Evaluation.

Dr. Luitfred D. Kissoly is the Head and Lecturer in the Department of Economics and Social Studies, under the School of Spatial Planning and Social Sciences (SSPSS). He obtained his PhD, from Leibniz Universität Hannover in Germany in 2016. His research focus was on the food security implications of smallholders' integration in agricultural value chains. Dr Kissoly's key research interests are on Food Security Economics, Agri-food Value Chains, Urban Food Systems, Household-level Welfare Analysis, and related aspects in Development Economics. Dr. Kissoly has participated in a various research projects, both national and international funded including BMBF, DFG, World Bank, ACIAR, and IDRC). These include Trans-Sec (https://www.trans-sec.org), TISA (aciar.gov.au/project/lwr-2016-137), African Food Systems (https://www.idrc.ca/en/view-all-projects-countries/Tanzania).

ORCID

Basil Msuha http://orcid.org/0000-0001-5751-7340

Data access statement

Research data supporting this publication are available from the National Bureau of Statistics repository located at: https://www.nbs.go.tz/tnada/index.php/catalog/30

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Appendix A. Methods of Analysis

A| Analytical Framework

To estimate the impact of productive social safety nets on households' vulnerability to food insecurity, we make use of two steps: First, we estimate the vulnerability to food insecurity index (VFI) of each household (PSSN participants and non-participants) using the vulnerability as expected poverty (VEP) approach. Second, we estimate the impact of PSSN on VFI using the instrumental variable (IV) approach via Two-Stage Least Squares (2SLS).

A1| Estimating Vulnerability to Food Insecurity (VFI): The VEP Approach

The outcome variable of interest in this study is the vulnerability to food insecurity (VFI). We first estimated VFI before evaluating the impact of PSSN on VFI. There are three widely used approaches for estimating VFI: vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU), and vulnerability as uninsured exposure to risk (VER) (Chaudhuri et al., 2002). While both approaches express "vulnerability" as a function of expected "mean" and "variance" of household "consumption," VEP is the most appropriate in estimating VFI especially in developing countries because it uses cross-sectional data and easy to interpret, unlike VEU and VER which relies on panel data, which are mostly limited (Mahanta & Das, 2021). Because our study used cross-sectional data, the VEP approach is more appropriate for this matter. This approach has been widely used in the empirical estimation of vulnerability (Chaudhuri et al., 2002).

Following the VEP approach (Chaudhuri et al., 2002), the equation (1) defines VFI as follows:

$$VFI_{ht} = \Pr(C_{h,t+1} < \text{ fpl } |\text{Xh}) \tag{Ap-1}$$

Where:

VFIht	=	The vulnerability to food insecurity index of household "h" at a time "t".
Ch,t + 1	=	The future per capita food consumption level (at a time "t + 1")
fpl	=	The defined food poverty line (TZS 33,748 per adult per month) (NBS, 2020).
X_h	=	The current set of observable household characteristics for household *h*

Equation (Ap-1) implies that The VFI of a household (VFI_{ht}) is the likelihood that the future household per capita food consumption ($C_{h,t+1}$) will be less than the established food poverty line (fpl). We used the Tanzanian food poverty line (TZS 33,748) as a measure of household welfare, which is the minimum food bundle containing 2,200 kilocalories per adult per day for one month or TZS 33,748 per adult equivalent per month. To estimate the vulnerability to food insecurity (VFI), we first predicted the future per capita food expenditure of households. The functional form is expressed as follows (Ap-2):

$$\ln \text{FCE}_i = \beta_0 + \beta_1 X_i + e_i \tag{Ap-2}$$

Where:

$\ln \text{FCE}_i$	=	The log of per capita food expenditure for the i-th household
Xi	=	A set of observable household characteristics
β	=	A vector of parameters to be estimated
e_i	=	A disturbance term with a mean zero and assuming heteroscedastic (non-homoscedastic)

We allow the variance of e_i in equation (Ap-2) to vary across households depending on observable heteroscedastic household characteristics (Xi). If estimated as is, may yield biased and inefficient estimates. To correct this problem, the squared residuals from equation (Ap-3) were regressed with a set of observable household characteristics (Xi), as expressed in equation (Ap-3).

$$\delta_{e_i}^2 = \theta_0 + \theta_1 X_i + \eta_i \tag{Ap-3}$$

Where:

$\delta^2_{e_i}$	=	Squared residuals from equation (3)
Xi	=	A set of observable household characteristics
θ	=	A vector of parameters to be estimated
η_i	=	The error term

Both equations (Ap-2) and (Ap-3) assume unequal variance in the error term (heteroscedastic rather than homoscedastic) but depend on X_i – thus, β and θ cannot be estimated using OLS. We estimate them using three-stage Feasible General Least Squares (FGLS) (Amemiya, 1977). Then, the expected mean (equation Ap-4) and variance (equation Ap-5) of per capita food expenditure of each household are obtained as follows:

$$E[\ln \mathrm{FCE_i}|X_i] = X_i\hat{\beta} \tag{Ap-4}$$

$$V[\ln \mathrm{FCE_i}|X_i] = \hat{\delta}^2_{e_i} = X_i\hat{\theta} \tag{Ap-5}$$

Finally, assuming that the household per capita food expenditure is log-normally distributed and following the VEP approach (Chaudhuri et al., 2002), the probability that a household will remain food poor or fall below the food poverty line in the future (VFI) is empirically estimated using equation (Ap-6) as follows:

$$\hat{\mathrm{VFI}}_\mathrm{i} = \hat{\Pr}(\ln \mathrm{C_i} < \ \mathrm{TZS}\ 33,748|\mathrm{X_i}) = \ \Phi\left(\frac{\ln(\mathrm{TZS}\ 33,748)\text{-}\mathrm{Xi}\hat{\beta}}{\sqrt{\mathrm{Xi}\hat{\theta}}}\right) \tag{Ap-6}$$

Where:

Φ(.)	=	Denotes cumulative density of the standard normal distribution function
TZS 33,748	=	The food poverty line
$\hat{\beta}$	=	denote mean per capita food expenditure (predicted "yhat")
$\hat{\theta}$	=	The estimated variance of per capita food expenditure
X_i	=	Set of observable household characteristics

A2| Impact Estimation: Instrumental variable (IV) approach

Unlike randomized controlled trials (RCTs), which are capable of handling confounders (both measured and unmeasured) between treatment and comparison groups through randomization, quasi-experimental designs usually suffer from confounding effects. Within the RCTs, unmeasured confounders were regarded as random because design confounders were expected to be distributed equally across the treatment and comparison groups.

In quasi-experimental settings, "matching methods" including propensity score matching (PSM), regression adjustment (RA), inverse-probability weights (IPW), doubly robust methods (StataCorp., 2021), and kernel-based propensity score matching (kmatch) (Jann, 2017) have been widely used, but they can only address the measured confounders. They do so by assuming that there are "no unobserved differences" associated with the outcomes of interest between the treatment and comparison groups (Gertler et al., 2016). As a result, "matching methods" are usually used in combination with other methods that can account for unmeasured confounders. Popular methods include instrumental variables (IV), regression discontinuity design (RDD), difference-in-differences (DID) (Gertler et al., 2016), and the endogenous switching regression method (ESR) (Lee, 1982).

The IV is suitable for evaluating the impact of programs that use an eligibility rule and imperfect compliance exists, that is, not everyone complies with the assignment rule (Gertler et al., 2016). We define eligibility rule as an instrument (Z) with respect to the PSSN program in Tanzania as follows:

$$\mathrm{Eligibility(Z)} = \begin{cases} 1 \text{ if aefd} < \textit{TZS } 33,748 \text{ is eligible to PSSN} \\ 0 \text{ if aefd} > \textit{TZS } 33,748 \text{ not eligible to PSSN} \end{cases}$$

where aefd denotes monthly food consumption and TZS 33,748 denote a food poverty line. Those households who are extremely poor are eligible for the PSSN program (World Bank, 2019b), which accounts for approximately 4 million Tanzanians (NBS, 2019). About 1.1 million Tanzanians are participating in the PSSN (World Bank, 2019b), subsequently leading to imperfect compliance with the assignment rule. This suggests that even if the cut-off rule is the only determining factor for eligibility, imperfect compliance occurs, preventing some eligible patients from receiving treatment. Therefore, the use of IV was deemed appropriate.

The IV must satisfy two conditions (Angrist & Pischke, 2009):

Should correlate with the treatment i.e. participation to the program (PSSN)

$$\mathrm{Corr}\ (\mathrm{Z},\ \mathrm{PSSN}) \ > \ 0 \tag{Ap-7}$$

It should affect the outcome (VP) only through its effect on treatment, that is, participation in the program (PSSN). That is, the instrument should not correlate with the error term.

$$\mathrm{Corr}\ (\mathrm{Z},\ \varepsilon) \ = \ 0 \tag{Ap-8}$$

To avoid a weak IV identification problem in the context of a binary treatment variable (PSSN) arising from the first stage (Angrist & Pischke, 2009) we follow Wooldridge (2010) and Xu (Xu, 2021) as the most efficient way of obtaining optimal IV than using a direct approach. Using the Probit model, we regress our binary treatment variable (PSSN) on the eligibility rule (Z) and a set of covariates (X_i), *results are presented as Supplementary Appendix 2*. Then, we use the predicted probability of PSSN obtained as the instrumental variable (IV) for the treatment (PSSN) in the *two-stage least square* (2SLS). The probability of participation $[P(PSSN_i|Z_i, X_i)]$ as its orthogonal projection is considered the optimal IV (Wooldridge, 2010). To evaluate the impact of PSSN on VFI, we specify a two-stage least squares under the IV framework as follows:

Stage I

$$PSSN_i = \delta_0 + \delta_1 Z_i + \delta_2 X_i + \varepsilon_i \quad \text{(Ap-9)}$$

Stage II

$$VFI_i = \alpha_0 + \alpha_1 \hat{PSSN}_i + \alpha_2 X_i + \varepsilon_i \quad \text{(Ap-10)}$$

Where:

VFI_i	=	Denotes vulnerability to food insecurity index (outcome variable) obtained from Equation (Ap-6)
$PSSN_i$	=	Dummy for treatment 1 = if household i is enrolled in PSSN program and 0 otherwise
Zi	=	Denotes eligibility rule =1 if household i is eligible to PSSN program
$\hat{PSSN}_i$	=	Probability of being enrolled in the PSSN program for household *i* which is estimated IV generated in equation (Ap-9)
X_i	=	Denotes the set of covariates
ε_i	=	Part of VFI that is not explained by PSSN participation or by observed characteristics

The estimation procedure was conducted in STATA (version 17) using the "ivregress" command (StataCorp., 2021), as illustrated in Section A3.

A3| Empirical Estimation of VFI Using STATA

Using global command in STATA we declare the following observable household characteristics (Age, Age squared, Sex, Household size, Household size squared, Dependency ratio, Marital status, Location, Livestock, Employment, Remittance, Income sources, Food assistance, Health subsidy, Business ownership) as "global xlist"

Step ONE:

We regress the log of per capita food consumption expenditure ($\ln FCE_i$) with the set of observable household characteristics above ($xlist), then we predict y, (ii) residual, and (iii) generate residual squares as follows:

```
regress ln FCE_i $xlist, vce(robust)
predict y
predict residual, resid
generate residsqr = residual^2
```

Step TWO:

We use the residual square from step one as the dependent variable, regress with a set of observable household characteristics, and then predict the variance

```
regress residsqr $xlist, vce(robust)
predict var
```

Step THREE:

We use the residual square again as the dependent variable and regress with a set of observable household characteristics by weighting (aweight = 1/var), then generate the square root variance (standard deviation) or sqrrtvar

```
regress residsqr $xlist [aweight = 1/var], vce(robust)
generate sqrrtvar = var^(1/2)
```

FINALLY:

We use the log of per capita food expenditure as the dependent variable and regress with independent variables by weighting square root variance [aweight = 1/sqrrtvar], predicted expected per capita food expenditure (yhat), and estimated VFI using ln of the food poverty line (10.43). (log of food poverty line minus expected per capita food expenditure) divided by the standard deviation or square root variance (sqrrtvar).

```
regress ln FCE_i $xlist [aweight = 1/sqrrtvar], vce(robust)
predict yhat
generate Vi = normal((10.42668-yhat)/sqrrtvar)
```

Note: The complete STATA do file for these procedures can be provided upon request from the corresponding author (basil.msuha@gmail.com).