A Sufficient Statistic Insight into the *Mtukula Pakhomo* Social Insurance Program

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Abstract

This paper presents an empirical examination of consumption smoothing and the intricate interplay between private and social insurance in the face of macroeconomic shocks, with a particular focus on the resulting welfare implications. The approach combines a reduced form method (propensity score matching) and a structural analysis. This allowed for an empirically compelling identification and statements on the welfare impact of a specific social insurance program. Results revealed that the program significantly benefits recipient households, with discernible positive effects on their marginal welfare across different levels of risk aversion and disutility of effort. Notably, the benefits are most pronounced among highly risk averse households that often tend to be the ultra poor. It demonstrated that the provision of cash transfers enables households faced with an adverse shock to avoid resorting to costly consumption smoothing mechanisms. Furthermore, the impact of the program exhibits a pronounced difference between female-headed households and their male counterparts. Female-headed households experience a notably higher positive effect compared to their male counterparts, underscoring the program's potential to alleviate gender-based economic disparities.

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1 Introduction

Over the past decades, social insurance programs have become a major agenda for most governments especially in low and middle income countries with an aim to protect the poorest and most vulnerable households against adverse shocks. These programs have played an increasing role in promoting equity, strengthening resilience, and improving long-term human capital outcomes (World Bank, 2018a). In Malawi, one of the core safety net programs by the Government is the Social Cash Transfer Program (SCTP), locally known as *Mtukula Pakhomo* [1] Program. World Bank (2018a) acknowledges that the role of this program is a matter of considerable technical and political debate. Technically, the debate has been whether to target specific categories of beneficiaries[2], emphasize productivity or direct welfare interventions, and accuracy and efficiency of targeting beneficiaries (Chinsinga, 2009). Politically, questions about the appropriateness and feasibility of safety nets often dominate the discourse. Some studies (Chinsinga, 2009; Kalebe-Nyamongo and Marquette, 2014) have highlighted the concern among technical and political elites on the danger of creating a dependency culture or welfare trap.

A large body of literature has made progress in connecting theoretical and empirical work on social insurance to make empirical statements on welfare and optimal policy (Chetty and Finkelstein, 2013; Gruber, 1997; Chetty, 2006). Although there has been considerable growth in academic research on the effects of social insurance programs on the behaviour of economic agents, particularly in the developed country context, the primary focus has been on estimating the moral hazard costs rather than the benefits (Gruber, 1997). Extensive studies have also focused on unemployment insurance with regards to costs and benefits, along with well documented literature on optimal policy.

Motivation for social insurance work dates back to the seminal work of Akerlof (1970) and Rothschild and Stiglitz (1976). Feldstein (1978) is an important critic of the unemployment insurance program. Partly stimulated by Feldstein's criticism, (Baily, 1978) developed a normative model of social insurance. Chetty and Looney (2006) adopted the model by Baily (1978) and Chetty (2006) to show that welfare gains from increasing insurance cannot be directly inferred from the size of consumption drops. They argued that evaluation of welfare consequences of insurance policies must determine why and how households smooth consumption.

[1] This is the name of the program in chichewa (local language) meaning household welfare enhancement

[2] The SCTP targets the poorest 10 percent of the population

In studies on developing countries, Chetty and Looney (2006) noted that most focused on estimating the response of household consumption to income fluctuations. Consequently, this gives a common perspective that welfare costs of risk and benefits of insurance are small if there are no large changes in consumption due to income shocks. This brought into question whether empirical estimates of the effect of income shocks on consumption have clear policy implications. Their model revealed that welfare gains from increasing insurance cannot be directly inferred from the size of consumption drops alone. This is because the value of insurance may be very large even where consumption does not fluctuate much. For instance, households that are close to subsistence level of consumption are risk averse to cutting consumption further when income falls for fear of starvation. As a result, these households use any means available to avoid a substantial drop in consumption such as taking children out of school. They thus asserted that social safety nets could be valuable in low-income economies even when consumption is not very sensitive to shocks.

The literature thus shows that modern tools connecting theory to data have not fully explored the derivation of robust formulas and empirically estimable parameters for direct interventions by government, particularly in developing countries. Most of these are limited in that there is either a wealth of evidence on reduced form impacts or a rich theoretical literature on optimal policy design. This paper adopts the "sufficient statistic[3]" approach presented by Chetty and Finkelstein (2013) to investigate the evidence of consumption smoothing and welfare consequences of the SCTP. An evaluation of different cash transfer programs reveals a significant and positive impact on beneficiary households not only in Malawi but in low and middle income countries in Africa (Bastagli et al., 2019; World Bank, 2018a,b; Abdoulayi et al., 2016; Handa et al., 2015; Abdoulayi et al., 2014). These impacts have been across a myriad of outcomes including consumption, poverty, education, health and nutrition, among others. Cash transfers have improved long term food security through reduction of predictable but chronic food shortages that perpetuate the cycle of poverty (Miller et al., 2011). In other words, the evidence shows that households have been able to smooth consumption (directly or indirectly) as a result of benefiting from the transfer.

Chetty (2008b) argues that the "sufficient statistic" approach provides some middle ground between competing paradigms for policy evaluation and welfare analysis (the "structural approach" and "reduced form" approach). On the one hand, it is noted that the former approach specifies complete models of economic behaviour and estimates the primitives of such models. With the fully estimated model, the effects of

[3]The term sufficient statistic is borrowed from the statistics literature: conditional on statistics that appear in the formula, other statistics that can be calculated from the same sample provide no additional information about the welfare consequences of the policy (Chetty, 2008b).

counterfactuals in policy changes and economic environment on behaviour and welfare is simulated. The criticism is that the identification of all primitive parameters in an empirically compelling manner is difficult due to issues around selection effects, simultaneity bias and omitted variables. On the other hand, the latter strategy estimates statistical relationships with particular attention to identification concerns using research designs that exploit quasi experimental exogenous variation. The criticism is that the estimated parameters do not change with different policy choices thereby limiting the relevance for the analysis of the well-being of individuals or households. The argument is, therefore, that papers that develop "sufficient statistic" formulas combine advantages of reduced form empirics (transparent and credible identification) and structural models (ability to make precise statements about welfare).

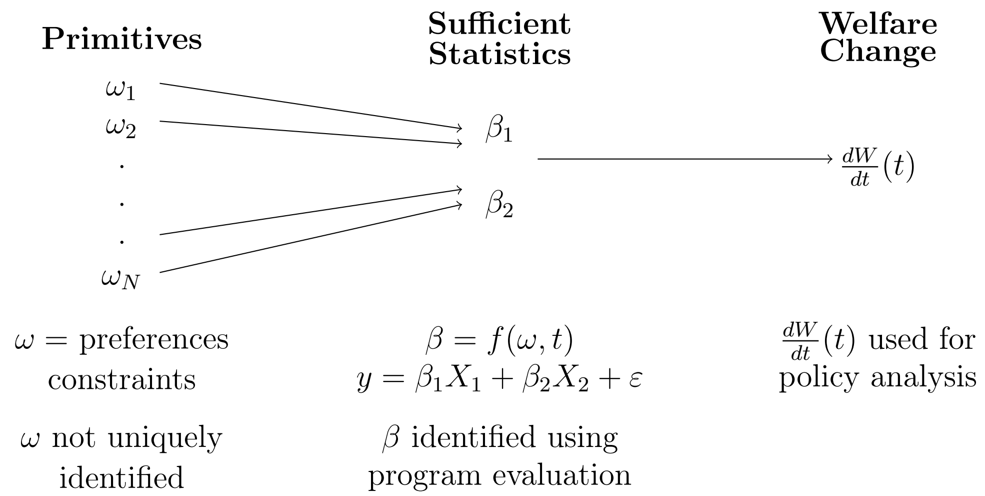
The central concept of the sufficient statistic approach (illustrated in Figure 1) is to derive formulas for welfare consequences of policies as functions of high level elasticities estimated in program evaluation rather than deep primitives (Chetty, 2008b). In simple terms, the idea is that a structural approach analyses the underlying factors or primitives (ω) that drive the impact of policy (t) on welfare (ω), represented as $\frac{dW}{dt}$. Alternatively, the sufficient statistic approach rather than identifying all the detailed primitives (ω) that influence welfare, focuses on a smaller set of high-level parameters (β) which are determined by a reduced form or program evaluation method. This study thus employs the propensity score matching (PSM) method to estimate the parameters to make valid statistical inference for welfare analysis in a structural model.

Main results from the study indicate an increase in consumption of beneficiary households by 22 percent and 15 percent for the poorest and poorer, respectively. On the one hand, female headed households saw a larger increase at 24 percent and 16 percent for the poorest and poorer households than their male counterparts at 16 percent and 12 percent. These results were then simulated against varying levels of risk aversion and an estimate of the moral hazard to establish marginal gains in welfare which were found to be positive.

This study contributes to existing literature in several ways. Firstly, although there have been some studies that have analysed social insurance through a combination of structural (welfare analysis) and reduced form (policy evaluation) approaches, most focused on the moral hazard costs, unemployment insurance and in a developing country. This study derives robust formulae and empirically estimable parameters to analyze not only the moral hazard costs but, equally important, the benefits of social insurance and in a developing country. Secondly, by using the sufficient statistic approach, the study not only explores consumption smoothing but also the welfare gains for beneficiary households. This is unlike most studies that have evaluated the SCTP. Finally, heterogeneity is also explored with regards to stratified groups of households by poverty classification and gender of the household head.

The rest of the paper is organized as follows. A description of the *Mtukula Pakhomo* program outlining the history, objective, coverage, funding and targeting among others in Section 2. Data and methodology are presented in Section 3. The methodology includes both reduced form (program evaluation) and structural (theoretical) approaches which have been combined to present a sufficient statistic approach. Results and analysis are discussed in Section 4. The conclusions are drawn in Section **??**.

Figure 1 The Sufficient Statistic Approach



Source: Chetty (2008b)

Notes: Consider a policy instrument t that affects social welfare $W(t)$. The structural approach maps the primitives (w) directly to the effects of the policy on welfare $\frac{dW}{dt}$. The sufficient-statistic approach leaves w unidentified and instead identifies a smaller set of high-level parameters (β) using program-evaluation methods, e.g., via a regression of an outcome y on exogenous variables X. The β vector is sufficient for welfare analysis in that any vector w consistent with β implies the same value of $\frac{dW}{dt}$. Identifying β does not identify w because there are multiple w vectors consistent with a single β vector.

2 *Mtukula Pakhomo* Program

2.1 Background

The SCTP is an unconditional cash transfer program targeting ultra poor and labour constrained households. It began with a pilot district (Mchinji) in 2006. The inception phase (2006-2012) targeted households in Mchinji, Likoma, Chitipa and Phalombe districts. Between 2013 and 2016, the program was expanded to reach additional districts. Retargeting[4] activities were also conducted during this period. The SCTP Management Information System was also introduced in this phase. From 2017 to present, the program rolled out in all 28 districts (Figure 2). Malawi's integrated social registry, known as the Unified Beneficiary Registry (UBR[5]), was introduced in this phase.

The SCTP is currently funded by four development partners, namely, the Irish Aid (8 percent of households in 2 districts - Balaka and Ntcheu), the German Government through KfW (21 percent of households in 7 districts - Chitipa, Likoma, Machinga, Mangochi, Mchinji, Phalombe and Salima), the European Union (21 percent of households in 7 districts - Chikwawa, Mulanje, Mzimba, Mwanza, Neno, Nsanje and Zomba) and the World Bank (44 percent of households in 11 districts - Blantyre, Chiradzulu, Dedza, Dowa, Karonga, Kasungu, Lilongwe, Nkhatabay, Nkhotakota, Ntchisi, and Rumphi). About 6 percent of households (in 1 district - Thyolo) are supported by the Government. The SCTP currently provides bi-monthly or monthly cash transfers to about 8 percent of the country's household population.

The objective of the SCTP is to promote the alleviation of poverty through the bolstering of beneficiary resilience through financial support. Studies (Miller et al., 2011; Baird et al., 2011; Abdoulayi et al., 2014; Handa et al., 2015; Abdoulayi et al., 2016; Ralston et al., 2017; Brugh et al., 2018) have revealed the proven impacts of the program in terms of asset accumulation, food security, women's economic and social empowerment, and livelihood diversification among the poorest households. A detailed breakdown of transfer amounts by household size and number of children in school is provided in Table 1.

[4]Eligibility status of existing beneficiaries is verified and program coverage increased to 10 percent at district level. It entails recollecting beneficiaries and new households' data every 4 years of SCTP intervention in a geographical area (Government of Malawi, 2020a)

[5]Provides a consolidated source of information on the socio-economic status of households to determine their potential eligibility for social protection programs (Lindert et al., 2018)

Table 1 Transfer Amounts by Household Size and Number of Children in School

Household Size	Monthly Cash Benefit	Primary School	Secondary School	Primary School Incentive*
1 Member	MWK 4,000[a]	No. of Children x MWK 1,000[e]	No. of Children x MWK 2,000[f]	No. of Children x MWK 1,000[e]
2 Members	MWK 5,000[b]	No. of Children x MWK 1,000[e]	No. of Children x MWK 2,000[f]	No. of Children x MWK 1,000[e]
3 Members	MWK 6,500[c]	No. of Children x MWK 1,000[e]	No. of Children x MWK 2,000[f]	No. of Children x MWK 1,000[e]
≥4 Members	MWK 8,000[d]	No. of Children x MWK 1,000[e]	No. of Children x MWK 2,000[f]	No. of Children x MWK 1,000[e]

a $2.80, b $3.50, c $4.60, d $5.60, e $0.70, f $1.40

Source: Author based on Administrative Data

* Incentive to send to primary school those children that are not enrolled but are of school going age (5-15 years old)

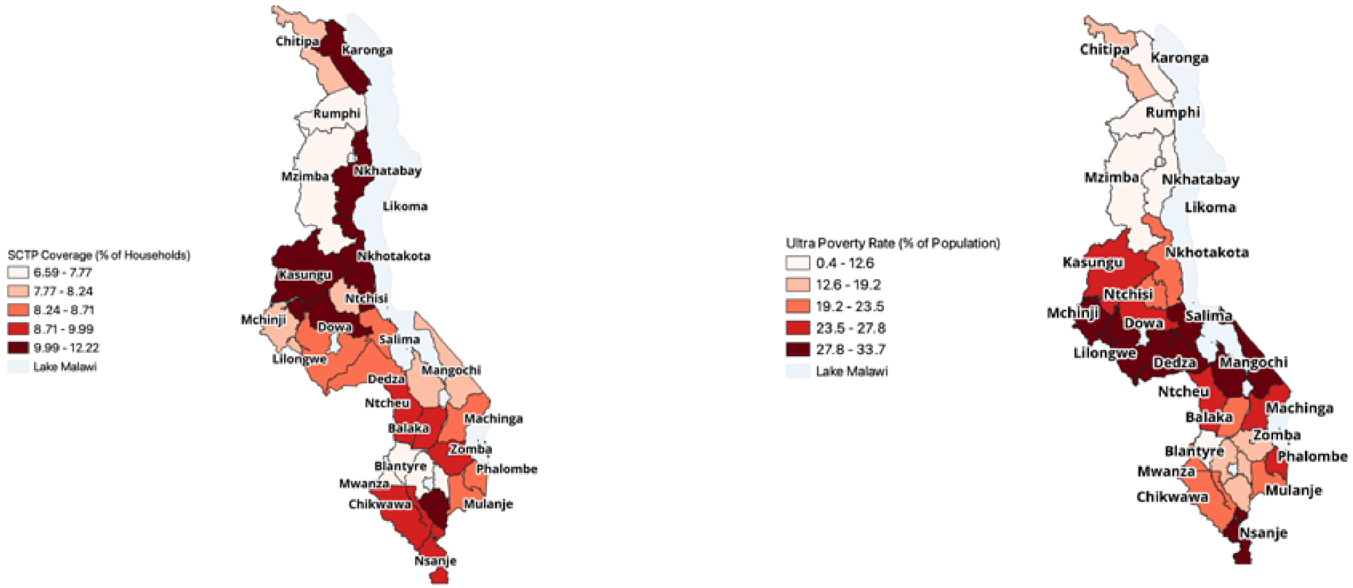
Notes: Conversion from Malawi Kwacha (MWK) to United States Dollar ($) based on Reserve Bank of Malawi exchange rate data

Table 2 Poverty Classification By PMT Score

Wealth Quintile	**PMT Score Value**	
	Bottom Cut-Off	**Top Cut-Off**
Poorest	Lowest	-0.6361184
Poorer	-0.6361183	-0.1281465
Poor	-0.1281464	0.6418340
Better	0.64183410	2.5360910
Rich	2.5360920	Highest

Source: Government of Malawi (2020b)

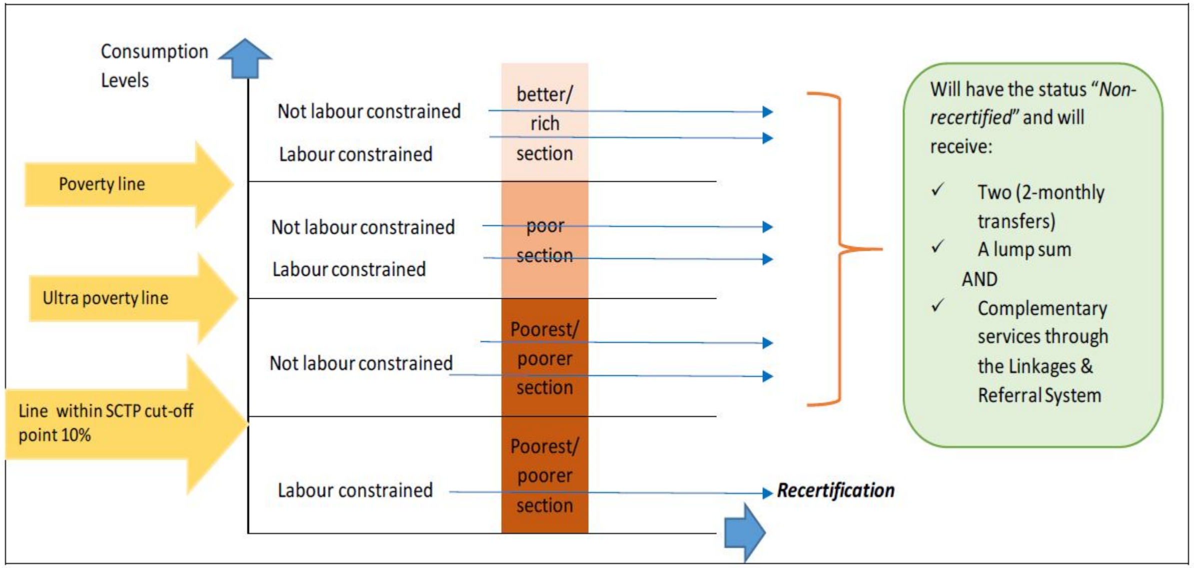
Figure 2 Distribution of SCTP Beneficiaries (Left) and Ultra Poverty (Right) by District



Source: Author based on Administrative and Poverty Data

Notes: The left panel shows coverage of the program (percentage of household) and the right panel shows incidence of ultra poverty (percentage of population). It illustrates that the districts with high poverty incidence also have a relatively larger proportion of households benefiting from the program.

Figure 3 Recertified and Non-Recertified Households



Source: Government of Malawi (2020a)

Notes: See Table 3 for definition of recertified and non-recertified households

2.2 Eligibility Criteria

The eligibility status is constructed as follows: Firstly, the households have to be *ultra poor*. The NSO (2020) defines individuals who reside in households with consumption lower than the poverty line as "poor". Using the minimum food consumption as an additional measure, the "ultra-poor" are identified as households whose consumption per capita on food and non- food items is lower than the minimum food consumption. For the purposes of the SCTP, households classified as *poorest* and *poorer* are considered ultra poor (Figure 3). This stratification is based on the decision table and cut-off points from a proxy means test (PMT) model (Table 2).

The Ministry of Finance, Economic Planning and Development is responsible for the development of the PMT formula. The current PMT score is based on the fourth Integrated Household Survey (IHS4) conducted by the National Statistical Office. Social Support Programs by Government use the harmonized data collection tool to identify households for inclusion in the UBR. It considers household characteristics found in both the IHS4 and the UBR. Government of Malawi (2020b) describes the PMT model which is developed based on a national household survey with a methodology that relies on household assets and other indicators (proxies) to estimate household welfare. This is because household income in developing countries is often difficult and expensive to measure accurately. The proxies in the model include demographic characteristics (such as dependency ratio and education of household head); housing characteristics (such as type of roof, floor, wall, latrine, water source and lighting source); household and productive assets (such as television, bicycle, bed, livestock, poultry and land ownership); economic characteristics (source of livelihood such as subsistence or commercial agriculture and formal and informal employment) and food security (such as number of meals eaten by the household). The PMT uses a set of 26 proxies which is weighted based on estimated impact on household expenditure using the Principal Components Analysis estimation method.

Secondly, eligibility requires satisfying the condition of being *labour constrained*. "Labour constrained" is defined as having a ratio of "not fit to work" to "fit to work" of more than three. Household members are defined as "unfit" if they are below 19 or above 64 years of age, or if they are aged 19 to 64 but have a chronic illness or disability, or are otherwise unable to work such as members aged 19 - 25 but attending school. A household is labour constrained if there are no "fit to work" members in the household, or if the ratio of unfit to fit exceeds three (Government of Malawi, 2020a).

Thirdly, beneficiary households have to be ranked within the program's *10% cut-*

off point of a selected geographical area. Population statistics from the National Statistical Office are used to determine the 10 percent SCTP coverage. Regarding geographical mapping, the country is demarcated into four administrative levels, namely, District, Traditional Authority, Group Village Head and Village. Two more levels are created for purposes of the SCTP known as Village Clusters and Zones (Government of Malawi, 2020a)[6].

2.3 Overview of the SCTP Operational Cycle

Although the responsibility of the UBR process lies with the Ministry of Finance, Economic Planning and Development, it's implementation and supervision is delegated to the Ministry of Gender, Community Development and Social Welfare. The latter is also responsible for the implementation of all SCTP activities at national and district levels. Government of Malawi (2020a) describe the operational cycle of the SCTP which includes data collection of current beneficiaries and new households through the UBR process; data transfer from the UBR to the SCTP MIS; data analysis and classification of households; selection of beneficiaries; and enrollment of the newly identified and recertified households.

Data collection and classification activities are done through the UBR process using the harmonized data collection tool which targets 100 percent of household coverage per geographical area. Each household in the UBR is ranked by wealth quintile based on the PMT score. In line with the SCTP, this paper focuses on the poorest and poorer households only.

Data transfer from the UBR to the SCTP-MIS is done through a program specific Application Program Interface. The modalities for data transfer are three-fold, namely, SCTP beneficiaries from a specific district/traditional authority/village cluster, independent of eligibility status; all eligible new households from a specific district/traditional authority/village cluster; and individual record associated with a unique identifier, namely, the ML-code in the SCTP MIS and/or UBR code in the UBR system.

Data analysis and classification commences as part of the retargeting process, once data is transferred and accepted. After verification and quality checks, the data is processed to: (i) determine current beneficiaries to be non-recertified based on failure

[6] A village cluster is made up of villages with a maximum of 2,000 households. It is further divided into a maximum of three zones

to meet one or both of the eligibility criteria; (ii) define the allocation of pre-eligible households for each village cluster. This is based on four factors, namely, the *floor* (current number of beneficiaries), *quota* (bottom 10 percent of households based on NSO population statistics, *pre-eligibility* (existing and newly identified pre-eligible households), and *allocation* (beneficiary slots per village cluster). The allocation can be adjusted if the district quota (maximum number of beneficiaries to be assigned at district level) is greater or less than the total allocation; and (iii) project the number of potential beneficiaries. Table 3 provides a summary of projected statuses that are assigned to households. The results of the data analysis of the retargeting results are approved by the retargeting committee at the central level. This step was key in determining the identification strategy for evaluating the program. Even though the eligibility criteria is clear, the fact that SCTP enrollment is 10 percent of households per district (regardless of the poverty score) meant that a household could be classified with a lower PMT score in one district but not receive the transfer whilst a household with a higher PMT score in another district could benefit based on the aforementioned four factors in each respective district.Furthermore, the allocation at village cluster also means that being selected into the program is not only made at district level but also at village cluster levels.

Table 3 Recertified and Non-Recertified Households

Type of Household	Projected Status	Years in the SCTP	Reason	Meaning
Current	Eligible	Number of years that the district enrolled it's beneficiaries the SCTP	Recertified	Total existing beneficiaries that meet the eligibility criteria and fall within the programme's allocation.
	Non-recertified		Pre-eligible	Total ML-codes transferred in the SCTP-MIS and outside the programme's cut-off point.
	Non-recertified		Ineligible	Household no longer meets the criteria
	Non Reported & non-interviewed		Not found	The household was not found during the UBR data collection
New	Eligible		New	UBR code transferred in the SCTP-MIS and part of the programme's cut-off point.
	Annulled		Duplicated	UBR code transferred in the SCTP-MIS and the UBR code is reported as duplicated
	Pre-eligible		New	Meet the eligibility criteria but outside the programme's cut-off point

Source: Government of Malawi (2020a)

3 Data and Methodology

Selection of beneficiaries is done after presentation, validation and approval at the SCTP community and district approval meetings. For the former, the results are generated from the SCTP MIS as follows: Firstly, all pre-eligible households ordered by PMT scores with indication of type of household (new and existing) as well as the allocation of the number of households that can be selected for the SCTP. Secondly, non-recertified households due to ineligibility. The community validates the list and ranked order with results processed in the SCTP MIS. The latter is then presented with the list of eligible households (current and new) generated from the MIS with information including geographical location, VC allocation, ML code, PMT score, poverty classification, and ranking (according to the new PMT score). The final selection of eligible households to be enrolled in the program is made at this level. This study focused on those households that were existing and enrolled as the treatment group whilst those that were newly identified as pre-eligible but not enrolled were treated as the control group.

Enrollment of recertified and newly selected households is next. This includes providing information on main receiver of the transfer (such as household head or member aged at least 14 years old) or alternative transfer receiver (such as trusted and well known person by household head aged at least 14 years old. A report card or payment of school fees for each child attending school is also provided. The information is screen by a screening officer and household oriented by oriented officer before their data is uploaded in the MIS by an enrollment officer using their household code as indicated on their UBR receipt.

3.1 Data Description

This paper uses administrative data from the UBR and SCTP MIS. It includes data on household identification, program registration, PMT scores and household characteristics such as age, gender, marital status and education level. Data from the UBR and MIS are merged to identify beneficiaries and non beneficiaries as well as controlling for background characteristics.

Given that the UBR and MIS were introduced in different phases, not all the districts are fully aligned between the two databases. The selection of districts was thus based on several factors which included districts that are fully aligned between the UBR and the MIS, available data from the most recent retargeting exercise (2022), households registered in the same year, districts that have eligible households that were either enrolled or not, and districts where data had been collected at 100 percent of households per geographical area[7]. On the basis of the foregoing, the selected districts were Dedza and Nkhatabay, both funded by the World Bank.

The merging of data sets is a multi-stage process. MIS data is available in different modules so the first step was to merge the files with data on enrollment and targeting. The idea was to match households that were selected and enrolled into the SCTP to those that were targeted as eligible. The targeting file contained data on all households as sourced from the UBR before the data reconciliation and validation processes earlier outlined. The unique identifier used here is the ML code that identifies households and members in the SCTP MIS.

The merged sample was then restricted to existing households that were recertified (treatment group) and newly identified households that were classified as pre-eligible (control group). As defined by Government of Malawi (2020a), the former comprised existing beneficiaries that met the elibility criteria and fell within the program's allocation whilst the latter comprised those that met the eligibility criteria but fell outside the program's cut off point (Table 3). The data set was further restricted to households that registered in the program in the same year between the last retargeting exercise (2019) and the current one (2022). This was in order to restrict the receipt of transfers to the same period.

The consolidated dataset from the MIS is then merged with the UBR data using the UBR code. The targeting file in the MIS contains both the ML code and the code from the UBR known as the pre-printed number form in the MIS. In the UBR, this is known as the form number. This UBR code is then used to match data from the MIS and UBR.

The outcome variable of interest is the average number of meals eaten by the household per day. It has four categories, namely, none, one, two or three. This is used as a proxy for consumption. In literature, most studies on developing countries use consumption response to income fluctuations as a measure of insurance (Chetty and Looney, 2006; Dercon, 2002; Morduch, 1995; Townsend, 1994). Data on other commonly used measures of consumption such as expenditure and income is not collected in the survey hence meals eaten was considered the best proxy. It should also be noted that the focus of this study was on food security as measured by the average number of meals taken by the household per day. It does not explore other

[7]It should be noted that UBR data collection in some districts (particularly those that were first targeted in 2019) only covered 50 percent of households per geographical area.

indicators of diet quantity such as caloric availability, food-energy deficiency or depth of hunger. Furthermore, it also does not consider the diet quality as measured by indicators such as household diet diversity score and food expenditures as shares of the different food group categories.

A sub-group analysis was done for the average meals eaten per day by female and male headed households. This was done inorder to explore gender differences on the effect of the program.

The household characteristics that have been controlled for include the PMT score, gender of the head of household, age of the household head, whether or not the household head attained any level of education, the household size, whether or not a member of the household has a disability or chronic illness, and the household dependency ratio. The interview month and district fixed effects are also controlled. The households are grouped into five strata and this study focuses on the sub samples of the bottom two strata considered as the ultra poor (20 percent). These are sub divided into the poorest (bottom 10 percent) and the poorer. The summary of the household characteristics by these two strata are presented in Table 4 and Table 5. The gender disaggregated summary statistics are presented in Table 6 and Table 7 for female headed households. Male headed households summary statistics are presented in Table 8 and Table 9.

On the one hand, the data for the poorest households shows that the average household size is 5, with older household heads being enrolled at an average age of 59 years old compared to those not enrolled at an average of 49 years old. According to the marital status, the majority (47 percent) of treated households are widows compared to 44 percent in the untreated group that are married. Almost all the household heads have no formal education. There's also a higher proportion of households with members that have a disability or are chronically ill. Most of the treated households are also female headed households at 78 percent compared to 60 percent in the untreated group. The average age for a treated female headed household is 58 years old compared to counterpart males at 62 years old. Most of the treated female headed households (57 percent) are widowed unlike the male headed households that are married (79 percent).

On the other hand, poorer households have a similar average household size of 5. An even older household head is enrolled at an average age of 64 years compared to 52 years for the unenrolled. The majority (50 percent) of treated households heads are widowed compared to 48 percent in the control group that are married. With regards to education, at least 48 percent in the treated group have some level of education up to Secondary School (50 percent have no education) compared to 59 percent in the control (35 percent with no education). The proportion of a household member with a disability or chronic illness is higher in the treated group. 75 percent of treated households are female headed households compared to 55 percent in the control group. Female heads have an average age of 63 years old in the enrolled group whilst male heads have an average age of 65 years old.

Table 4 Descriptive Statistics: Full Sample - Poorest

	All			***Treated***			***Untreated***		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Consumption Measure									
Average Meals Eaten by Household	1.93	0.44	1068	2.05	0.36	594	1.79	0.49	474
Household Characteristics									
Head of Household is Male	0.30	0.46	1068	0.22	0.41	594	0.40	0.49	474
Head of Household is Female	0.70	0.46	1068	0.78	0.41	594	0.60	0.49	474
Household Size	4.71	2.04	1068	4.84	2.06	594	4.54	2.01	474
Age of Household Head	54.51	18.19	1068	58.69	16.64	594	49.26	18.71	474
Head of Household has Never Married	0.03	0.17	1068	0.03	0.18	594	0.03	0.17	474
Head of Household is Married	0.37	0.48	1068	0.31	0.46	594	0.44	0.50	474
Head of Household is Seperated	0.11	0.31	1068	0.09	0.29	594	0.12	0.33	474
Head of Household is Divorced	0.10	0.31	1068	0.10	0.29	594	0.12	0.32	474
Head of Household is Widowed	0.39	0.49	1068	0.47	0.50	594	0.29	0.45	474
Head of Household has No Education	1.00	0.03	1068	1.00	0.00	594	1.00	0.05	474
Head of Household has Primary Education	0.00	0.00	1068	0.00	0.00	594	0.00	0.00	474
Head of Household has Secondary Education	0.00	0.03	1068	0.00	0.00	594	0.00	0.05	474
Head of Household has Training College Education	0.00	0.00	1068	0.00	0.00	594	0.00	0.00	474
Head of Household has University Education	0.00	0.00	1068	0.00	0.00	594	0.00	0.00	474
Household Member has Disability	0.09	0.29	973	0.12	0.32	557	0.06	0.24	416
Household Member has Chronic Illness	0.15	0.36	973	0.16	0.37	557	0.14	0.35	416
Household Dependency Ratio	3.07	2.44	973	3.39	2.51	557	2.64	2.27	416

Table 5 Descriptive Statistics: Full Sample - Poorer

	All			***Treated***			***Untreated***		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Consumption Measure									
Average Meals Eaten by Household	2.04	0.52	10243	2.18	0.52	3404	1.97	0.51	6839
Household Characteristics									
Head of Household is Male	0.39	0.49	10243	0.25	0.43	3404	0.45	0.50	6839
Head of Household is Female	0.61	0.49	10243	0.75	0.43	3404	0.55	0.50	6839
Household Size	4.95	2.59	10243	4.82	2.88	3404	5.02	2.43	6839
Age of Household Head	55.61	18.77	10243	63.57	17.09	3404	51.65	18.31	6839
Head of Household has Never Married	0.03	0.17	10243	0.03	0.17	3404	0.03	0.17	6839
Head of Household is Married	0.43	0.49	10243	0.31	0.46	3404	0.48	0.50	6839
Head of Household is Seperated	0.09	0.29	10243	0.06	0.25	3404	0.10	0.30	6839
Head of Household is Divorced	0.11	0.32	10243	0.10	0.30	3404	0.12	0.33	6839
Head of Household is Widowed	0.34	0.47	10243	0.50	0.50	3404	0.26	0.44	6839
Head of Household has No Education	0.40	0.49	10243	0.50	0.50	3404	0.35	0.48	6839
Head of Household has Primary Education	0.01	0.07	10243	0.00	0.07	3404	0.01	0.07	6839
Head of Household has Secondary Education	0.55	0.50	10243	0.48	0.50	3404	0.59	0.49	6839
Head of Household has Training College Education	0.04	0.20	10243	0.02	0.12	3404	0.05	0.23	6839
Head of Household has University Education	0.00	0.00	10243	0.00	0.00	3404	0.00	0.00	6839
Household Member has Disability	0.09	0.29	7922	0.12	0.33	2740	0.08	0.27	5182
Household Member has Chronic Illness	0.19	0.39	7922	0.21	0.41	2740	0.17	0.38	5182
Household Dependency Ratio	2.58	2.35	7922	2.21	2.53	2740	2.78	2.23	5182

Table 6 Descriptive Statistics: Female Headed Households - Poorest

	All			***Treated***			***Untreated***		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Consumption Measure									
Average Household Meals if Head is Female	1.95	0.45	746	2.06	0.38	463	1.75	0.49	283
Household Characteristics									
Female Headed Household Size	4.56	1.88	746	4.65	1.92	463	4.41	1.82	283
Age of Female Head of Household	55.43	17.49	746	57.84	16.71	463	51.49	18.06	283
Female Head of Household has Never Married	0.03	0.16	746	0.03	0.16	463	0.02	0.16	283
Female Head of Household is Married	0.17	0.37	746	0.17	0.38	463	0.15	0.36	283
Female Head of Household is Seperated	0.14	0.35	746	0.11	0.32	463	0.19	0.40	283
Female Head of Household is Divorced	0.15	0.35	746	0.12	0.32	463	0.19	0.40	283
Female Head of Household is Widowed	0.52	0.50	746	0.57	0.50	463	0.43	0.50	283
Female Head of Household has No Education	1.00	0.00	746	1.00	0.00	463	1.00	0.00	283
Female Head of Household has Primary Education	0.00	0.00	746	0.00	0.00	463	0.00	0.00	283
Female Head of Household has Secondary Education	0.00	0.00	746	0.00	0.00	463	0.00	0.00	283
Female Head of Household has Training College Education	0.00	0.00	746	0.00	0.00	463	0.00	0.00	283
Female Head of Household has University Education	0.00	0.00	746	0.00	0.00	463	0.00	0.00	283
Female Headed Household Member has Disability	0.09	0.28	688	0.11	0.31	439	0.05	0.21	249
Female Headed Household Member has Chronic Illness	0.17	0.38	688	0.18	0.38	439	0.16	0.37	249
Female Headed Household Dependency Ratio	3.25	2.48	746	3.42	2.52	463	2.96	2.39	283

Table 7 Descriptive Statistics: Female Headed Households - Poorer

	All			***Treated***			***Untreated***		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Consumption Measure									
Average Household Meals if Head is Female	2.06	0.53	6282	2.19	0.52	2543	1.96	0.51	3739
Household Characteristics									
Female Headed Household Size	4.53	2.44	6282	4.62	2.85	2543	4.46	2.11	3739
Age of Female Head of Household	56.66	19.12	6282	63.14	17.26	2543	52.25	19.06	3739
Female Head of Household has Never Married	0.02	0.15	6282	0.03	0.16	2543	0.02	0.14	3739
Female Head of Household is Married	0.16	0.37	6282	0.15	0.36	2543	0.17	0.37	3739
Female Head of Household is Seperated	0.13	0.34	6282	0.08	0.27	2543	0.17	0.37	3739
Female Head of Household is Divorced	0.17	0.38	6282	0.12	0.32	2543	0.21	0.40	3739
Female Head of Household is Widowed	0.52	0.50	6282	0.63	0.48	2543	0.44	0.50	3739
Female Head of Household has No Education	0.44	0.50	6282	0.54	0.50	2543	0.38	0.48	3739
Female Head of Household has Primary Education	0.01	0.07	6282	0.00	0.07	2543	0.01	0.07	3739
Female Head of Household has Secondary Education	0.53	0.50	6282	0.45	0.50	2543	0.59	0.49	3739
Female Head of Household has Training College Education	0.02	0.15	6282	0.01	0.09	2543	0.03	0.17	3739
Female Head of Household has University Education	0.00	0.00	6282	0.00	0.00	2543	0.00	0.00	3739
Female Headed Household Member has Disability	0.10	0.29	5093	0.11	0.31	2099	0.08	0.28	2994
Female Headed Household Member has Chronic Illness	0.21	0.41	5093	0.22	0.42	2099	0.20	0.40	2994
Female Headed Household Dependency Ratio	2.72	2.53	6282	2.35	2.65	2543	2.98	2.41	3739

Table 8 Descriptive Statistics: Male Headed Households - Poorest

	All			***Treated***			***Untreated***		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Consumption Measure									
Average Household Meals if Head is Male	1.91	0.42	320	2.01	0.29	129	1.84	0.48	191
Household Characteristics									
Male Headed Household Size	5.05	2.34	320	5.53	2.40	129	4.72	2.25	191
Age of Male Head of Household	52.60	19.43	320	62.41	15.17	129	45.97	19.22	191
Male Head of Household has Never Married	0.04	0.19	320	0.04	0.19	129	0.04	0.19	191
Male Head of Household is Married	0.84	0.37	320	0.79	0.41	129	0.87	0.33	191
Male Head of Household is Seperated	0.02	0.15	320	0.03	0.17	129	0.02	0.12	191
Male Head of Household is Divorced	0.01	0.08	320	0.02	0.12	129	0.00	0.00	191
Male Head of Household is Widowed	0.09	0.29	320	0.12	0.33	129	0.07	0.26	191
Male Head of Household has No Education	1.00	0.06	320	1.00	0.00	129	0.99	0.07	191
Male Head of Household has Primary Education	0.00	0.00	320	0.00	0.00	129	0.00	0.00	191
Male Head of Household has Secondary Education	0.00	0.06	320	0.00	0.00	129	0.01	0.07	191
Male Head of Household has Training College Education	0.00	0.00	320	0.00	0.00	129	0.00	0.00	191
Male Head of Household has University Education	0.00	0.00	320	0.00	0.00	129	0.00	0.00	191
Male Headed Household Member has Disability	0.12	0.32	284	0.16	0.37	117	0.08	0.28	167
Male Headed Household Member has Chronic Illness	0.11	0.32	284	0.12	0.33	117	0.11	0.31	167
Male Headed Household Dependency Ratio	2.87	2.27	320	3.43	2.57	129	2.49	1.96	191

Table 9 Descriptive Statistics: Male Headed Households - Poorer

	All			***Treated***			***Untreated***		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Consumption Measure									
Average Household Meals if Head is Male	2.01	0.50	3958	2.13	0.50	858	1.98	0.49	3100
Household Characteristics									
Male Headed Household Size	5.63	2.67	3958	5.42	2.89	858	5.68	2.61	3100
Age of Male Head of Household	53.89	18.07	3958	64.65	16.55	858	50.91	17.33	3100
Male Head of Household has Never Married	0.04	0.19	3958	0.04	0.20	858	0.04	0.19	3100
Male Head of Household is Married	0.85	0.36	3958	0.78	0.41	858	0.86	0.34	3100
Male Head of Household is Seperated	0.03	0.16	3958	0.02	0.15	858	0.03	0.16	3100
Male Head of Household is Divorced	0.03	0.16	3958	0.04	0.20	858	0.02	0.14	3100
Male Head of Household is Widowed	0.06	0.24	3958	0.12	0.32	858	0.05	0.22	3100
Male Head of Household has No Education	0.33	0.47	3958	0.38	0.49	858	0.32	0.47	3100
Male Head of Household has Primary Education	0.01	0.08	3958	0.01	0.08	858	0.01	0.08	3100
Male Head of Household has Secondary Education	0.59	0.49	3958	0.58	0.49	858	0.59	0.49	3100
Male Head of Household has Training College Education	0.07	0.26	3958	0.04	0.19	858	0.08	0.28	3100
Male Head of Household has University Education	0.00	0.00	3958	0.00	0.00	858	0.00	0.00	3100
Male Headed Household Member has Disability	0.09	0.28	2828	0.15	0.36	640	0.07	0.26	2188
Male Headed Household Member has Chronic Illness	0.15	0.35	2828	0.18	0.38	640	0.14	0.35	2188
Male Headed Household Dependency Ratio	2.90	2.13	3958	2.70	2.50	858	2.96	2.02	3100

3.2 Empirical Strategy

3.2.1 Propensity Score Matching

The empirical approach adopts a reduced form analysis. It is worth noting that the SCTP has a clear assignment rule based on whether a household is ultra poor and labour constrained. However, the poverty classification that determines the 10 percent cut-off point varies. This is because selection takes into account the floor, quota, pre-eligibility and allocation at village cluster level within each district (Sub Section ??). This, therefore, renders the use of methodologies such as the Regression Discontinuity Design impossible. The unavailability of baseline data also further limited use of other impact evaluation methods.

This paper thus employs the PSM method developed by Rosenbaum and Rubin (1983) to balance covariates inorder to address selection on observables. The technique is used to construct a conterfactual comparison group.

The average treatment effect that is estimated is as follows:

$$E(Y_i^T - Y_i^C \mid T_i = 1, X_i) = E(Y_i^T \mid T_i = 1, X_i) - E(Y_i^C \mid T_i = 1, X_i) \tag{1}$$

$E(Y_i^T \mid T_i = 1)$ is observed, and $E(Y_i^C \mid T_i = 1)$ is the counterfactual that needs to be constructed using propensity score matching.

Y_i is the average meals eaten per day by the household and is denoted as Y_i^T for those households that received the cash transfer and Y_i^C for non-beneficiaries. T_i is the treatment status where $T_i = 1$ represents a beneficiary household and $T_i = 0$ represents households that are not enrolled in the program. X_i represents observable characteristics which include PMT score, age, gender, marital status and education.

3.2.2 Conditional Independence and Overlap Assumptions

One of the key identifying assumptions of the PSM method is *conditional independence* (Rubin, 1990) which is also known as unconfoundedness, selection on observables, exogeneity or ignorability (Imbens, 2015).

$$(Y_i^T, Y_i^C) \perp T_i \,|\, X_i \tag{2}$$

This denotes that given the observed covariates X_i, the treatment T_i and outcomes for treated and untreated groups are independent.

Another key assumption is *overlap* or *common support* (Rosenbaum and Rubin, 1983).

$$0 < \Pr(T_i = 1|X_i) < 1 \tag{3}$$

This denotes that conditional on the covariates, probability of being enrolled in the social cash transfer program is a value between 0 (impossible) to 1 (certain). So, there must be overlap between the treated and untreated groups for sufficient matches.

3.2.3 Implementation Steps

A poisson regression is used to estimate the propensity score. Cameron and Trivedi (2013) describe it as the benchmark model for count data (number of occurrences of an event) taking discrete values. This model is estimated because it has a count dependent variable (number of meals taken by the household) rather than one that assumes some natural order, in which case an ordered logistic model would have been more suitable (Maddala, 1983). An overdispersion test was conducted to ascertain whether the equidispersion assumption holds and if not whether alternative count models were more appropriate. The overall performance of the model was also tested using the Pearson Statistic, Deviance Statistic, Pseudo R-Squared and Chi-Square Goodness of Fit tests (Cameron and Trivedi, 2013).

As noted by Caliendo and Kopeinig (2008), the matching strategy builds on the conditional independence assumption so the chosen covariates should credibly satisfy this condition. This also points to the importance of exclusion and/or inclusion of particular variables as it can lead to seriously biased results (Heckman et al., 1997; Dehejia and Wahba, 1999). Covariates should be observable characteristics not affected by the program itself but correlated to the treatment. This ensures that the matched households have similar characteristics but only differ in that one group received the treatment and the other did not (Gertler et al., 2016; Imbens, 2015; Cunningham, 2021). The primary determining choice was thus characteristics that determine enrollment. In this case, the main covariate choice for matching is the PMT score for poorest and poorer households only, as it is one of the three criteria for enrollment. The second criteria that all eligible households are labour constrained was applied to all the sampled households so it was not relevant. For the third criteria (10 percent cut off for each district), the PMT score is primarily used to rank households before determining selection into the program at VC level. Other covariates that are unaffected by the program but may affect the participation decision are included, namely, age, gender, marital status and education (for poorer households where it does not perfectly predict treatment status) of the household head. This improved the matched households interms of reduced bias and variance. In some instances the model had to be re-specified to include higher order terms (age) and interaction terms (marriage and age) to achieve balance across the groups. The data was matched after pooling the sub groups. A comparison with data matched at district level before pooling not only saw more observations dropped but the standardized differences in means were also slightly larger.

This study follows the guidance in literature (Caliendo and Kopeinig, 2008; Leuven and Sianesi, 2018; Garrido et al., 2014; Lunt, 2014) on constructing and evaluating the propensity score using different matching and weighting algorithms. The approaches considered in this paper include the nearest neighbour matching, caliper and radius matching, kernel matching, inverse probability of treatment weighting (IPTW) and Mahalanobis. Garrido et al. (2014) highlight that the choice of the matching or weighting algorithm is guided by the tradeoff between variables' effects on bias (distance of estimated treatment effect from true effect) and efficiency (precision of estimated treatment effect). Of these approaches, the IPTW and Mahalanobis had the most reduced bias and variance (Table 10 and Table 11). To account for uncertainty in treatment effect standard errors, the bootstrapped and Abadie-Imbens standard errors (Sianesi, 2004; Abadie and Imbens, 2016) are calculated for the respective selected weighting and matching methods. This is done because the propensity score and treatment effect estimates were done separately. For valid and reliable inference the analysis also accounted for correlation within clusters by clustering at the VC level.

As can be seen in the output from Table 12 - Table 14 and Table 15 - Table 17, the covariates are well balanced after matching. On average, the results show a more than 95 percent reduction in standardized differences in bias with the absolute value less than 5 percent. Furthermore, the t-test is also insignificant across all covariates after matching [8]. This depicts how well the data matched in the treatment and comparison groups. An evaluation of the common support in the distribution of the propensity scores of the treated and untreated groups appears to be adequate (Figure 4 and Figure 5). As depicted in the density plots and boxes in Panels A and B of Figure 6

[8] It is recognized that the use of statistical significance tests to assess balance in propensity score matched samples is discouraged as these are sensitive to sample size (Imai et al., 2008; Austin, 2009). However, this is simply complementing the diagnostic results from the standardized mean differences

and Figure 7, an overlap in the propensity scores after matching the data is achieved. Similarly, balance for matched data between treated and untreated groups is also satisfactory as illustrated in Panels C and D of Figure 6 and Figure 7.

Table 10 Sample Sizes and Standardized Differences in Covariates - Poorest

Sample Type	*All*	*Treated*	*Untreated*	*Mean Bias (%)*	*Median Bias (%)*	*Variance (%)*
Original	1,077	474	603	22.2	11.6	75
NNM 1:1 with Caliper with Replacement	1,066	474	592	4.5	2.2	0
NNM 1:2 with Caliper with Replacement	1,055	474	581	3.5	2.4	0
Kernel Matching	1,055	474	581	3.0	1.8	0
Inverse Probability of Treatment Weighting	1,054	473	581	0.5	0.1	0
Mahalanobis	1,068	474	594	0.5	0.1	0

Note: Selection of the matching algorithm presents a trade off between bias and efficiency. The approach adopted in this paper is to identify the estimator with the most reduction in the standardized differences in the mean, median and variance of covariates whilst retaining a good number of observations from the original sample (Caliendo and Kopeinig, 2008; Garrido et al., 2014).

Table 11 Sample Sizes and Standardized Differences in Covariates - Poorer

Sample Type	*All*	*Treated*	*Untreated*	*Mean Bias (%)*	*Median Bias (%)*	*Variance (%)*
Original	10,253	3,414	6,839	45.9	43.10	50
NNM 1:1 with Caliper with Replacement	10,251	3,412	6,839	3.8	3.9	0
NNM 1:2 with Caliper with Replacement	10,251	3,412	6,839	4.9	4.8	0
Kernel Matching	10,251	3,412	6,839	3.1	1.0	50
Inverse Probability of Treatment Weighting	10,243	3,404	6,839	0.2	0.0	0
Mahalanobis	10,243	3,404	6,839	0.1	0.0	0

Note: Selection of the matching algorithm presents a trade off between bias and efficiency. The approach adopted in this paper is to identify the estimator with the most reduction in the standardized differences in the mean, median and variance of covariates whilst retaining a good number of observations from the original sample (Caliendo and Kopeinig, 2008; Garrido et al., 2014).

Table 12 Balance of Covariates Before and After Matching - Full Sample (Poorest)

Variable	Unmatched Matched	Mean Treated	Mean Untreated	%bias	%reduct |bias|	t-test t	t-test p>|t|
PMT	U	-0.7521	-0.7447	-11.3		-1.84	0.066
	M	-0.7515	-0.7516	0.1	99.1	0.02	0.987
Married	U	.31841	.44304	-25.9		-4.23	0.000
	M	.30808	.30976	-0.3	98.6	-0.06	0.950
Gender of Household Head	U	.78441	.59705	41.4		6.81	0.000
	M	.78283	.78283	0.0	100.0	0.00	1.000
Age of Household Head	U	58.944	49.264	54.5		8.94	0.000
	M	.78283	.78283	0.0	96.2	0.00	1.000
PMT Squared	U	.57021	.55852	11.6		1.89	0.060
	M	.56923	.56919	0.0	99.6	0.01	0.994
Married&Age	U	18.008	19.171	-4.4		-0.72	0.474
	M	17.136	17.015	0.5	89.6	0.08	0.938
Head of Household went to School*	U	0	.00211	-6.5		-1.13	0.260
	M	0	0	0.0	100.0		

* Household Head went to primary school or secondary school or training college or university

Note: The table shows that the treatment and control groups are balanced after matching. This can be seen from the standardized mean differences of confounders between the treated and untreated groups. The magnitude of the reduction in the bias is more than 90 percent and a standardized difference in means equal to or very close to zero implies balance. The t-test is also insignificant implying that there is no significant difference in the covariates between the treatment and control groups.

Table 13 Balance of Covariates Before and After Matching - Female Headed Households (Poorest)

Variable	Unmatched Matched	Mean Treated	Mean Untreated	%bias	%reduct |bias|	t-test t	t-test p>|t|
PMT	U	-.7494	-.74671	-4.3		-0.57	0.569
	M	-.7492	-.74907	-0.2	94.9	-0.03	0.974
Married	U	.18816	.15194	9.6		1.27	0.205
	M	.17495	.17495	0.0	100.0	0.00	1.000
Age of Household Head	U	57.95	51.488	36.9		4.94	0.000
	M	57.84	57.715	0.7	98.1	0.11	0.909
PMT Squared	U	.56574	.56119	4.7		0.62	0.534
	M	.56535	.56501	0.4	92.5	0.05	0.958
Married*Age	U	9.6237	6.3145	17.6		2.27	0.023
	M	8.5335	8.5097	0.1	99.3	0.02	0.985

Note: The table shows that the treatment and control groups are balanced after matching. This can be seen from the standardized mean differences of confounders between the treated and untreated groups. The magnitude of the reduction in the bias is more than 90 percent and a standardized difference in means equal to or very close to zero implies balance. The t-test is also insignificant implying that there is no significant difference in the covariates between the treatment and control groups.

Table 14 Balance of Covariates Before and After Matching - Male Headed Households (Poorest)

Variable	**Unmatched Matched**	**Mean Treated**	**Mean Untreated**	**%bias**	**%reduct |bias|**	**t-test t**	**t-test p>|t|**
PMT	U	-.76195	-.7418	-28.1		-2.51	0.012
	M	-.76072	-.7622	2.1	92.5	0.16	0.872
Married	U	.7923	.87435	-22.1		-1.98	0.049
	M	.7907	.79845	-2.1	90.6	-0.15	0.878
Age of Household Head	U	62.538	45.969	95.7		8.23	0.000
	M	62.411	61.69	4.2	95.6	0.39	0.699
PMT Squared	U	48.515	38.22	40.6		3.64	0.000
	M	48.279	47.992	1.1	97.2	0.08	0.933
Married*Age	U	.58646	.55457	28.9		2.58	0.010
	M	.58444	.58643	-1.8	93.8	-0.14	0.891

Note: The table shows that the treatment and control groups are balanced after matching. This can be seen from the standardized mean differences of confounders between the treated and untreated groups. The magnitude of the reduction in the bias is more than 90 percent and a standardized difference in means equal to or very close to zero implies balance. The t-test is also insignificant implying that there is no significant difference in the covariates between the treatment and control groups.

Table 15 Balance of Covariates Before and After Matching - Full Sample (Poorer)

Variable	**Unmatched Matched**	**Mean Treated**	**Mean Untreated**	**%bias**	**%reduct |bias|**	**t-test t**	**t-test p>|t|**
PMT	U	-.40907	-.33318	-53.4		-25.60	0.000
	M	-.40859	-.40858	-0.0	100.00	-0.00	0.997
Married	U	.31195	.48267	-35.4		-16.70	0.000
	M	.31228	.31228	0.0	100.0	0.00	1.000
Gender of Household Head	U	.7481	.54672	43.1		20.12	0.000
	M	.7477	.74765	0.0	100.00	0.00	1.000
Age of Household Head	U	63.621	51.646	67.5		31.88	0.000
	M	63.566	63.514	0.3	99.6	0.13	0.898
Head of Household went to School*	U	.50088	.64776	-30.0		-14.44	0.000
	M	50206	.50206	0.0	100.0	0.00	1.000

* Household Head went to primary school or secondary school or training college or university

Note: The table shows that the treatment and control groups are balanced after matching. This can be seen from the standardized mean differences of confounders between the treated and untreated groups. The magnitude of the reduction in the bias is more than 99 percent and a standardized difference in means equal to or very close to zero implies balance. The t-test is also insignificant implying that there is no significant difference in the covariates between the treatment and control groups.

Table 16 Balance of Covariates Before and After Matching - Female Headed Households (Poorer)

Variable	Unmatched Matched	Mean Treated	Mean Untreated	%bias	%reduct |bias|	t-test t	t-test p>|t|
PMT	U	-.41454	-.34233	-50.9		-19.90	0.000
	M	-.41369	-.41349	-0.1	99.7	-0.05	0.960
Married	U	.15388	.16635	-3.4		-1.32	0.186
	M	.15297	.15297	0.0	100.0	-0.00	1.000
Age of Household Head	U	63.255	52.254	60.4		23.33	0.000
	M	63.145	63.127	0.1	99.8	0.04	0.971
Head of Household went to School	U	.46124	.62236	-32.8		-12.80	0.000
	M	.46284	.46284	0.0	100.0	0.00	1.000

* Household Head went to primary school or secondary school or training college or university

Note: The table shows that the treatment and control groups are balanced after matching. This can be seen from the standardized mean differences of confounders between the treated and untreated groups. The magnitude of the reduction in the bias is more than 99 percent and a standardized difference in means equal to or very close to zero implies balance. The t-test is also insignificant implying that there is no significant difference in the covariates between the treatment and control groups.

Table 17 Balance of Covariates Before and After Matching - Male Headed Households (Poorer)

Variable	Unmatched Matched	Mean Treated	Mean Untreated	%bias	%reduct |bias|	t-test t	t-test p>|t|
PMT	U	-.39282	-.32214	-50.1		-13.03	0.000
	M	-.3918	-.39205	0.2	99.6	-0.05	0.960
Married	U	.15388	.16635	-3.4		-1.32	0.186
	M	.15297	.15297	0.0	100.0	-0.00	1.000
Age of Household Head	U	64.71	50.912	81.4		20.85	0.000
	M	64.63	64.544	0.5	99.4	0.11	0.914
Head of Household went to School*	U	.6186	.67839	-12.5		-3.29	0.001
	M	.6230	.62995	0.0	100.0	0.00	1.000

* Household Head went to primary school or secondary school or training college or university

Note: The table shows that the treatment and control groups are balanced after matching. This can be seen from the standardized mean differences of confounders between the treated and untreated groups. The magnitude of the reduction in the bias is more than 99 percent and a standardized difference in means equal to or very close to zero implies balance. The t-test is also insignificant implying that there is no significant difference in the covariates between the treatment and control groups.

Figure 4 Distribution of Propensity Score across Treatment and Comparison Groups - Poorest

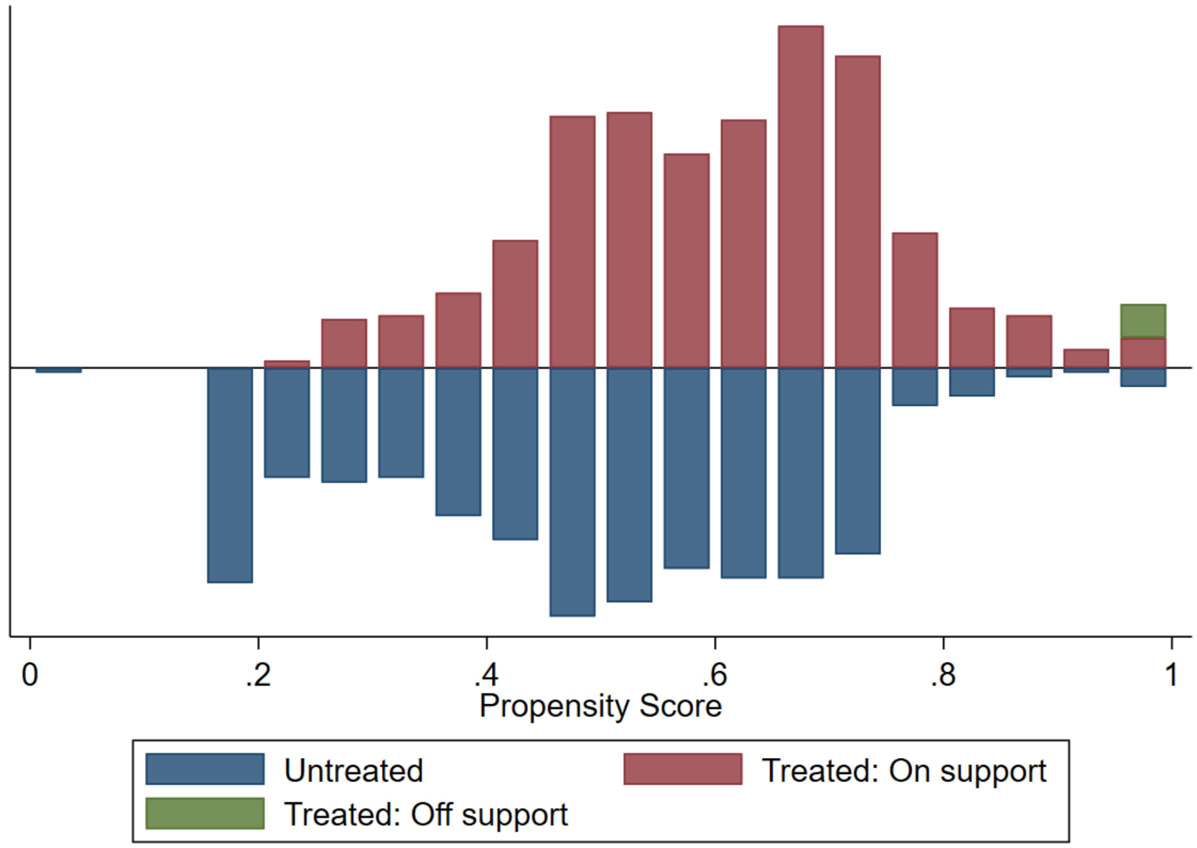


Figure 5 Distribution of Propensity Score across Treatment and Comparison Groups - Poorest

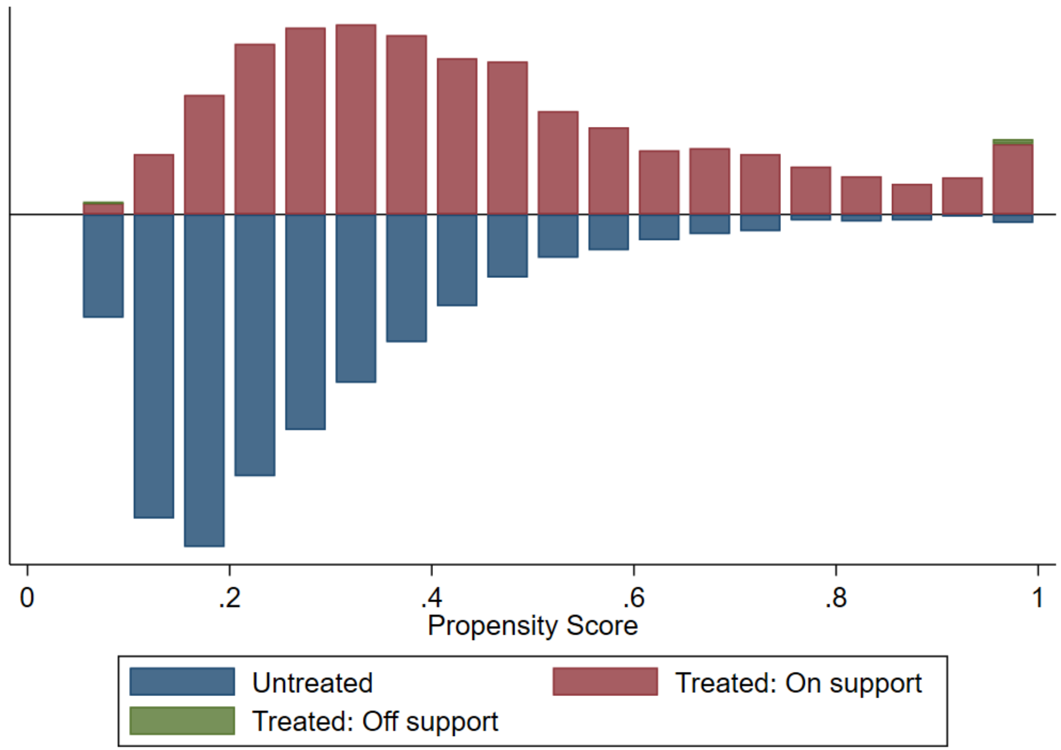


Figure 6 Assessing Matching Quality - Poorest

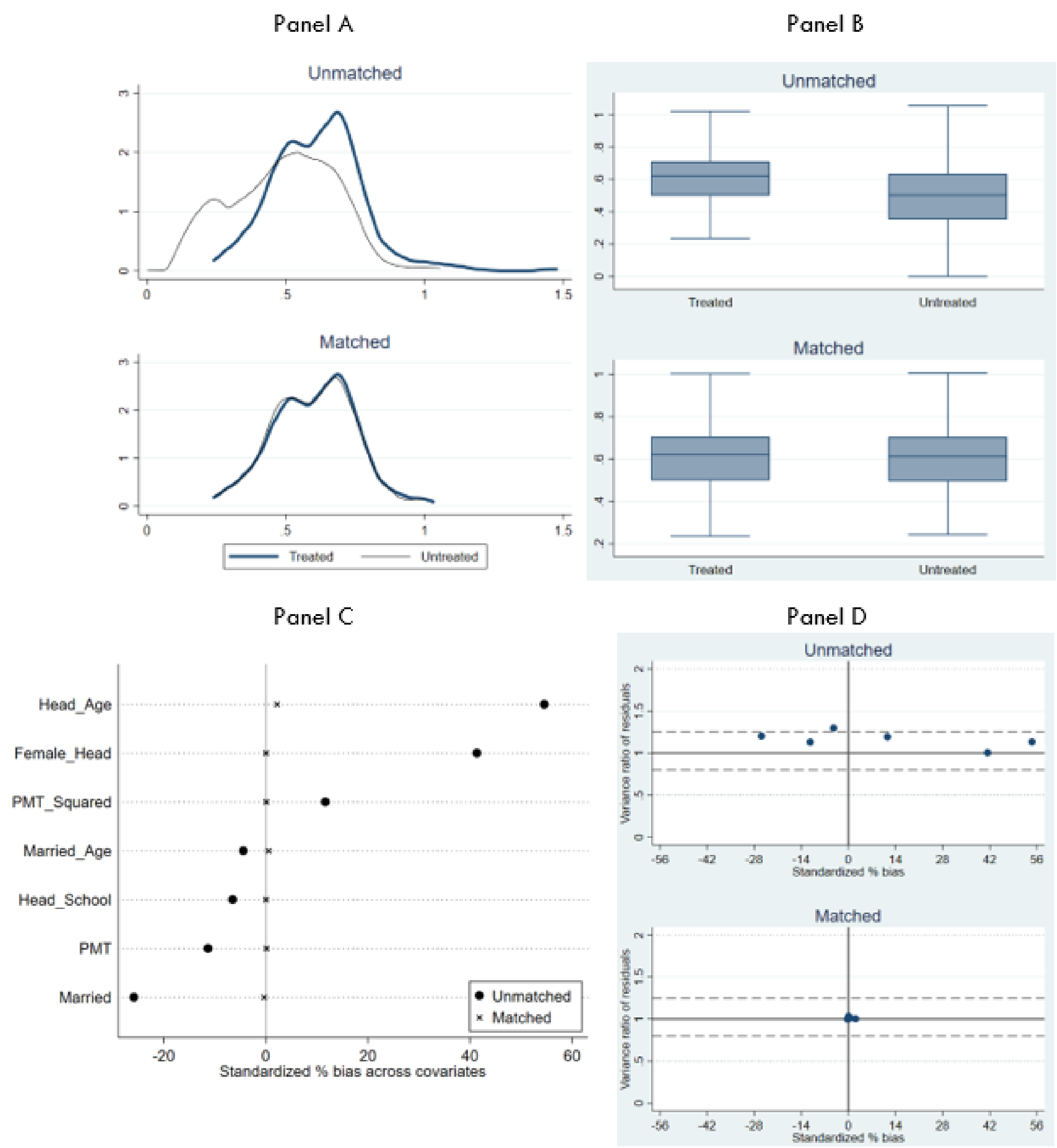
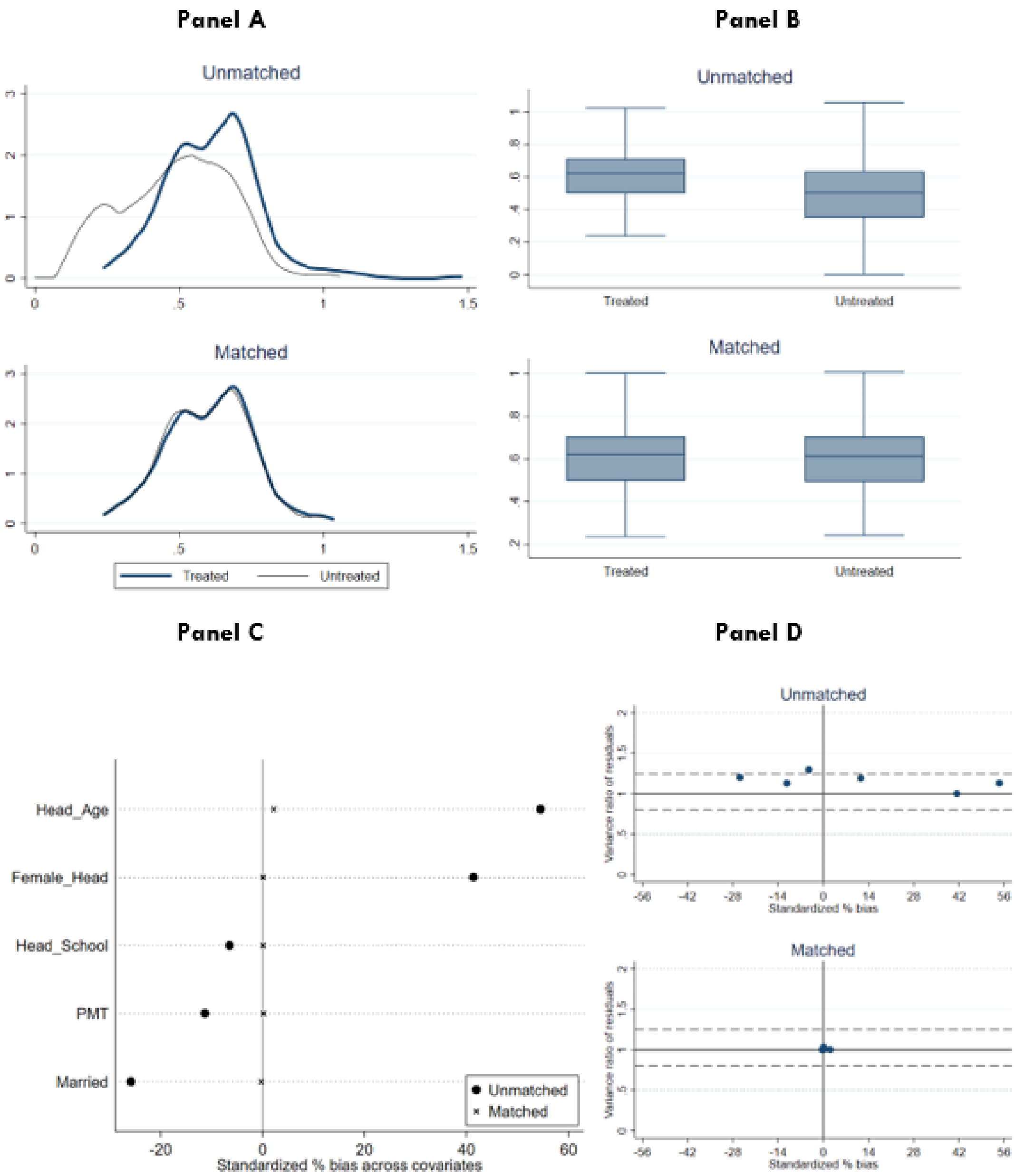


Figure 7 Assessing Matching Quality - Poorer



3.3 Theoretical Strategy

The coefficients derived from analysis of treatment effects using PSM are used in the sufficient statistic approach in this paper. The model follows closely the work of Gruber (1997) and the extension by Chetty and Finkelstein (2013) in using the sufficient statistic approach which seeks formulas for optimal policy. It allows for social insurance welfare evaluation. The optimal level of benefits is written in terms of empirically estimable parameters derived from an impact evaluation methodology.

We begin with a static model which considers two states of nature i.e. ultra poor and non ultra poor. The level of individual income in the respective states is denoted w_0 and w_1 thus $w_0 < w_1$. The states could reflect negative income shocks through risks such as unemployment, natural disasters and illness, among others.

The government pays a benefit b to the ultra poor financed by an actuarially fair tax $\tau(b) = \frac{(1-e)}{e}b$ in the non ultra poor state. Assume individuals enter the model with exogenously determined assets A.

Consumption by the ultra poor is denoted as:

$$c_0 = A + w_0 + b \tag{4}$$

Consumption by the non ultra poor is denoted as:

$$c_1 = A + w_1 - \tau(b) \tag{5}$$

Let $u(c)$ denote the agent's utility as a function of consumption in the ultra poor state and $v(c)$ as utility in the non ultra poor state, allowing for state dependent utility. Assuming that utility is state independent implies $u = v$. Both are assumed to be smooth and strictly concave.

The model also considers the moral hazard problem. If individual behaviour is not distorted by social insurance provision then the planner can set b to perfectly smooth marginal utilities, $u'(c_0) = v'(c_1)$. The model assumes that if a level of effort e is exerted at a cost $\psi(e)$, the agent can control probability of being in the ultra poor state. The probability of being in the non ultra poor state is given by $e \in [0, 1]$.

The agent chooses e to maximize expected utility:

$$\max V(e) = evc_1 + (1-e)uc_0 - \psi(e) \tag{6}$$

First order condition for the maximization problem, assuming tax and benefit levels are fixed:

$$vc_1 - uc_0 = \psi'(e) \tag{7}$$

The social planner's problem is to choose a benefit level that maximizes the agent's expected utility accounting for the endogenous effort.

$$\begin{aligned} &\max_b W(b) = ev(A + w(_1 - \tau(b)) + (1-e)u(A + w_0 + b) - \psi(e) \\ &\text{s.t. } \ e = e(b) \end{aligned} \tag{8}$$

Differentiating 8 and using the FOC for e in 7 yields[9] :

$$\begin{aligned} \frac{dW(b)}{db} &= (1-e)u'(c_0) - \left[\frac{d\tau}{db}\right] ev'(c_1) \\ &= (1-e)\left[u'(c_0) - \big(\frac{\varepsilon_{1-e,b}}{e} + 1\big)v'(c_1)\right] = 0 \end{aligned} \tag{9}$$

3.4 Sufficient Statistic Approach

Chetty and Finkelstein (2013) outline three approaches in modern literature on social insurance to recover the marginal utility gap, namely, consumption fluctuation (Gruber, 1997); liquidity and substitution effects (Chetty, 2008a); and reservation wages (Shimer and Werning, 2007). This paper focuses on the consumption smoothing approach by Gruber (1997). It is derived using the sufficient statistic methodology to policy evaluation.

Chetty (2008b) summarizes that the sufficient statistic approach combines the advantages of reduced-form empirics (transparent and credible identification) with an important advantage of structural models (ability to make precise statements about welfare). It seeks to derive formulas for the welfare consequences of policies that are a function of high-level elasticities and relatively robust to changes in underlying model behaviour.

The consumption gap between the ultra poor and non ultra poor states is computed as:

[9]See Appendix for details

$$\frac{u'(c_0) - v'(c_1)}{v'(c_1)} \tag{10}$$

The net cost to the government of the social cash transfer due to behavioral responses is measured by:

$$\frac{\varepsilon_{1-e,b}}{e} \tag{11}$$

where ε is the elasticity of the probability of being poor with respect to the level of benefit.

At the optimal benefit level b^* there should be no welfare loss. The marginal welfare gain from increasing the benefit level $M_W(b) = 0$ thus:

$$\frac{u'(c_0) - v'(c_1)}{v'(c_1)} = \frac{\varepsilon_{1-e,b}}{e} \tag{12}$$

Equation 12 can be rewritten interms of replacement ratio:

$$\frac{r}{1-r} = -\frac{u'(c_0) - v'(c_1)}{v\prime(c_1)} \frac{e}{\varepsilon_{1-e,w_1-b}} \tag{13}$$

where $\varepsilon_{1-e}, w(1) - b$ is the elasticity of the probability of being poor with respect to the net wage.

Allowing for state dependent utility yields the following:

$$\frac{u'(c_0) - v'(c_1)}{v'(c_1)} = \gamma \frac{\Delta c}{c_1}(b) \tag{14}$$

where γ is the coefficient of relative risk aversion evaluated at $c(0)$ and $\Delta c(1)$

The benefit of the transfer program can be obtained by plugging equation 14 into equation 12:

$$M_W(b) = \gamma \frac{\Delta c}{(c_1)}(b) - \frac{\varepsilon_{1-e,b}}{e} \qquad (15)$$

This follows the extension of Gruber's approach by Chetty and Finkelstein (2013) revealing that risk aversion, the observed consumption drop from a good to a bad state and the elasticity are together sufficient to determine the marginal welfare consequences of Increasing or decreasing the level of benefits.

4 Results

4.1 Empirical Results

The impact of the cash transfer program is measured on average meals eaten per day by the household. A sub group analysis is also done on the average meals eaten per day by female and male headed households. This is done inorder to explore gender differences from the program treatment effects. For the former, the hypothesis is that enrollment in the program increases the average number of meals taken by the household per day. For the latter, the assumption is that if the cash transfer starts to move the needle around addressing gender disparities that disempower women then the effect is expected to be larger for female headed households.

Specifically, the results for the poorest households are shown in Table 18. An intuitive interpretation of the poisson regression coefficient requires taking an exponential of the estimated coefficient. This gives us the incidence rate ratio (IRR). The results thus indicate that a unit increase in the cash transfer leads to a proportionate increase in the expected count of average meals eaten by households by 1.21 times more for the treated poorest households. For the gender disaggregated households, the increase is higher in female headed households estimated at 1.23 times more compared to male headed households estimated at 1.16 times more. In other words, a 1 percent increase in the cash transfer is estimated to increase meals eaten by households by about 21 percent ($p < 0.01$) and 23 percent ($p < 0.01$) and 16 percent ($p < 0.01$) for female and male headed households, respectively.

For the treated poorer households, the results in Table 19 show that a 1 percent increase in the cash transfer resulted in a 15 percent ($p < 0.01$), 16 percent ($p < 0.01$) and 12 percent ($p < 0.01$) increase in the expected count of average meals eaten by all the households, female headed households and male headed households, respectively.

These results are in line with expectations that the cash transfer has a positive impact on consumption for the ultra poor households. As expected, the impact is also much higher for the bottom poorest households as it is for female headed households compared to their male counterparts. Abdoulayi et al. (2014), Handa et al. (2015) and Abdoulayi et al. (2016), who conducted a baseline, midline and endline randomized control experiment on the Malawi SCTP, respectively, reported similar findings. Although these impacts differed in magnitude, the results are consistent across the follow up rounds. At endline, their analysis shows a 23 percent increase in consumption over the baseline. Their results also showed a consistent strong improvement in food security as demonstrated by a 15 percent rise in the number of meals per day.

The findings by Abdoulayi et al. (2016) highlighted the important fact that the value of the transfer matters considerably for both the range and depth of impact one can expect from the SCTP. They reported that cross-country evidence from the Transfer Project [10] suggests that maintaining a transfer size that is at least 20 percent of baseline consumption is important in generating wide-ranging program impacts. The highest share is among the bottom 10 percent of the poorest households where it is 27 per cent. Similarly, this suggests that impacts are likely to be larger among the poorest households.

As demonstrated by the analysis in this paper, the results from the evaluation not only showed strong impacts among the poorest only but across all households with the inclusion of the poorer households (Handa et al., 2015; Abdoulayi et al., 2016). Our analysis further showed the positive results from these two groups separately and by gender of the household head.

Studies in the literature on other African countries have found similar results interms of the program impact on consumption and food security by beneficiaries. These include Ralston et al. (2017) who found that total and food consumption rose by 24 percent and 23 percent, respectively. Brugh et al. (2018) found that the program is associated with an average increase of 11 percentage points in the likelihood of consuming more than one meal.

[10] A multi-country cash transfer research initiative established in 2008. It is a collaborative network between UNICEF Innocenti, FAO, University of North Carolina, UNICEF Regional and Country Offices, national governments, and local research partners

4.2 Sensitivity Analysis

As a robustness check, the study considered varying the approach in several ways. One was to have a pooled sample of ultra poor households (the poorest and the poorer as one group) as has been done in most of the studies evaluating the SCTP (Miller et al., 2011; Baird et al., 2011; Abdoulayi et al., 2014; Handa et al., 2015; Abdoulayi et al., 2016; Ralston et al., 2017; Brugh et al., 2018). The results in Table 20 are consistent, showing an average increase in meals for the treated households by 15 percent ($p < 0.01$), 16 percent ($p < 0.01$) and 12 percent ($p < 0.01$) for all, female headed and male headed households, respectively.

Another variation was analysis of the two districts individually. Although the magnitude differed, the results at district level were also consistent with the findings from the pooled analysis.

Table 18 Impact of *Mtukula Pakhomo* on Meals Taken by Household - Poorest

Variable	Meals All Households	Meals Female Headed	Meals Male Headed
Poorest Treated (β)	0.194***	0.211***	0.152***
	(0.0146)	(0.0168)	(0.0428)
Poorest Treated (IRR=exp(β))	1.215***	1.235***	1.164***
	(0.0177)	(0.0208)	(0.0498)
PMT	-8.806***	-8.197***	-10.25***
	(2.293)	(2.827)	(2.770)
Female Household Head	-0.0153		
	(0.0130)		
Age of Household Head	0.000576	-1.38e-05	-0.00171
	(0.000902)	(0.000919)	(0.00157)
Head went to School	0.104***		
	(0.0132)		
Household Size	-0.00791***	-0.00583	-0.00902*
	(0.00295)	(0.00540)	(0.00507)
Head has Never Married	-0.140***	-0.213***	-0.00375
	(0.0408)	(0.0591)	(0.103)
Head is Separated	-0.112***	-0.197***	0.231**
	(0.0425)	(0.0520)	(0.107)
Head is Divorced	-0.169***	-0.243***	0.0388
	(0.0561)	(0.0583)	(0.0978)
Head is Widowed	-0.169***	-0.256***	0.136
	(0.0494)	(0.0590)	(0.113)
Observations	973	688	284

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Table presents results from the poisson regression estimation. It also reports the incidence rate rate ratio (IRR) which is the estimated coefficient obtained by exponentiating the poisson regression coefficient. Results for disability, chronic illness and dependency ratio not shown for brevity. The model controlled for district fixed effects and month of interview.

Table 19 Impact of *Mtukula Pakhomo* on Meals Taken by Household - Poorer

Variable	Meals All Households	Meals Female Headed	Meals Male Headed
Poorer Treated (β)	0.141***	0.150***	0.115***
	(0.0124)	(0.0137)	(0.0157)
Poorer Treated (IRR=exp(β))	1.215***	1.235***	1.164***
	(0.0177)	(0.0208)	(0.0498)
PMT	0.145***	0.167***	0.0996**
	(0.0377)	(0.0390)	(0.0450)
Female Household Head	0.0164**		
	(0.00789)		
Age of Household Head	-0.000409*	-0.000330	-0.000382
	(0.000238)	(0.000302)	(0.000487)
Head went to School	-0.0200**	-0.0235**	-0.0116
	(0.00910)	(0.00967)	(0.0130)
Household Size	0.00567**	0.00754**	0.00182
	(0.00238)	(0.00293)	(0.00510)
Head has Never Married	0.00140	-0.00872	0.00317
	(0.0166)	(0.0276)	(0.0244)
Head is Separated	0.00467	0.00846	-0.0209
	(0.0173)	(0.0186)	(0.0203)
Head is Divorced	-0.0142	-0.0123	-0.0209
	(0.0114)	(0.0131)	(0.0298)
Head is Widowed	-0.0119	-0.0154	-0.00782
	(0.0105)	(0.0138)	(0.0190)
Observations	7,922	5,093	2,828

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Table presents results from the poisson regression estimation. It also reports the incidence rate rate ratio (IRR) which is the estimated coefficient obtained by exponentiating the poisson regression coefficient. Results for disability, chronic illness and dependency ratio not shown for brevity. The model controlled for district fixed effects and month of interview.

Table 20 Impact of *Mtukula Pakhomo* on Meals Taken by Household - Poorest and Poorer

Variable	Meals All Households	Meals Female Headed	Meals Male Headed
Treated (β)	0.141***	0.151***	0.113***
	(0.0115)	(0.0127)	(0.0148)
Treated (IRR=exp(β))	1.151***	1.119***	1.164***
	(0.0133)	(0.0145)	(0.0165)
PMT	0.146***	0.171***	0.0966**
	(0.0385)	(0.0401)	(0.0448)
Female Household Head	0.0140*		
	(0.00803)		
Age of Household Head	-0.000486**	-0.000404	-0.000460
	(0.000221)	(0.000286)	(0.000491)
Head went to School	-0.0190**	-0.0217**	-0.0112
	(0.00865)	(0.00971)	(0.0128)
Household Size	0.00410*	0.00605**	0.000542
	(0.00239)	(0.00265)	(0.00510)
Head has Never Married	-0.00231	-0.00865	-0.00287
	(0.0147)	(0.0241)	(0.0224)
Head is Separated	0.00397	0.00703	-0.00936
	(0.0159)	(0.0170)	(0.0200)
Head is Divorced	-0.0176	-0.0159	-0.0205
	(0.0111)	(0.0126)	(0.0288)
Head is Widowed	-0.0127	-0.0177	0.000596
	(0.00939)	(0.0131)	(0.0182)
Observations	8,908	5,794	3,111

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Table presents results from the poisson regression estimation. It also reports the incidence rate rate ratio (IRR) which is the estimated coefficient obtained by exponentiating the poisson regression coefficient. Results for disability, chronic illness and dependency ratio not shown for brevity. The model controlled for district fixed effects and month of interview.

4.3 Welfare Gain from Social Insurance

The welfare gain can be calculated from Equation 15 in Section 3.4 and the β that has been estimated in Table 18, Table 19 and Table 20 in Section 4.1.

Restating Equation 15

$M_W(b) = \gamma\frac{\Delta c}{(c_1)}(b) - \frac{\varepsilon_{1-e,b}}{e}$

The *benefit of the program* is represented by $\gamma\frac{\Delta c}{(c_1)}(b)$ whilst the *moral hazard cost* is given by $\frac{\varepsilon_{1-e,b}}{e}$. A positive (negative) difference means the program has positive (negative) welfare consequences. Optimality is achieved where the two are equal.

The change in consumption is represented by $\frac{\Delta c}{c_1}$. This is the exponentiated coefficient (IRR) from Table 18, Table 19 and Table 20. Panel A in Table 21 for all households, Table 21 for female headed households and Table 21 for male headed households presents the estimated change in consumption from our model.

The marginal welfare gain is simulated with different levels of risk aversion (γ) as illustrated in Panel B of Table 21, Table 22 and Table 23. When $\gamma = 1$, the utility function represents a risk neutral situation where individuals or households are neither risk-averse nor risk-loving. As $\gamma = 1$ increases, it means that the household is more risk averse hence a higher value is placed on the provision of social insurance.

For the cost of the program, we have a naive estimate of the moral hazard. As we have data on ultra poverty rates before the program was fully rolled out in all districts, the difference between the incidence of poverty in the districts with and without the program is taken as the moral hazard. This is the essence of the program itself as the selection is not at random. In other words, the program is likely to exist where the incidence of ultra poverty is high. Nonetheless, this will only bias the estimate of the moral hazard upward. Even with very low levels of γ the marginal benefit is still positive so it does not change the interpretation of our results. To get the disutility of effort ($\varepsilon_{1-e,b}$) we estimate an OLS regression with ultra poverty incidence as our dependent variable. The independent variable is a dummy of whether the program exists or not in the respective districts. We control for the following factors at district level, namely, region (north, centre and south), population, proportion of households in employment and tribe (chewa, lambya, lomwe, ngoni, nyanja, sena, tonga, tumbuka and yao). The estimated coefficient (**??**) is used as the cost of the program.

Taking into account the risk aversion, observed change in consumption and the

Table 21 Change in Consumption and Simulation of Welfare Gains from the *Mtukula Pakhomo* Program - All Households

Household Group (All)	Coefficient of Relative Risk Aversion (γ)				
	1	2	3	4	5
			A. Change in Consumption (Δc/c)		
Poorest	0.215	0.215	0.215	0.215	0.215
Poorer	0.151	0.151	0.151	0.151	0.151
Poorest and Poorer	0.151	0.151	0.151	0.151	0.151
			B. Marginal Welfare Gain (γΔc/c)		
Poorest	0.215	0.430	0.645	0.860	1.075
Poorer	0.151	0.302	0.453	0.604	0.755
Poorest and Poorer	0.151	0.302	0.453	0.604	0.755
			C. Disutility of Effort (ε1-e,b/e)		
Δ in Ultra Poverty Incidence	0.057	0.057	0.057	0.057	0.057

Source: Author based on approach by Chetty and Looney (2006)

Notes: Panel A shows the estimated change in consumption from the treatment effect analysis. Panel B is a simulation of the marginal welfare gain based on different levels of risk aversion. Panel C is the estimated moral hazard cost.

effort required, we have a sufficient statistic to determine the welfare implications of the program. The difference between the simulated benefit and the estimated moral hazard cost is positive which means there is an improvement in welfare of households that benefit from the SCTP. It follows to further argue that the level of benefit as currently estimated is actually far from optimal.

Table 22 Change in Consumption and Simulation of Welfare Gains from the *Mtukula Pakhomo* Program - Female Headed Households

Household Group (Female Headed)	Coefficient of Relative Risk Aversion (γ)				
	1	2	3	4	5
	A. Change in Consumption ($\Delta c/c$)				
Poorest	0.235	0.235	0.235	0.235	0.235
Poorer	0.162	0.162	0.162	0.162	0.162
Poorest and Poorer	0.163	0.163	0.163	0.163	0.163
	B. Marginal Welfare Gain ($\gamma\Delta c/c$)				
Poorest	0.235	0.470	0.705	0.940	1.175
Poorer	0.162	0.324	0.486	0.648	0.810
Poorest and Poorer	0.163	0.326	0.489	0.652	0.815
	C. Disutility of Effort ($\varepsilon 1$-$e,b/e$)				
Δ in Ultra Poverty Incidence	0.054	0.054	0.054	0.054	0.054

Source: Author based on approach by Chetty and Looney (2006)

Notes: Panel A shows the estimated change in consumption from the treatment effect analysis. Panel B is a simulation of the marginal welfare gain based on different levels of risk aversion. Panel C is the estimated moral hazard cost.

Table 23 Change in Consumption and Simulation of Welfare Gains from the *Mtukula Pakhomo* Program - Male Headed Households

Household Group (Male Headed)	Coefficient of Relative Risk Aversion (γ)				
	1	2	3	4	5
	A. Change in Consumption ($\Delta c/c$)				
Poorest	0.163	0.163	0.163	0.163	0.163
Poorer	0.122	0.122	0.122	0.122	0.122
Poorest and Poorer	0.119	0.119	0.119	0.119	0.119
	B. Marginal Welfare Gain ($\gamma\Delta c/c$)				
Poorest	0.163	0.326	0.489	0.652	0.815
Poorer	0.122	0.244	0.366	0.488	0.610
Poorest and Poorer	0.119	0.238	0.357	0.476	0.595
	C. Disutility of Effort ($\varepsilon 1\text{-}e,b/e$)				
Δ in Ultra Poverty Incidence	0.060	0.060	0.060	0.060	0.060

Source: Author based on approach by Chetty and Looney (2006)

Notes: Panel A shows the estimated change in consumption from the treatment effect analysis. Panel B is a simulation of the marginal welfare gain based on different levels of risk aversion. Panel C is the estimated moral hazard cost.

5 Conclusion

The study findings align to results from previous studies investigating the effect of the SCTP on consumption and food security. More specifically, the Mtukula Pakhomo program does increase consumption levels (as proxied by meals eaten) by approximately 21 percent and and 16 percent for treated poorest and poorer households, respectively.

The results also demonstrate that the cash transfer helped move the needle around addressing some gender disparities that disempower women with regards to financial constraints. Consumption levels for female headed households increased by about 23 percent and 16 percent for the poorest and poorer households, respectively. The respective results for male headed households were 16 percent and 12 percent.

The findings from this paper have empirically and structurally demonstrated that the *Mtukula Pakhomo* program has positive marginal welfare consequences for households. For highly risk averse households (poor households tend to be more risk averse than their non-poor counterparts), there is a strong argument to provide more benefits so that households can avoid resorting to costly consumption smoothing mechanisms when faced with an adverse shock. As the estimated change in consumption is significant, the case for the provision of social insurance is even greater to prevent households from experiencing substantial hardships. Even with small adjustments in benefit levels, the impact could be significant particularly where the disutility of effort is high. Overall, policymakers should thus aim to balance the provision of optimal support whilst ensuring the sustainability and efficiency of the program.

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Appendix

The agent chooses e to maximize expected utility:

First order condition for the maximization problem, assuming tax and benefit levels are fixed:

$$v(c_1) - u(c_0) = \psi'(e) \tag{16}$$

The social planner's problem is to choose a benefit level that maximizes the agent's expected utility accounting for the endogenous effort:

$$\begin{aligned} &\max_b W(b) = ev(A + w_1 - \tau(b)) + (1 - e)u(A + w_0 + b) - \psi(e) \\ &\text{s.t. } \ e = e(b) \end{aligned} \tag{17}$$

Differentiating (17) and using the FOC for e in (16) yields:

$$\begin{aligned}
\frac{dW(b)}{db} &= \frac{d(1-e)u(A+w_0+b)e}{db} - \frac{dev(A+w_1-\tau(b))}{db} - \frac{d\psi(e)}{db} \\
&= (1-e)u'(c_0) - \left[\frac{d\tau}{db}\right] ev'(c_1) \\
&= (1-e)u'(c_0) - \left[\frac{\frac{d(1-e)b}{e}}{db}\right] ev'(c_1) \\
&= (1-e)u'(c_0) - \left[\frac{\frac{d(1-e)be}{db} - \frac{de(1-e)b}{db}}{e^2}\right] ev'(c_1) \\
&= (1-e)u'(c_0) - \left[\frac{\frac{d(1-e)b}{db} - \frac{de}{db}\frac{(1-e)b}{e}}{e^2}\right] ev'(c_1) \\
&= (1-e)u'(c_0) - \left[\frac{\frac{d(1-e)b}{db}}{e^2} - \frac{\frac{de}{db}\frac{(1-e)b}{e}}{e^2}\right] ev'(c_1)
\end{aligned}$$

$$
\begin{aligned}
&= (1-e)u'(c_0) - \left[\frac{\frac{d(1-e)b}{db}}{e^2} - \frac{\frac{db}{db}(1-e)}{e^2}\right] ev'(c_1) \\
&= (1-e)u'(c_0) - \left[\frac{d(1-e)b}{db} - (1-e)\right] ev'(c_1) \\
&= (1-e)u'(c_0) - \left[\frac{d(1-e)}{db}\frac{b}{1-e} + 1\right] ev'(c_1) \\
&= (1-e)\left[u'(c_0) - \big(\frac{d(1-e)}{db}\frac{b}{1-e} + 1\big)ev'(c_1)\right] \\
&= (1-e)\left[u'(c_0) - \big(\frac{\varepsilon_{1-e,b}}{e} + 1\big)v'(c_1)\right] = 0 \qquad (18)
\end{aligned}
$$

where $\varepsilon_{1-e,b} = \frac{d(1-e)}{db}\frac{b}{1-e}$ denotes the elasticity of the probability of being in an ultra poor state with respect to the benefit level.