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The impact of government cash transfer on household welfare and its influence on the adverse effects of health shocks: Kenya's experience

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Abstract

This study assessed the impact of the Government Cash Transfer (GCT) on households' welfare and its influence on those who experienced health shocks. The endogenous switching probit technique that addresses potential selection bias in the mode was employed. The average treatment effects on the treated (ATTs) show that beneficiary households were likely to be more food-poor by 27.41 percent but less asset-poor by 40.11 percent. This can be attributed to delays in the disbursement of the cash transfer. The results based on the average treatment effect on the untreated (ATU) and average treatment effect (ATE) suggest that overall, GCT has the potential to improve household food consumption but not asset levels. A possible pointer that it may not be sufficient to improve these two welfare indicators concurrently. The real value of the GCT has also continued to diminish while the various expenditure items increase due to inflation. Further, the results for poor households that also experienced health shocks suggest that GCT has the potential to cushion households' welfare against health shocks. This study proposes an increase in the amount of the GCT and a consideration to change the funds disbursement policy to monthly instead of bi-monthly.

1. Introduction

To alleviate the suffering of households due to extreme poverty, Cash Transfer (CT) has been embraced by most economies, including Kenya, as a social protection tool. CT programs, especially unconditional ones like the Kenyan GCT, that allow beneficiaries to decide on their expenditures, come in handy to meet a number of needs, including healthcare expenditures, more so in an economy where health financing is a challenge. In Kenya, only half of the 47,564,296 persons were covered under the National Health Insurance Fund (NHIF) according to the 2019 census report. This increased to 31,641,417 people by the financial year 2022/2023. However, even with the change from NHIF to Social Health Insurance (SHI) in 2023, and the aggressive mobilisation of people to enrol, there were only 32,341,441 persons registered in the financial year 2023/2024, against a total projected population of 52,428,290. This translates to 61.9 percent of the population covered (KNBS, 2025).

The use of CT, among other shock coping strategies, though not acting as a substitute for improved public basic services, is an important complement that can cushion households from health shocks, and thus also protect them from plunging into poverty. Some CT recipient households in Kenya have used some of the proceeds to meet their healthcare costs, indicating the important role it plays in relieving households from health shock burdens (Gok, 2022; Haushofer and Shapiro, 2013). Despite the GCT being implemented in Kenya for over 20 years now and being used for various household needs, poverty levels remain high. In the year 2015, when the study survey was commenced, the proportion of those living below the poverty line was 36.1 percent. In 2019, it was 33.6 percent, only slightly lower than the Sub-Saharan Africa (SSA) region average of 34.9 percent in the same year (World Bank, 2024). It has since increased to 39.8 percent in 2022, with 3 in every 10 households poor (KNBS, 2024). This inconsistent trend in poverty reduction despite continued implementation of such programmes calls for an assessment of the impact GCT has on various households' welfare, as well as on those that experienced health shocks.

Kenya started the implementation of CT in 2004/2025 with the rollout of Orphans and Vulnerable Children (OVC) OVC-CT to households caring for OVCs. The regular GCT has since been extended to include other vulnerable groups. Other CT programs in Kenya include the Older Persons Cash Transfer (OPCT), initiated in the 2008/2009 financial year, targeting very poor households that have a member who is 65 years old and above, and the Persons with Severe Disability Cash Transfer (PWSD-CT), which commenced in the financial year 2010/2011. The Older CT-OVC, OPCT, and PWSD-CT entails the provision of Ksh 2,000 per month, payable bi-monthly to the beneficiaries. There is also the Hunger Safety Net Programme (HSNP), which aims to reduce poverty among extremely vulnerable households from Northern Kenya that are prone to drought. The HSNP started in the 2013/2014 financial year, with beneficiaries receiving a cash payment of Ksh 2,300 per month, which increased to Ksh 2,450 in 2014/15, Ksh 2,550 in 2015/16, and currently Ksh 2,700 per month since 2016. There has been a progressive increase in the number of GCT programme beneficiaries. By the financial year 2023/2024, the total cash transfer beneficiaries were 1,946,142, up from 1,196719 in the financial year 2022/2023 (KNBS, 2025). However, despite the increase in coverage, not all registered beneficiaries receive the transfers annually, nor are all vulnerable households under the four categories registered in the programme. The Gok (2021) social protection, culture and recreation sector report indicated that 125,000 CT-OVC and OPCT beneficiaries did not get a transfer in 2020/2021 due to inadequate funding.

To improve the impact of the CT program, the Government of Kenya, in 2014, introduced additional measures to complement the program through the Health Insurance Subsidy Programme (HISP) targeting orphans, elderly persons, and individuals with severe disabilities. However, as of the 2021/2022 financial year, only 44.7 percent of National Safety Net Programme (NSNP) beneficiaries were enrolled in the National Health Insurance Fund (NHIF). This barely covers half of the households under the CT program nationally, implying that the majority of CT recipient households either use part of the cash they receive to mitigate the unfavourable effects of health shocks or resort to other informal shock-coping mechanisms that could be detrimental to their welfare, such as the disposal of their assets or going without meals. However, in a bid to influence health indicators, the government is currently implementing nutritional improvement through the Cash and Health Education (NICHE) program in five counties (Kitui, Kilifi, Marsabit, West Porkot, and Turkana) where CT recipient households are offered an additional Ksh 500 each month per child below two years or a pregnant mother but cupped at two beneficiaries per household over and above the standard transfer (UNICEF, 2022). There exist a number of studies on the influence of transfers received by households from government and non-governmental initiatives on various welfare indicators. On human development, inequality and poverty in general is that of Manda et al. (2020). On food and consumption, there are Asfaw et al. (2014), Kipruto et al. (2024), Njoki and Wairimu (2023), and Ongudi et al. (2024) studies. Those that have considered both food consumption/expenditure and asset include Egger et al. (2020) and Haushofer and Shapiro (2013), (2016), who were mainly in rural areas. The transfers considered in these two studies were also of large values not like the regular GCT. The other study that also examined both food expenditure and assets is that of Merttens et al. (2017), which evaluated HSNPS only.

Despite these documented studies, most of them are based on certain parts of the country and not nationwide coverage due to the high cost of undertaking experimental studies employed in CT impact assessment. This study aims to provide more insight into the impact of the GCT programme (which includes all the four regular CTs) on households' welfare using data drawn from the Kenya Integrated Household Budget Survey 2015/2016 survey to assess the impact of CT on households' food and asset poverty. A closely related study to this current one that used the same data set is that of Kipruto et al. (2024), which focused on CT effects on food consumption and dietary diversity and not an impact assessment, employing linear regression and probit estimations that do not correct for the potential endogeneity of the CT. The use of cross-sectional data in this current study, employing an endogenous switching probit that addresses any potential endogeneity in the model arising from selection bias, shows that an impact assessment on CT that offers robust findings is possible using readily available data collected by the government and not just the use of an experimental approach that would be costly to undertake. The consideration of both asset levels alongside food consumption in this study also highlights the possible trade-off between consumption and asset acquisition, which will contribute to the debate on the adequacy of the transfer to meet a number of households' needs concurrently.

There is also limited empirical evidence on the mitigating factors of the CT against shocks to households' welfare. Those studies that considered shocks include Asfaw et al. (2017) in Zambia, which considered weather shocks and Mitra et al. (2016), which focused on health shocks in Vietnam. In Kenya, a study that considered health shock is that of

Kansiime et al. (2021), an online survey for Uganda and Kenya that employed probit regression and did not account for possible endogeneity in the model. It is also considered a covariate and not an idiosyncratic health shock. With the low coverage of households into the health insurance in Kenya, and with evidence that some Kenya households use some of the savings from the CT to meet their healthcare costs, see Gok (2022), this current study therefore, also contributes to knowledge and informing policy in its assessment of the effect of the GCT program as a risk cushioning tool for households that have experienced health shocks.

The subsequent sections of this paper are organised as follows: Section 2 reviews the literature, Section 3 presents the study methodology and data description, Section 4 outlines the preliminary results and discussion, and Section 5 concludes the study and offers policy recommendations.

2. Literature review

The impact of CT on households' food and asset poverty can be assessed using households' utility maximisation theories and an examination of their marginal propensity to consume. Resource-constrained households' welfare maximisation is hampered, but CT helps reduce the resource gap. However, it is noted in Christelisa et al. (2017) that only a substantial change in income from the CT can help overcome the distortion arising from the liquidity constraint, which can enable households to save/acquire assets as well as meet their consumption needs. The assessment of CT's ability to mitigate the negative effects of health shocks follows the conceptual framework in Arnold et al. (2011), where unconditional CT increases households' predictable income and can meet other households' needs, including healthcare, by helping poor and vulnerable households overcome access barriers to services such as health.

Empirically, there are conflicting results on the effect of CT on household welfare. Studies that found a positive effect on food consumption include Asfaw et al. (2014), Haushofer and Shapiro (2016), Haushofer and Shapiro (2013), Merttens et al. (2017), Hidrobo et al. (2018), and Dasgupta and Robinson (2021). While Covarrubias et al. (2012), Haushofer and Shapiro (2013), Merttens et al. (2017), and Hidrobo et al. (2018) found asset holding to increase. Those that found decreased or insignificant improvements in food consumption include Kipruto et al. (2024) and Bastagli et al. (2016). However, some studies found CT to improve some food security indicators, but not all aspects, such as that of Manda et al. (2020), who found Kenyan OVC-CT to improve a household's dietary diversity, but not their food consumption per adult equivalent.

From the literature reviewed, there are few studies on the influence of CT on cushioning households against health shocks (Asfaw et al., 2017 and Mitra et al., 2016). In Kenya, only the Kansiime et al. (2021) study, which considered a covariate health shock (COVID-19), examined the influence of CT on cushioning households' welfare against health shocks. Various studies have used different techniques to evaluate the effect/impact of CT on household welfare. Asfaw et al. (2014) and Covarrubias et al. (2012) used Difference in Difference (DID). Randomised Control Trials (RCTs) were conducted by Haushofer and Shapiro (2013), Haushofer and Shapiro (2016), and Egger et al. (2020). Propensity Score Matching (PSM) was employed by Covarrubias et al. (2012). The Fixed Effects (FE) technique was used by Mitra et al. (2016). Some studies have used cross-sectional data employing multivariate logistic regression and probit, such as those of Buigut et al. (2015) and Kipruto et al. (2024).

3. Methodology

We estimate the impact of the GCT on household welfare and its shock mitigation effect by specifying household welfare measures as follows.

$$\pi = \alpha_1 + \alpha_2 \mathrm{GCT} + \alpha_3 S + \alpha_4 \theta + \varepsilon \qquad 1$$

where π represents welfare measures given by food and asset poverty, both given in binary form. $\alpha_2\mathrm{GCT}$ is a dummy variable representing the treatment (T), receipt of the GCT. $\alpha_3 S$ is a binary variable representing self-reported shocks by the household and $\alpha_4\theta$ represents the various household and community features (age, employment status, gender and education level of household's head, household size, region of residence, and health cover).

In using cross-sectional data to assess the impact of social intervention, the endogenous switching probit technique fronted by Lokshin and Sajaia (2011), which accounts for selection bias, can be applied. This estimation is then followed by the computation of the average treatment effects.

The criterion function for the binary outcome in Equation (1) is given by

$$T_i = 1 \ if \ \delta Z_i + \mu_i > 0 \qquad 2$$

$T_i = 0 \;\; if \; \delta Z_i + \mu_i \leq 0$

Where T_i represents treatment (GCT). The binary outcome (whether poor or not poor) is represented by

$$\pi_{1i}^* = \alpha_1 X_{1i} + \varepsilon_{1i} \; ; \quad \pi_{1i} = I(\pi_{1i}^* > 0) \qquad 3$$

$$\pi_{0i}^* = \alpha_0 X_{0i} + \varepsilon_{0i} \quad \pi_{0i} = I(\pi_{0i}^* > 0) \qquad 4$$

where π_{1i}^* and π_{0i}^* are latent variables that determine the observed binary outcome π_1 and π_0 (household being poor or not poor, respectively). X_1 and X_0 are vectors of weakly exogenous variables, Z is a vector of variables that determines a switch between regimes. α_1, α_0 and δ are vectors of parameters, whereas μ_i, ε_{1i} and ε_{0i} are error terms that are jointly and normally distributed with a zero mean[1]. The Z variable in the treatment model contains a selection instrument not included in the X variable to help solve the potential endogeneity problem of the GCT in the first-stage estimation, thus satisfying the exclusion restriction. This study uses distance to a financial institution as the selection instrument because beneficiaries must present themselves in person to collect the cash.

The model is then estimated using the full information maximum likelihood (FIML) endogenous switching probit model under the assumption of joint normality of the error term in both the selection and outcome equations (Lokshin and Sajaia, 2011). After the estimation, we obtained the effects of treatment on the treated (TT), untreated (TU), and the treatment effect (TE). The average treatment effects, namely, the average treatment effect on the treated (ATT), average treatment effect on the untreated (ATU), and average treatment effect (ATE), are then computed.

3.1 Data and variables

This study used data drawn from the KIHBS 2015/2016[2]. Although the survey had 21,773 households from 2,400 clusters, comprising 988 urban and 1,412 rural areas, CT generally targets poor households. Therefore, this study does not include all 21,773 households, but only retained poor households that were below the poverty line. A monthly total expenditure below Ksh 3,252.735 for rural households and Ksh 5,995.902 for urban households was considered poor for the survey. This translates to 8,265 households being considered for the impact of GCT on household welfare. Further, for the mitigation effect of GCT on households that experienced health shocks, the data were collapsed to include only poor households that reported illness, death, or both, leading to a total of 4,717 households in this analysis.

Variable Definition

Dependent Variables

The dependent variables in this study are asset-poor and food-poor. Asset-poor was obtained by constructing an asset index for each household using Multiple Correspondence Analysis (MCA) based on household possessions. The household possessions used in the computation of the asset index were housing quality (walling, roofing, flooring, electricity (source of lighting), sanitation, cooking energy and roof), agricultural farm ownership and land holdings, means of transport (motorcycle, bicycle, car) and other items like computer, television, internet connection and mobile phone. The summary statistics for these items are provided in Appendix 1. After calculating the MCA index, we formed a quintile grouping from which households were categorised as either asset poor if they were in the two lower quintile groups and assigned the value (1) or non-asset poor if they were in the 3rd, 4th, and 5th groups, assigned the value (0).

The food-poor categorisation was based on monetary measures according to Greer and Thorbecke's (1986) definition, in which poverty lines are derived based on adult equivalent food expenditure per person per month. For KIHBS 2015/2016, this was set at Ksh 1,954 and Ksh 2,551 for food poverty in the rural and urban areas, respectively. Those that were below these thresholds were deemed food poor and assigned value (1), and those not food poor were assigned value (0).

[1] more details on the procedure see Lokshin and Sajaia, 2011

[2] Data Access Statement: Research data supporting this publication can be accessed at https://statistics.knbs.or.ke/nada/index.php/auth/login/?destination=catalog/13/get-microdata

Treatment Variable

Receipt of GCT was considered for households that received cash from the government only, under OVCT, OPCT, PWSD-CT, or HSNP. Based on these criteria, households were categorised as either benefiting from GCT, assigned a value of one (1), or non-beneficiary households, assigned a value of zero (0). Other variables and their measurement explanations are presented in Table 1.

Table 1: Other variables included in the study

Variables	Measurements
Health shock	The health shock variable was formed from both the illness and death variables described above. Households that had any member ill or any experience of death were considered to have a health shock. Households that experienced a health shock were then assigned the value 1, and 0 otherwise.
Age of household head	The age of the household head was measured in years.
Rural residence	Households that reside in rural areas were assigned the value 1, and 0 otherwise.
Female-headed Households	Female-headed households are assigned the value 1 and 0 otherwise.
No education	Household heads were considered as having no education if they had no education or had levels below primary education. A dummy value of 1 was assigned for no education and 0 otherwise.
Primary education	Household heads who had a primary education were assigned a dummy value of 1, and 0 otherwise.
Secondary and higher education	Household heads who had secondary education and above (post-primary, college, university, undergraduate and postgraduate) were considered as having secondary and higher education. For the poor household sample, those who had any education level above secondary were very few and, in some cases, missing, thus necessitating the merging. A dummy value of 1 was assigned to those with secondary and higher education, and 0 otherwise.
Household size	Household size is given by the number of people residing in the household.
Employed Household Head	Households whose head had any form of employment in the last 7 days and worked at least one hour as an employee for a wage were assigned the value 1, and 0 otherwise.
Health Insurance Cover	Households with any health insurance were assigned the value 1, and 0 otherwise.
Distance to the financial institution	Distance to the nearest financial institution is used as a selection instrument. It was obtained from the community-level data initially given in meters, kilometres and miles. They were then all converted to kilometres and used in the estimation as a continuous variable.

3.2 Descriptive statistics

Table 2 presents descriptive statistics. Only 379 households out of the sample considered received GCT. Of those who received the transfer, 81.5 percent witnessed a delay in CT remittance that was computed based on the proportion of the households that received less than the amount they are to receive in 12 months. On average, 67.4 percent of the entire sample were food poor. The GCT beneficiary households had higher food poverty rates (70.4 %) than non-beneficiary households (67.2 %). The average asset poverty level was 56.2 percent for all poor households, whereas that of GCT beneficiary households was 59.9 percent, which was 3.8 percent higher than that of non-beneficiary households. Of all the poor households, 57.2 percent reported experiencing health shocks. Those households that received GCT experienced more health shocks (60.2 %) than those of non-beneficiaries at 57.0 percent. There was no significant difference in the means of food, asset poverty, and health shocks for beneficiary and non-beneficiary households.

Table 2: Descriptive statistics

Variable	All Households N=8265	Recipient Household N= 379	Non-Recipient Household N= 7,886	Mean difference (T-test)
	Mean	Mean	Mean	
Treatment Variable (Binary)				
Receipt of GCT=1 and non-recipient of GCT=0				
Outcome Variable				
Food Poor	0.674	0.704	0.672	-0.032 (0.025)
Asset Poverty	0.562	0.599	0.561	-0.038 (0.026)
Continuous Independent Variables				
Age of Household Head	47.27	59.86	46.67	-13.134***(0.841)
Household Size	5.294	5.401	5.289	-0.112 (0.134)
Binary Independent Variables				
Health Shock	0.572	0.602	0.570	-0.031 (0.026)
Rural	0.578	0.578	0.578	0.0003 (0.026)
Female Head	0.355	0.530	0.346	-0.184***(0.025)
No Education	0.343	0.786	0.321	-0.465***(0.024)
Primary Education	0.461	0.172	0.475	0.304 ***(0.026)
Secondary and Higher Education	0.196	0.042	0.204	0.161***(0.021)
Employed Household Head	0.222	0.100	0.228	0.128***(0.022)
Health Cover	0.097	0.045	0.100	0.055***(0.016)
Instrumental Variable				
Distance to Financial Institution in km	20.74	29.90	20.30	-9.596***(1.399)
Other Variables on GCT and Health Cover				
Delay in CT		0.815		
NHIF Cover		0.875	0.913	

4. Estimation Results and Discussion

Before estimating the model, the presence of endogeneity was established, and a validity test was conducted on the instrument. From the results in Appendix 3, distance to financial institutions was significant at the 1 percent level of significance for the GCT variable, but insignificant for food and asset-poor variables. Hence, it is not directly correlated with food and asset-poor variables, thus making it a valid instrument in the model. No education was used as a reference category. It should be noted that the results from the endogenous switching probit estimates can only be used to show the direction of the effect of the independent variable, but not for the interpretation of the magnitude. Therefore, the discussion of the results on the effects is based on the signs and statistical significance.

4.1 Effect of various household characteristics on household welfare

Table 3 presents the results for all poor households below the poverty line (a sample of 8,265 households), while Table 4 presents result for poor households that also experienced a health shock (a sample of 4,717 households). Columns (1) and (4) present the selection equation estimates for food and asset-poor models, respectively. Columns (2) and (5) present the coefficients of the probability of being food and asset poor for households that receive GCT, while columns (3) and (6) present the coefficients for households that did not receive GCT.

From Table 3, the Wald Chi-square statistics are statistically significant at the 1 percent level for both food and asset models, indicating that the explanatory variables in the models have strong explanatory power. In the food-poor model, the correlation coefficient ρ_1 was positive and significant, while ρ_0 was negative and significant. For the asset-poor models, the correlation coefficient ρ_1 is insignificant, whereas ρ_0 is positive and significant for the correlations between the error terms in the equations determining the GCT and the household being asset-poor. The log-likelihood-ratio test of the joint independence of equations for both food-poor and asset-poor models rejected the null hypothesis, H_0, that $\rho_1 = \rho_0 = 0$ at a 1 percent level of significance. These results suggest that the unobservable variables in the selection equation are significantly associated with the unobservable variables in the food and asset poor models, thus qualifying the use of an endogenous switching probit estimation to achieve unbiased and efficient parameters.

Table 3: Endogenous Switching Probit Regression Results for GCT Welfare of All Poor Households

Variables	(1) Selection Equation: Receiving GCT	Outcome Equation: Food-poor		(4) Selection Equation: Receiving GCT	Outcome Equation: Asset Poor	
		(2) GCT Recipients	(3) GCT Non-recipient		(5) GCT Recipients	(6) GCT Non-recipient
Age of Household Head	0.0158***	0.0133***	-0.000005	0.0169***	-0.00447	0.0109***
	(0.0017)	(0.0027)	(0.0013)	(0.0017)	(0.0073)	(0.0010)
Rural	-0.266***	-0.126	0.236***	-0.254***	0.446***	0.655***
	(0.0610)	(0.0844)	(0.0324)	(0.0596)	(0.141)	(0.0304)
Female Head	0.190***	0.190**	0.119***	0.209***	-0.00340	-0.0244
	(0.0571)	(0.0827)	(0.0353)	(0.0560)	(0.150)	(0.0323)
Primary Education	-0.659***	-0.489***	0.0104	-0.671***	0.648***	0.0888**
	(0.0656)	(0.144)	(0.0600)	(0.0654)	(0.196)	(0.0353)
Secondary and Higher Education	-0.804***	-0.683***	0.0986	-0.803***	0.446	-0.0277
	(0.110)	(0.201)	(0.0684)	(0.110)	(0.404)	(0.0464)
Household Size	0.0269***	0.0578***	0.0977***	0.0372***	0.0100	0.0703***
	(0.0101)	(0.0184)	(0.0068)	(0.0109)	(0.0322)	(0.0059)
Employed Household head	-0.0231	0.131	0.0444	0.00697	-0.106	-0.232***
	(0.0855)	(0.148)	(0.0384)	(0.0841)	(0.186)	(0.0379)
Health Cover	-0.0261	-0.0291	-0.0924*	0.0207	-0.113	-0.139***
	(0.118)	(0.183)	(0.0514)	(0.116)	(0.260)	(0.0514)
Distance to Financial Institution	0.0033***			0.0036***		
	(0.0009)			(0.0009)		
Constant	-2.337***	-2.442***	-0.288***	-2.480***	1.351	-1.007***
	(0.146)	(0.277)	(0.0745)	(0.152)	(1.138)	(0.0735)
Number of Observations	8,249			8,249		
Wald chi2(10)	380.47***			394.40***		
Log pseudo-likelihood	-6314.255			-6384.505		
ρ_1	0.9345***			0.7274***		
	(0.0736)			(0.3338)		
ρ_0	-0.3406			0.9968		
	(0.3083)			(14.62)		
LR test of independent eqns. chi2(2)	8.14 **			15.90***		

Standard errors in parentheses; and * represent the level of significance as follows: * p < 0.1, ** p < 0.05, *** p < 0.01
Source: Author's estimation using KIHBS 2015/2016 data

The results in Table 3 show that age is positively associated with being food-poor for GCT recipient households and asset-poor for GCT non-recipient households, both at a 1 percent level of significance. Most of the GCT beneficiaries are headed by older persons. From Table 2, the average age of the household head was 59.86 years. The GCT targets poor older persons of 60 years and above. The older a person is, the less likely they are to engage in the active labour force, and this may contribute to the increased food and asset poverty. This finding concurs with the literature that shows that households are more likely to be poor as the household head's age increases (Achia et al., 2010), but contradicts the findings of Muyanga et al. (2013), who found that households' welfare improves with the increase in age of the household head.

Residing in rural areas was positively associated with being food-poor for non-recipient households and asset poverty for both GCT recipient and non-recipient households at a 1 percent level of significance. However, it was negatively significant at the 10 percent level for a household being food-poor for the GCT recipient households. These findings are comparable to those of Muyanga et al. (2013), who found households in rural areas to be poor.

The female-headed variable was positive and statistically significant at the 1 percent level for food poverty for both GCT recipient and non-recipient households, but insignificant for asset poverty for both groups. These results echo the findings of other studies that found households headed by females to be more impoverished than those headed by males (Dasgupta and Robinson, 2021; Muyanga et al., 2013).

For the households' head education variables, primary and secondary & higher education were both negative and statistically significant for food poverty, only for GCT-recipient households at the 1 percent level of significance. Having some form of education exposes one to the importance of prioritising food that is critical for the health of household members, which could have led to an improvement in food expenditure. However, the increase in asset poverty for those whose heads had primary level education could hint at the possibility of households disposing of some assets to smooth food consumption when they are cash constrained, as Table 2 indicates that 81.5 per cent of beneficiaries experienced a delay in GCT remittance. Some studies found that higher educational attainment improves welfare (Achia et al., 2010; Muyanga et al., 2013b; Oiro et al., 2004). However, Muyanga et al. (2013) noted that though higher education increased asset holding, certain investments, such as a child's education, decreased. In this current study, it can be postulated that the improved food expenditures amidst the delays in disbursement could have been attained through the drain of asset holding.

Household size was positively associated with food poverty for both GCT recipient and non-recipient households. However, it is positive and significantly associated with asset poverty only for non-GCT recipients. These findings agree with the literature that found that higher numbers of household members cause households to have poorer welfare indicators (Eurosystem Household Finance and Consumption Network, 2013).

Household head employment was negatively and significantly associated with asset poverty for GCT non-recipient households. These results imply that employment is likely to improve asset holding. However, it was insignificant for food poverty for the GCT recipient households and asset poverty for the non-receivers. Only 10 percent of GCT recipients had some form of employment. Moreover, these findings could show that the kind of employment these poor households are engaged in, which could either be agriculture or the informal sector that is prominent in Kenya, is insensitive to poverty reduction. Oiro et al. (2004) also found that employment in these areas in Kenya was associated with higher chances of being poor. Having any form of health cover was negative and statistically significant for GCT non-recipient households for food and asset poverty. Households with health cover were less likely to be poor. O'Donnell (2024) also found that health coverage lessens the effect of health shocks on household welfare more especially in economies where the supply-side health systems are improved.

Table 4: Endogenous Switching Probit Regression for the Effect of GCT on Poor Households that have Experienced Health Shocks

Variables	(1) Selection Equation: Receiving GCT	Outcome Equation: Food-poor		(4) Selection Equation: Receiving GCT	Outcome Equation: Asset Poor	
		(2) GCT Recipients	(3) GCT Non-Recipients		(5) GCT Recipients	(6) GCT Non-Recipient
Age of Household head	0.0162***	0.0122***	-0.00015	0.0171***	-0.0042	0.0095***
	(0.00222)	(0.0034)	(0.00162)	(0.00225)	(0.0065)	(0.0013)
Rural	-0.389***	-0.142	0.248***	-0.371***	0.366**	0.632***
	(0.0785)	(0.116)	(0.0438)	(0.0778)	(0.153)	(0.0438)
Female Head	0.178**	0.115	0.0944**	0.197***	0.0415	-0.0491
	(0.0754)	(0.112)	(0.0455)	(0.0744)	(0.174)	(0.0429)
Primary Education	-0.665***	-0.486***	-0.0133	-0.663***	0.656***	0.152***
	(0.0851)	(0.177)	(0.0748)	(0.0850)	(0.229)	(0.0526)
Secondary and Higher Education	-0.618***	-0.650***	0.103	-0.599***	0.317	0.0566
	(0.133)	(0.212)	(0.0843)	(0.133)	(0.373)	(0.0672)
Household Size	0.0344***	0.0643***	0.0964***	0.0447***	0.0159	0.0484***
	(0.0129)	(0.0218)	(0.0093)	(0.0139)	(0.0354)	(0.00774)
Employed Household head	-0.0936	0.273	0.0290	-0.0797	-0.139	-0.210***
	(0.117)	(0.226)	(0.0520)	(0.116)	(0.266)	(0.0507)
Health Cover	-0.178	-0.375	-0.199***	-0.123	0.143	-0.177***
	(0.162)	(0.265)	(0.0680)	(0.162)	(0.382)	(0.0678)
Distance to Financial Institution	0.0056***			0.0061***		

Variables	(1) Selection Equation: Receiving GCT	Outcome Equation: Food-poor (2) GCT Recipients	(3) GCT Non-Recipients	(4) Selection Equation: Receiving GCT	Outcome Equation: Asset Poor (5) GCT Recipients	(6) GCT Non-Recipient
	(0.0013)			(0.0012)		
Constant	-2.365***	-2.315***	-0.226**	-2.510***	1.234	-0.814***
	(0.198)	(0.353)	(0.105)	(0.204)	(0.960)	(0.103)
Number of Observations	4,717			4,717		
Wald chi2(10)	246.03***			255.66***		
Log pseudo-likelihood	-3566.49			-3698.29		
ρ_1	0.9388*** (0.0711)			-0.6863*** (0.2785)		
ρ_0	-0.3221 (0.3323)			0.6417*** (0.2529)		
LR test of independent eqns. chi2(2)	11.66 ***			8.30**		

Standard errors in parentheses; and * represent the level of significance as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Author's estimation using KIHBS 2015/2016 data

From Table 4, the Wald Chi-square statistic is also statistically significant at the 1 percent level. Furthermore, in the food-poor model, the correlation coefficient ρ_1 is positive and significant, whereas ρ_0 is insignificant. For the asset-poor models, the correlation coefficient ρ_1 is negative, while ρ_0 is positive, and both are significant for the correlations between the error terms in the equations determining the government cash transfer and the household being asset-poor. The log-likelihood-ratio test of the joint independence of equations for both food and asset-poor models rejected H_0, where $\rho_1 = \rho_0 = 0$. These results suggest that the unobservable variables in the selection equation are significantly associated with the unobservable variables in both models, justifying the use of the endogenous switching probit estimator.

Similar to the results for all poor households discussed above, findings from the sample that experienced health shock also show that the age of a household head was positively associated with being food-poor for GCT recipient households and asset-poor for GCT non-recipient households, both at the 1 percent level of significance. Regardless of a household experiencing a health shock, as the household head's age increases, their welfare worsens. From Appendix 2, the average age of the household head who received GCT was 60.9 years old. As a person grows older, they are less likely to engage in the active labour force and thus more likely to be food and asset poor. Residing in rural areas was positively associated with being food-poor for non-recipient households and positively associated with asset poverty for both GCT recipient and non-recipient households at a 1 percent level of significance for households that experienced a health shock. These findings were similar to those reported by Muyanga et al. (2013).

Similar to the overall poor household sample results, the female-headed household variable was positive and statistically significant only for the food-poor GCT non-recipient households. This implies that for non-recipient households, having a female head increases the chances of the household being food poor. These findings concurred with studies that found female-headed households to be generally poor (Dasgupta and Robinson, 2021; Muyanga et al., 2013).

Like the overall poor sample results discussed above, primary as well as secondary & higher education levels were negative and statistically significant at a 1 percent level for the CT recipient households. Education exposes one to the importance of food for health. This could have contributed to the improvement in food expenditure while asset poverty increased for those whose heads had a primary level education. Muyanga et al. (2013) noted that some investments by the household decrease households' assets, even though higher education should increase asset holding. The findings in this current study can be postulated that the improved food expenditures could have been realised through the disposal of assets to smooth consumption. Moreover, having a primary education level may not be adequate to enable one to acquire specialised skills to engage in the labour force, which can lead them to accumulate more assets.

Household size was positive and statistically significant for food poverty for both GCT recipient and non-recipient households, and asset poverty, but only for GCT non-recipients. This implies that the more the household members, the more likely they are to be food and asset-poor. Therefore, larger household size negatively affects welfare, regardless of whether a household has experienced a health shock.

Household head employment is negatively and significantly associated with food asset poverty for non-recipient households at the 1 percent level of significance. Health cover was negative and statistically significant for food and asset poverty only for GCT non-recipient households, which was also similar to the overall poor household sample results. This implies that having health cover of any form is likely to reduce food and asset poverty for poor households. Similar results have been reported by O'Donnell (2024).

4.2 Impact of the GCT on Households' Welfare

To determine the impact of GCT on household welfare, the coefficients obtained from the endogenous switching probit regression in Tables 3 and 4 are used to estimate the mean treatment parameter estimates given in Table 5.

4.2.1 Treatment Effects of the GCT on Households' Welfare

In Table 5, column A outlines the average effects for food and asset-poor poor for all households, while column B presents the results for only those households that experienced health shocks. The results show that all the average treatment effects are statistically significant at the 1 percent level of significance.

Table 5: Treatment Effects

Treatment effect only for all poor households (Column A)			Treatment effect for poor households that also experienced health shocks (Column B)		
For the Poor household sample	**Food Poor**	**Asset Poor**	**For a sample of 4717 households**	**Food Poor**	**Asset Poor**
ATT	0.2741***	-0.4011***	ATT	0.2626***	-0.3563***
	(0.0063)	(0.0059)		(0.0083)	(0.0049)
ATU	-0.6582***	0.4115***	ATU	-0.6598***	0.3859***
	(0.00107)	(0.0019)		(0.0011)	(0.0017)
ATE	-0.6157***	0.3764***	ATE	-0.6167***	0.3510***
	(0.0011)	(0.0019)		(0.0011)	(0.0017)

Standard errors in parentheses; and * represent the level of significance as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' computation based on study results estimated using KIHBS 2015/2016 data

The results in Table 5 (column A) show that the ATT of the food-poor model for households that received GCT was positive for all poor households. This suggests the GCT recipient households had a 27.41 percent higher probability of being food poor compared with the counterfactual scenario of households that did not receive the GCT. This finding is not unique, as Kipruto et al. (2024) also found a reduction in food expenditure for the CT beneficiaries. Njoki and Wairimu (2023) also found the Kenyan OVC-CT to be insignificant for household food consumption. However, this finding contradicts that of Ongudi et al. (2024), who found HSNP to increase beneficiary households' micronutrient intake more than non-beneficiaries.

In contrast, the ATT of the asset-poor model was negative. This implies that households that received the GCT had a 40.11 percent lower chance of being asset-poor. These results are similar to those of Hidrobo et al. (2018), Merttens et al. (2017) and Covarrubias et al. (2012), who found that social protection programs increase asset holdings and savings. A possible explanation for these results is that food consumption decreases while asset levels improve in the Kenyan context because of delays in the disbursement of transfers, leading to the inability to plan and smooth food consumption by the poor households. The descriptive statistics in Table 2 show that 81.5 percent of the GCT recipient households witnessed a delay in CT remittance. Overall, these results confirm the findings that noted monetary welfare measures such as household food expenditure decreased in welfare due to prioritisation of savings over consumption (Bastagli et al., 2016). However, these findings differ from those of Asfaw et al. (2014), Haushofer and Shapiro (2016), Haushofer and Shapiro (2013), Merttens et al. (2017), Hidrobo et al. (2018), and Dasgupta and Robinson (2021), who found transfers to improve consumption levels.

The ATU and ATE of the food-poor model were negative, whereas those of the asset-poor model were positive. The ATU for the food poor implies that the GCT non-recipient households' food consumption would have improved by 65.82 percent had they received CT. While the ATU for asset-poor indicates that households without GCT would have had a 41.15 percent higher chance of being asset-poor had they received the GCT. The ATE for the food-poor also implies that CT is likely to improve food consumption by 61.57 percent. However, the ATE values for the asset-poor suggest that a randomly selected household has a 37.64 percent higher chance of being asset-poor. The ATEs had the same directional effects as the ATU for both models. Because the ATU values represent many untreated households compared with treated, the ATE also had the same directional effect. Overall, the ATU and ATE values for the food-poor indicate that the GCT has the potential to improve food consumption. These results concur with the findings of Manda et al. (2020), who found CT to reduce poverty, although their study focused on poverty headcount and not food consumption.

Regarding the mitigation effect on households that experienced health shocks, the results in Table 5, column B, show that the ATT of the food-poor model for poor households that also experienced health shocks was positive, indicating that these households have a 26.26 percent higher probability of being food-poor compared with the counterfactual scenario that does not receive GCT. The ATT results for the asset-poor model imply that the GCT has the potential to lower asset poverty by 35.63 percent for recipient households. Even though these households experienced health shocks, they were still able to improve their assets through the GCT. It is noticeable that the diminishing effect on food consumption is not as much for households that have experienced a health shock compared to all poor households, while their asset levels have also not improved much. This suggests that households with either a sick or injured member could also have prioritized food consumption to improve the health of the invalid and engage in low purchases of more assets when they receive the transfers, as some GCT funds could have been used for seeking health care. The descriptive statistic for households that experienced health shocks in Appendix 2 shows that only 3.5 percent of GCT recipient households had some form of health cover, while the non-recipient households were 10 percent. Further, Appendix 2 shows that CGT recipient households spent an average of Ksh 2099 on outpatient expenses in four weeks. This is more compared to the non-recipient households that only spent an average of Ksh 976.8. An examination of the effect of GCT on outpatient expenditure, whose results are provided in Appendix 5, indicates that households that received GCT are likely to have increased outpatient health expenditure by 24 percent compared to non-recipient households. This can explain why the impact of GCT on reducing asset poverty among households that experienced health shocks was not much. An indication that the GCT comes in handy in accessing outpatient health care and is thus able to help overcome barriers related to healthcare demand (Arnold et al., 2011).

The ATU and ATE for the food poor for those with health shocks suggest that the GCT has the potential to reduce food poverty by 65.98 percent and 61.67 percent for untreated and randomly selected households, respectively. The ATU for the asset-poor model indicates that households without the GCT would have had a 38.59 percent higher chance of being asset-poor had they received the GCT. While the ATE implies that a randomly selected household that experienced health shocks is likely to have a 35.1 percent higher chance of being asset-poor had they received the GCT. Again, the magnitudes were not as high as the overall poor household values. These findings imply that the Kenyan GCT is, in a way, able to mitigate the negative effect of health shocks on households' welfare. These results are not unique, as Buigut et al. (2015) and Asfaw et al. (2017) also found CT to reduce food poverty when households face shocks. However, this contradicts that of Mitra et al. (2016), who found public and private transfers to play little or an insignificant role in cushioning households against health shocks.

Apart from the delays in the transfers, the non-improvement of both food and asset poverty concurrently could also imply that the amount of transfer is little to meet a number of competing expenditures. The results presented in Appendix 4 show that even though inflation has been increasing in Kenya, the government has not increased the monthly amount it gives the beneficiary household of CT-OVC, OP-CT and PWSD-CT from Ksh 2,000. Using computation from 2013 when all the four GCT programmes were running, the estimated real value of the CT-OVC, OP-CT and PWSD-CT was Ksh 1,024.66 in 2024, while it could have been Ksh 3,903.73 to keep up with inflation. On the other hand, since the commencement of implementation of the HSNP transfer in 2013, the government increased its amount progressively for its first four years, which was approximately similar to its desired amount if adjusted for inflation. However, from 2017, its real value eroded to Ksh 1,674.98 in 2024, while its desired amount should have been Ksh 4489.29. The real value of the GCT transfers has therefore been eroded over time, which may result in the GCT not being able to produce the desired impact on various households' welfare indicators.

5. Conclusion and Policy Implications

This study assessed the impact of GCT on household welfare, mainly on food and asset poverty, while also examining its mitigation effect on the welfare of households that experienced health shocks using data drawn from KIHBS 2015/2016. We employed endogenous switching probit regression techniques in the analysis to control for endogeneity arising from selection bias and then estimated the ATT, ATE, and ATU. Descriptive statistics show that, on average, 67.4 percent of poor households were food poor. The CT recipient poor households had 3.2 percent higher food poverty rates than non-recipient households at 67.2 percent. The average asset poverty level was 56.2 percent. Only 379 households out of 8,265 poor households received GCT. The CT beneficiary households were 3.8 percent more asset-poor than their non-beneficiary counterparts (56.1%). Households that received GCT experienced more health shocks (60.2 %) than non-beneficiaries at 57.0 percent. The ATT results show that those households that received the regular Kenyan GCT were more likely to be food-poor by 27.41 percent, while the ATT for asset-poor indicates that the GCT has the potential to reduce recipient households' chances of being asset-poor by 41.11 percent. This reverse impact shows that CT recipient households in Kenya channel their remittances towards the accumulation of assets rather than on food expenditure. Although these transfers are assigned to recipient households monthly, the government policy is that they are disbursed bi-monthly. However, due to implementation challenges, the government is unable to consistently send the remittance to beneficiaries every two months. Households, therefore, receive these funds in a lump sum arising from the delays, and hence the tendency to acquire assets with the transfers. The descriptive statistics indicate that 81.5 percent of the households experienced delays in remittance. The Kenya Social Protection Report 2020 also shows that, in 2018/2019, the government delivered six payment cycles to HSNP beneficiaries and only three to CT-OVC, OPCT, and PWSD. The three-payment cycle is below the bi-monthly remittance target. This makes it impossible for poor households to plan their food consumption. The non-attainment of food consumption smoothing even with increased assets can also be explained by liquidity limitations due to the tendency of poor households preferring to smooth assets rather than consumption, an explanation fronted in the poverty trap models. The ATU and ATE results for the food-poor show that GCT is likely to improve the food consumption of untreated households by 65.82 percent and that of a randomly selected household by 61.57 percent. This implies that overall, the GCT has the potential to improve poor households' food consumption if more poor households are enrolled in the program. However, its inability to improve both food consumption and asset levels for recipient households could also suggest that the size of the transfer is inadequate to impact many household welfare indicators because of competing needs. Regarding the GCT mitigation effect on health shocks, the ATT results show that poor households that also experienced health shocks and received the GCT were more likely to be food-poor by 26.26 percent, while the ATT for asset-poor households was likely to improve by 35.63 percent. Compared to all the poor households' results, the households that also experienced health shocks were not likely to have a greater diminishing effect on food consumption and were also unlikely to have more improvement in their asset levels. The ATU and ATE for the food poor for those who experienced health shocks suggest that the GCT can potentially reduce the probability of being food poor by 65.98 percent and 61.67 percent for untreated and randomly selected households, respectively. However, the ATU and ATE values indicate that their asset levels worsened. The difference in magnitude between the average treatment effects for all poor households and for poor households that also experienced health shocks suggests that some of the transfers could have been channelled towards dealing with health shocks, either in terms of buying food for the sick or for treatment. Indeed, recipients of CT in Kenya have been noted to use some remittances to meet their healthcare costs (Gok, 2022). These results suggest that GCT have the potential to cushion households against health shocks. Therefore, for GCT to reduce poverty levels and mitigate the adverse impact of health shocks on households, this study proposes improvement in the regularity of disbursements and enrollment of more poor households into the program. The Government can consider changing the disbursement policy from bi-monthly remittances to monthly disbursements, taking advantage of the widespread use of M-Pesa services across the entire country. M-Pesa can ease access, considering the mean distance to a financial institution for CT beneficiaries is 29.63 kilometres compared to 19.69 kilometres for non-beneficiaries. UNICEF (2022) also noted that difficulty in accessing CT at banks lowers the value of the transfer and thus is not able to make desirable changes. The current value of the GCT remitted to households has also been eroded over time. We propose an increase in the transfer to help poor households meet their various expenditure needs. Although the results indicate that the Kenyan GCT can lessen the impact of health shocks on households' welfare, GCT programs are not a panacea to cushion households from health shocks. Therefore, alongside increasing the amount of CT, we propose complementing the GCT with a subsidised health insurance for the poor to augment the income effects. Although the Government of Kenya has complemented the GCT program through an insurance subsidy program for the poor and vulnerable, only 160,442 households were covered by the HISP. This coverage is low considering approximately 1.2 million households are under the government CT program nationally. Enhanced HISP covering all GCT recipients is recommended. One drawback of this study is its inability to capture a range of welfare indicators, even though GCT has varied effects on various household welfare indicators, as various indicators may require different methodologies in their assessment. Future studies may examine the effect of health subsidies on the welfare of GCT beneficiaries.

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Appendix 1: Descriptive statistics for variables (all binary) used for constructing the asset index

Variable	N	Mean
Improved walling material	8254	0.303
Improved roofing material	8254	0.303
Improved flooring material	8255	0.287
Improved toilet	8265	0.214
Lighting using electricity	8249	0.311
Clean cooking energy	8245	0.058
Having a computer in the household	8265	0.007
Presence of a television	8265	0.102
Access to the internet	8265	0.111
Having cows	8265	0.717
Having goats	8265	0.645
Having sheep	8265	0.516
Having camel	8265	0.381
Having pigs	8265	0.364
Having chickens	8265	0.754
Having donkeys	8265	0.419
Having bee hive	8265	0.369
Having rabbit	8265	0.361
Owning and	8265	0.419
Having bicycle	8265	0.0115
Having Motor bike	8265	0.0106
Owning a car	7789	0.0009
Having a mobile phone	8261	0.819

Appendix 2: Descriptive statistics for Households that Experienced Health Shocks

Variable	Households that Experienced Health Shocks		Recipient Household		Non-Recipient Household	
	N	Mean	N	Mean	N	Mean
Food Poor	4726	0.689	228	0.715	4498	0.688
Asset Poverty	4726	0.591	228	0.596	4498	0.590
Health Cover	4722	0.097	228	0.035	4494	0.100
Outpatient Expenses	4612	1032	225	2099	4387	976.8
Illness diagnosed by a Health worker	4726	0.634	228	0.680	4498	0.631
Age of Household Head	4721	48.43	227	60.90	4494	47.80
Household Size	4726	5.496	228	5.618	4498	5.490
Rural	4726	0.593	228	0.535	4498	0.596
Female Head	4726	0.382	228	0.561	4498	0.373
No Education	4726	0.320	228	0.768	4498	0.297
Primary Education	4726	0.500	228	0.175	4498	0.516
Secondary and Higher Education	4726	0.180	228	0.057	4498	0.187
Employed Household Head	4726	0.207	228	0.088	4498	0.213
Distance to Financial Institution in km	4726	19.92	228	30.69	4498	19.37

Appendix 3: Validity Test for Distance to Financial Institution as Instrumental Variable

	All Poor Households			**Those who experience health shock**		
	GCT	Food Poor	Asset Poor	GCT	Food Poor	Asset Poor
Age of Household head	0.0013***	0.0004	0.0032***	0.0014***	0.0003	0.0028***
	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0005)
Rural	-0.021***	0.0777***	0.2485***	-0.033***	0.0828***	0.2393***
	(0.0050)	(0.0114)	(0.0106)	(0.0065)	(0.0146)	(0.0140)
Female Head	0.0164***	0.0449***	-0.0125	0.0158**	0.0327**	-0.0184
	(0.0049)	(0.0112)	(0.0113)	(0.0066)	(0.0145)	(0.0150)
Primary Education	-0.055***	-0.0108	0.0569***	-0.057***	-0.0206	0.0760***
	(0.0059)	(0.0130)	(0.0130)	(0.0079)	(0.0170)	(0.0174)
Secondary and Higher Education	-0.067***	0.0172	0.0162	-0.053***	0.0168	0.0388*
	(0.0096)	(0.0169)	(0.0168)	(0.0118)	(0.0225)	(0.0228)
Household Size	0.0023***	0.0342***	0.0250***	0.0030***	0.0334***	0.0173***
	(0.0008)	(0.0021)	(0.0022)	(0.0011)	(0.0028)	(0.0029)
Employed Household head	-0.0012	0.0166	-0.0822***	-0.0066	0.0110	-0.0735***
	(0.0070)	(0.0132)	(0.0131)	(0.0094)	(0.0175)	(0.0176)
Health Cover	-0.0008	-0.0317*	-0.0496***	-0.0141	-0.0719***	-0.0595**
	(0.0100)	(0.0178)	(0.0181)	(0.0143)	(0.0227)	(0.0236)
Distance to Financial Institution	0.0003***	-0.0001	-0.0003	0.0005***	-0.0003	-0.0004
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0003)	(0.0003)
Receipt of GCT		0.0143	0.0030		0.0137	0.0081
		(0.0254)	(0.0256)		(0.0323)	(0.0336)
N	8249	8249	8249	4717	4717	4717

Appendix 4: The Real value of the CT provided and the rate that is needed to keep up with inflation

The computations were carried out using the Consumer Price Index (CPI), with February 2019 as the base year (a CPI of 100). The inflation factor was then calculated using the formula CPT_t / CPT_{t-1}. The real value at time t was obtained using the formula (CT value at time t-1/IF at time t). The desired value at time t was computed using the formula (CT value at time t-1*IF at time t).

Year	CPI	Inflation Factor (IF)	Real Value of CT-OVC, OP-CT and PWSD-CT	Desired Value considering inflation	Current HSNP transfer	Real Value of HSNP	Desired Value of HSNP considering inflation
2013	71.57	1	2000.00	2000.00	2,300	2300.00	2300.00
2014	76.49	1.068781	1871.29	2137.56	2,450	2450.00	2458.20
2015	81.52	1.065822	1755.73	2278.26	2,550	2550.00	2620.00
2016	86.66	1.062971	1651.71	2421.73	2,700	2700.00	2784.98
2017	93.60	1.080057	1529.28	2615.60	2,700	2499.87	3007.94
2018	97.98	1.046841	1460.86	2738.12	2,700	2388.01	3148.84
2019	103.16	1.052868	1387.50	2882.88	2,700	2268.10	3315.31
2020	108.69	1.053606	1316.91	3037.42	2,700	2152.70	3493.03
2021	115.33	1.061091	1241.09	3222.98	2,700	2028.76	3706.42
2022	124.16	1.076563	1152.83	3469.74	2,700	1884.48	3990.20
2023	133.69	1.076756	1070.65	3736.06	2,700	1750.15	4296.47
2024	139.69	1.04488	1024.66	3903.73	2,700	1674.98	4489.29

Source: Author's Computation based on CPI obtained from Various Kenyan Economic Surveys

Appendix 5: Effect of GCT on Outpatient Expenditure

Variable	Outpatient Health Care Expenditure
Receipt of GCT	0.240*
	(0.124)
Age of Household head	0.0055***
	(0.0017)
Rural	-0.388***
	(0.0529)
Female Head	-0.183***
	(0.0559)
Primary Education	-0.441***
	(0.0636)
Secondary and Higher Education	-0.240***
	(0.0835)
Household size	0.0603***
	(0.0101)
Employed Household head	-0.0969
	(0.0660)
Health Cover	0.311***
	(0.0878)
Constant	5.788***
	(0.135)
Observations	3,807
R-squared	0.048