Smooth Sailing or Rough Waters? Shocks, Consumption and Welfare

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Abstract

This thesis empirically analyzes the concept of consumption smoothing and the role of private and social insurance in the midst of macroeconomic shocks and the subsequent welfare consequences. Chapter 1 assesses the degree of risk sharing amongst differentiated households (by employment sector and residence), in the presence of a large exchange rate shock in Malawi. The study initially tests the hypothesis of full consumption insurance which is not rejected. Next, a difference-in-differences approach is used to test for any heterogeneous effects across the population. The evidence shows that although an exchange rate shock may not have large re-distributional consequences it may impact resource allocations and the structural transformation process. Chapter 2 uses the "sufficient statistic" approach to evaluate the *Mtukula Pakhomo* social insurance program in Malawi. The approach combines a reduced form method (propensity score matching) and a structural approach. This allowed for an empirically compelling identification and statements on the welfare impact of a specific social insurance program. Results demonstrated that the program benefits recipient households with positive marginal welfare consequences. This was most prominent for 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. Chapter 3 estimates a Panel Vector Autoregressive model to study how structural shocks jointly affect the macroeconomy and health outcomes in the short run for Eswatini, Malawi, Mauritius, and Zambia. Results revealed a strong relationship between public health spending and health outcomes, evidence of rivalry for fiscal capacity across components of public spending and the detrimental effect of fluctuations in external financing. These findings have a clear policy relevance regarding government consumption and it's implications for improvements in population health and robust healthcare systems.

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Dedication

This thesis is dedicated to the cherished memory of my beloved father, Professor Benson Fillemon Kandoole, a true exemplar of the value of education. His enduring love, profound wisdom, and boundless support have been a guiding light throughout my life and academic journey. His spirit and legacy continue to inspire me every day.

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Author's Declaration

I declare that this thesis is a presentation of original work, and I am the sole author of the first and second chapters. The third chapter is co-authored with *Paulo Sanntos Monteiro*. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

I also declare that Chapter 3 was prepared under a Global Fund Project within the Centre for Health Economics. Chapter 3 is also being considered for publication in the SSM Health Systems Special Journal Issue.

Introduction

Most developing countries are faced with a challenge of matching limited resources against competing multiple ends. To achieve their development goals, countries need to allocate scarce resources efficiently between competing social and economic sectors. Fiscal and monetary policies are key tools for governments to affect income distribution, yet most developing countries have limited fiscal space with economies that are riddled with persistent deficits, high inflation, low international reserves and currency depreciation. Climate-induced shocks are another source of vulnerability that exacerbates macroeconomic instability and makes it harder for most countries to break the cycle of poverty.

The essays in this thesis attempt to understand the consumption behaviour of households and government responses in the presence of macroeconomic shocks. In so doing an attempt is made to understand the welfare consequences of such decisions. The conclusions drawn are thus important for policy design. The first two essays test the link between macroeconomic shocks and consumption smoothing by households using micro data and a combination of reduced form and structural models. The final essay departs from the analysis of private consumption at the household level to general government consumption and it's implications for the wider economy. A fiscal space analysis on health expenditure and the multiplier effects on the wider economy is conducted.

The models on consumption insurance and aggregate and idiosyncratic shocks, as highlighted by Blundell et al. (2008), have been characterized by two extremes. One hypothesis is that of complete markets where consumption is assumed to be completely insured against both transitory and permanent income shocks. The other is the traditional permanent income hypothesis which assumes that self insurance, for instance through borrowing or saving, allows intertemporal consumption smoothing against transitory shocks (Blundell et al., 2008, Deaton, 1992).

Chapter 1 contributes to the emerging body of knowledge that examines household heterogeneity, market (in)completeness, and aggregate shocks as noted in Kaplan and Violante (2018) and Kaplan et al. (2018). Firstly, the model tests the theory of full consumption insurance from observed data. Secondly, it explores the transmission mechanism of a macroeconomic shock on households in a Heterogeneous Agent (HA) model as opposed to the traditional Representative Agent (RA) model. This, therefore, allows us to investigate welfare effects of a devaluation on heterogeneous households across the population. Thirdly (and related to the second point), it provides evidence on the consequences of an exchange rate shock in structural transitions.

The paper uses panel household data for Malawi for the periods 2010, 2013 and 2016. The devaluation was undertaken in 2012 so the data covers the period before and after the policy. The approach taken is two pronged. Firstly, the hypothesis of full consumption insurance is tested using two baseline household consumption regressions models (first differences and growth rates). The theory states that households are insulated from all idiosyncratic shocks so the test is whether the marginal rates of substitution are equal across households. The evidence from the micro data fails to reject the hypothesis of perfect insurance. Secondly, a difference-in-differences impact evaluation approach is adopted to establish whether the devaluation had heterogeneous effects across households. These household are in two groups. The first group is by sector of employment in the traditional sector (agriculture) or modern sectors (industry and services). The second group is by residence (rural households or urban households).

The results indicate that households primarily employed in industry and services experienced a minuscule decline in consumption of about 0.02 percent ($p < 0.10$) and 0.12 percent ($p < 0.05$) relative to those employed in the agriculture sector. Another finding is that following the shock, weekly hours worked in services and industry declined by almost 1 percent ($p < 0.05$) relative to those of workers in agriculture. For urban households relative to rural households, the differential impact is more detrimental albeit also minuscule. Average urban household consumption decreased by only 0.10 percent ($p < 0.01$) relative to that of rural based households.

The modelling of the household response to an exchange rate shock in terms of sector of employment is not only important in understanding the mechanism of the real effects of the shock but potential welfare gains and losses. The analysis therefore goes beyond a reduced form causal relationship by focusing on households' occupational decision. This has broader policy implications for the aggregate economy in the context of productivity growth and structural transformation.

Chapter 2 contributes to existing literature in several ways. Firstly, it not only combines structural and program evaluation methods but fully explores the derivation of robust formulae and empirically estimable parameters on the provision of social insurance to ultra poor households in a developing country context. Secondly, by using this methodology (known as the sufficient statistic approach), the study not only explores consumption smoothing but also welfare estimations for the beneficiary households. Finally, the paper also explores heterogeneity across gender and stratified groups of the bottom 20 percent of the population.

The paper uses data from the social cash transfer program administered by the Government of Malawi between 2019 and 2022. It employed the propensity score matching (PSM) method using the Mahalanobis matching algorithm, selected based on the results from the trade off between bias and efficiency. The parameter β is identified to measure the change in consumption between households that received a cash transfer and households that did not receive a cash transfer. Thereafter, a theoretical strategy is employed where the coefficient (β) from the PSM is used in the structural model to estimate the marginal welfare gain or loss of the program.

The findings support the evidence that social insurance program increases consumption of beneficiary households relative to non beneficiaries. The estimated increase in consumption is 22 percent ($p < 0.01$) and 15 percent ($p < 0.01$) for the poorest and poorer households, respectively. The impact is also higher for female headed households at 24 percent ($p < 0.01$) and 16 percent ($p < 0.01$) for the beneficiary poorest and poorer households. This compares to 16 percent ($p < 0.01$) and 12 percent ($p < 0.01$) for their male counterparts. The marginal gain in the welfare of households from a unit increase of the cash transfer is also positive, especially for the poorest households (bottom 10 percent). The simulated results are consistent across different levels of risk aversion and disutility of effort.

Chapter 3 contributes to the literature on estimating vector autoregressions with panel data through a sample of four Sub Saharan African countries (Eswatini, Malawi, Mauritius, and Zambia). More specifically, it uncovers the two way relationship between the macroeconomy and health outcomes. It was developed in the context of health policy financing dialogue, recognizing the macroeconomic and fiscal realities of most low and low-middle income economies.

A panel vector autoregressive model with macro-finance and health blocks is employed to study how structural shocks jointly affect the macroeconomy and health outcomes in the short run. The model is estimated jointly for the four countries using annual data over a 20 year period from 2000 to 2019. It explores the dynamic transmission of three endogenous shocks (government expenditure, GDP growth, and health expenditure which is proxied by child mortality) and a fourth exogenous financial shock proxied by the corporate spread in emerging markets in Europe, Africa and the Middle East.

Structural impulse response functions are used to show the accumulated response of the endogenous variable in the model to each structural shock for a horizon of up to

10 years. The results are as follows: firstly, public investment in health has discernible impact on the quality of health outcomes. In other words, more spending lowers child mortality. This is what would be expected. Secondly, the short run impact of negative macroeconomic shocks puts adverse pressure on resources available in health. Again the intuition is confirmed that bad shocks are detrimental to investing in health. Thirdly, there is a clear incentive to favour expenditure on public investments with larger short-run multipliers compared to health expenditure. This recognises that there are different "rival" uses for resources available for public spending. Public policy makers thus trade off benefits of different resource uses. The results show that the fiscal multipliers on government spending other than health are larger than the short run fiscal multiplier for funding in health. Politicians may, therefore, neglect the long run benefits in health for investment in tangibles such as infrastructure. Fourthly, investing in health is particularly vulnerable to exogenous shocks such as fluctuations in the ease of access to international liquidity. External liquidity shocks have a substantially negative impact on health expenditure and are associated with worsening health outcomes.

The thesis concludes with a summary of key findings from the three essays and implications for policy and further research. Evidence presented has strong implications for macroeconomics, labour economics, health economics and welfare economics.

Chapter 1

Does a Devaluation Impact Households Differently? Labour Market and Rural Urban Dynamics

1.1 Introduction

This paper sets out to analyse the heterogeneous impact of a macroeconomic policy shock on household consumption patterns in Malawi. In particular, it considers an exchange rate shock, namely, the devaluation of the Malawi Kwacha (MWK), by 49 percent, in May 2012 following which the country adopted a flexible exchange rate regime. The policy response was aimed at addressing a severe scarcity of foreign exchange and fuel compounded by the suspension of development partner support as well as declining export prices for tobacco (the country's main export commodity).

Prior to the devaluation, the MWK had been trading at around MWK 140 to 150 per USD for over 5 years with the over-valuation leading to the flourishing of a parallel market with a premium of close to 100 percent at its peak. As a net importer, Malawi saw an escalation in import costs which led to a growing share of imports. Given that most industries import their raw materials and that fuel is a major input in production, through transport costs, the devaluation triggered a spike in inflation resulting in sharp adjustments in retail prices of goods and services.

The hypothesis is that adjustments in relative prices are expected to have affected households differently depending on their earnings and consumption baskets. In this study, households are examined in the following differentiated groups: (i) rural and urban households; and (ii) employment of household head in primary (agriculture); secondary (industry) or tertiary (services) sectors. This investigation therefore underscores the importance of understanding the distributional impact of the exchange rate changes on welfare of these differentiated households. Such an analysis is important for the design of an optimal policy that not only addresses the problem of a balance of payments deficit but more importantly protects the livelihood of households especially the poor and vulnerable ones.

This research will explore the main cross-sectional characteristics of households with regards to their earnings or incomes and consumption in 2010 which is the period before the devaluation and two periods after, that is, 2013 and 2016. The analysis is based on panel data from the Integrated Household Panel Survey (IHPS) conducted by the National Statistical Office (NSO) in the respective years.

In Malawi, like most developing countries, credit and insurance markets are limited which makes it difficult for households, particularly the much poorer ones, to diversify any risk that they are exposed to in order to smooth their consumption. Townsend (1995) highlights three related issues which are central to the nature of risk in developing countries. Firstly, the extent to which these risks are insurable. He argues that if the shock is idiosyncratic (specific to an individual or household) then resources can be locally pooled or insured whilst aggregate shocks (common to a population) make insurance more limited. Secondly, the availability of both formal or informal markets to manage the risks. These include storage facilities, land fragmentation and implicit insurance provided by family and friends networks, among others. Finally, the availability of financial institutions to offer implicit and explicit insurance. Examples include village banks, credit unions, local money lenders, national banks, rural credit programs and insurance companies.

Before estimating the heterogeneous impact of the devaluation, the investigation initially thus sets out to test the implications of the theory of consumption insurance. The theory states that changes in household consumption are determined by changes in aggregate consumption, independent of other idiosyncratic variables such as changes in household income. The hypothesis is that households are insulated from idiosyncratic shocks so the ratio of their marginal utilities are constant. A test of consumption insurance, therefore, ascertains whether consumers or households can effectively insure against changes in their income or wealth by formal institutions such as private insurance and Government programs or informal mechanisms such as gifts or loans from relatives, friends or neighbours (Cochrane, 1991).

There is a good body of literature (Attanasio and Rios-Rull, 2003, Blundell et al., 2008, Cochrane, 1991, Deaton, 1992, Mace, 1991, Townsend, 1995) that has tested the theory of full consumption by showing that changes in a household's consumption are determined by changes in aggregate consumption rather than idiosyncratic shocks on household income. Evidence from the literature also shows that the insurance is partial or limited. This is a result of the implications of risk sharing where a household is insulated from an individual shock through the networks they have. However, should the shock be systematic then risk sharing is limited leading to varying consumption across individuals or households.

To examine the distributional aspect of this analysis, a difference in differences

(DID) approach is employed to measure how differentiated households were impacted by the macroeconomic shock which in this paper is an exchange rate devaluation. Household consumption and income patterns will be used to model the impact of the price changes related to the devaluation. The analysis will consider the impact across rural and urban households and the different sectors of employment (agriculture, industry and services).

All the households in the sample were impacted by the devaluation. In order to identify the effect on the varied groups, the study defines treatment on the basis of the intensity of exposure. This is similar to the approach by Autor et al. (2014) who analyzed the effect of exposure to import competition on earnings and employment of US workers. Autor et al. (2013) also exploited cross-market variation in import exposure stemming from initial differences in industry specialization.

The definition of treatment and control groups is determined by the reliance on imports. For rural and urban households, data on consumer price indices in 2010 from the NSO is analyzed. The respective weights of food and non-food components for urban consumers was about 35 percent and 65 percent. This compares to about 70 percent and 30 percent for rural consumers. Within the food basket a large weight is placed on maize which is the staple and locally produced. Non-food items include beverages and alcohol, clothing and footwear, housing and transport items. This has more imports relative to the food category. Urban households are, therefore, likely to be more exposed to imports. They are thus classified as a treatment group with rural households as a control group.

For the primary, secondary and tertiary sectors of employment, the assumption is that the agriculture sector is the least exposed to imports relative to industry and services. This is premised on trade balance and employment data. The International Trade Centre trade map shows a persistent trade deficit on services and industry whilst agriculture has a surplus. This suggests that the agriculture sector exports more than it imports unlike industry and services. A further review of the data shows that the deficit is much larger in services than industry thereby implying that services are the most exposed to imports. Agriculture employment is therefore defined as a control with low intensity, industry and services as treated with medium and high intensities.

Furthermore, employment data by sector from the population and housing census conducted by the NSO in 2008 also reveals that about 70 percent of households are employed in agriculture with the rest in industry and services. The labour composition also provides insights in the sector's role in the local economy. Arguably, it suggests that agriculture is the least directly exposed to imports as it supports a significantly large proportion of the domestic workforce. It is also considered as a traditional sector which is typically labour intensive and not modernized.

It is acknowledged that the agriculture sector can also be exposed to imports through fertilizer which is largely imported and used in maize production. Nonetheless, it is also recognized that during the period under review, the Malawi Government was implementing the Farm Input Subsidy Program (FISP) which issued fixed value coupons to smallholder farmers at a subsidized level of 97 percent (World Bank, 2016) implying that any inflated import costs were largely borne by the Government. According to the NSO, smallholder farmers constitute about 80 percent of the farming population and are mostly rural based.

It is important to also note that the rural-urban divide presents a clearer delineation in consumption patterns, with rural areas primarily consuming domestic goods and urban households consuming more imported varieties. This distinction is less susceptible to bias compared to segmenting households based on their sector of employment which may entail various factors beyond consumption preferences. While acknowledging the clearer distinction provided by the rural-urban split in consumption patterns, it is essential to recognize that sector of employment remains a valid and pertinent factor in understanding household vulnerabilities to a macroeconomic shock such as a devaluation. Despite the complexities highlighted, sector of employment can capture nuanced dynamics such as income levels, skill sets, and exposure to global market fluctuations, all of which influence households' susceptibility to economic shocks. Therefore, while the rural-urban divide offers a more inherent categorization, sector of employment remains a key consideration in comprehensively analyzing the impact of a devaluation on households.

There may be other concerns around issues of endogeneity. For instance, that households with higher income levels or better access to resources may be more likely to reside in urban areas or engage in industry and services sectors, while poorer households are more likely to reside in rural areas and engage in agricultural activities. It is important to note, however, that unlike conventional intervention impact studies, the objective of this paper is to find evidence for the heterogenous impact of a macroeconomic shock affecting the entire population. This approach thus eliminates concerns around selection bias as the status of households is predetermined and not influenced by the shock.

Given that consumers possess diverse characteristics and consumption patterns, certain groups are anticipated to be more susceptible to welfare declines following a macroeconomic shock. Kaplan and Violante (2018) discussed emerging macroeconomic literature that analyzes the role of household heterogeneity in the response of the macroeconomy to aggregate shocks. It outlines an emerging framework that combines key features of Heterogeneous Agents (HA) with nominal rigidities, and New Keynesian (NK) economies, commonly known as HANK models. This was in response to the limitations of the Representative Agent New Keynesian (RANK) models. They assert that HANK models provide a rich theoretical framework for quantitative analysis of the interaction between cross-sectional distributions and aggregate dynamics. They argue that this offers a much more accurate representation of household consumption behavior, which can generate realistic distributions of income and wealth, whilst accommodating various sources of macroeconomic fluctuations. The HA framework is adopted in this study.

This paper also models the supply of labour in agriculture relative to industry and services. Early literature (Chenery and Syrquin, 1975, Clark, 1940, Kuznets and Murphy, 1966) documents how the process of modern economic growth is associated with a significant downsizing of the agriculture sector with reallocation of economic activity towards manufacturing and services. This reallocation process is referred to as structural transformation. It is characterized by gradual shifts from the traditional agrarian sector towards modern industrialized and service oriented sectors.

The contribution to literature can thus be summarized on three fronts. Firstly, the paper uses observed panel data from a household survey to test the concept of full consumption insurance. Secondly, it applies the HA framework by using micro data to investigate heterogeneous welfare effects of a macroeconomic shock on households across the population. Studies on welfare differentials on differentiated groups are limited. Thirdly, the research provides evidence on the redistributive consequences of an exchange rate shock in the structural transformation in a developing country context of Malawi.

The results from the baseline model present evidence that supports the hypothesis of perfect insurance. In line with this finding, results from the DID reveals that the exchange rate shock was more detrimental to households employed in industry and services relative to those employed in agriculture. Urban households were also worse off compared to rural households following the devaluation. The magnitude of the differences between these household groups, however, is not significantly different from zero. Notwithstanding this, it is acknowledged that in reality there can be no full insurance so it is imperative for policy makers to target affected households even though the impact may be marginal. Another key finding is that there is a reduction in hours worked in the modern sector (industry and services) relative to the traditional sector (agriculture). This has important implications for the structural transformation process of Malawi.

The rest of the sections are organised as follows: Section 1.2 describes the data used in the analysis. Section 1.3 presents the econometric methods employed in the research. Section 1.4 gives the findings from the empirical analysis. Section 1.5 draws conclusions from the findings.

1.2 Data Description

The analysis is based on data from three waves of the IHPS conducted in 2010, 2013 and 2016 by the NSO. The National Statistical Office (2017) reports that the panel study was integrated into the core Integrated Household Survey (IHS) program to study trends in poverty, socioeconomic and agricultural characteristics over time through a longitudinal survey. The data shows that the first round of the panel comprised about 1,619 with the second round growing to about 1,990 households. The third round of the panel survey had about 2,508 households. After data cleaning and based on a matched and balanced panel, our analysis is almost 1,000 households in each wave. In order to allow for temporal comparison and to control for inflation, the expenditures and earnings nominal data is converted into 2010 constant prices using the NSO Consumer Price Indices.

The timings of the surveys are of particular importance to this analysis as the period overlaps with the timing before and after the exchange rate devaluation. With the panel data on sampled households this makes it possible to analyse the consumption patterns of households pre and post the policy shocks. This data is thus suitable not only for testing the implications of risk sharing but also the differential welfare impact. The descriptive statistics are presented in Table 1.1.

1.2.1 Aggregate Consumption

Aggregate consumption data is sourced from the World Bank Macro Poverty Outlook database. The variable used is private consumption data in local currency unit for the respective years in each wave. Aggregate consumption is considered a contemporaneous determinant of household consumption as it is implied to be the same across households. In models of perfect risk sharing, where households strive to equalize growth rates of consumption, a common component to consumption emerges. This implies that fluctuations or changes in aggregate consumption reflect not only broader economic trends but also individual household behaviour.

1.2.2 Household Consumption

The imputed total household consumption constitutes expenditures on three components: a) Food which includes expenditure on food across 11 categories of cereals; grains and cereals products; roots, tubers and plantains; nuts and pulses; vegetables; meat, fish and animal products; fruits; cooked food from vendors; milk and milk products; sugar, fats and oil; beverages; and spices and miscellaneous; b) Non-food which is expenditure on non-food non-durable items such as education; health; housing utilities; clothing and footwear; and transport, among other items; and c) Durable goods include those providing utility overtime hence imputed using purchase value and the expected lifetime of the goods.

1.2.3 Household Income

Household income includes any reward earned from labour, assets or products. It comprises of wages or salaried income; casual work (locally known as ganyu); other income receipts from household enterprises; agriculture and livestock activities. Income at the household level excludes remittances, transfers, safety nets and credit to capture the risk element by taking a measure of income that has not been insured by both formal and informal insurance arrangements.

The estimation from diverse sources such as labour, assets, and products, was done with careful consideration of the challenges inherent in accurately capturing data. This is particularly the case for data from farming, informal work, and ganyu labour. These sectors often involve irregular income flows, seasonal fluctuations, and cash transactions, which may raise reliability concerns. To address these challenges, efforts to mitigate potential biases or inaccuracies, such as adjustments for under reporting or the utilization of imputation techniques for missing data, were thoroughly explored. However, it is important to highlight that these income streams may not be fully captured or properly measured in the available data.

1.2.4 Employment Sectors (Agriculture, Industry and Services)

This paper adopts the International Labour Organization (ILO) definition of (un)employment status based on a seven-day recall of economic activities by individual household head (National Statistical Office, 2014). The approach by the World Bank (2019) is followed where a household head is considered employed if s/he has worked for wage/salary or as a casual labourer or self-employed in agriculture or non-agriculture business in the past seven days. It further classifies employment sector based on the International Standard Industrial Classification (ISIC) code with a combination of seven day and past 12-month recall. For those employed for wage in the past seven days, the ISIC classification for their main wage job in the past 12 months is used; those self-employed in non-farm enterprises, the industrial classification from the enterprise module is used; those engaged in ganyu (casual employment), agriculture is assigned as the sector; and for those engaged in multiple economic activities, the industry of the job on which they have spent the largest amount of time is used (World Bank, 2019). These categories are then clustered into three sectors of employment, namely: a) Agriculture which includes those involved in agriculture; forestry; and fishing; b) Industry which includes those involved in mining and quarrying; manufacturing; construction; and utilities (electricity, gas and water); and c) Services which includes those involved in wholesale and retail trade; transport and storage; accommodation and food services; information and communication; finance and insurance; real estate; education; health; and other services.

1.2.5 Hours Worked

The analysis also considers a measure of hours worked in the three sectors across the three years. As described on the employment classification, a household head is classified by sector according to their primary sector of employment. Hours are classified by the sector of job for a respective household head. The jobs are classified as wage or salaried employment; non-agricultural self-employed; agricultural self-employed; apprenticeship and casual employment. All the hours worked in the primary sector of employment are attributed as labour in that sector. Gollin et al. (2011) highlight a potential concern which is that although individuals may be classified as employed in their primary sector of employment, they may also spend a significant proportion of their time in the secondary or tertiary sector. This would, therefore, imply that the differences in hours across sectors is being over or under counted relative to another. They note that for this to be quantitatively important the misallocated hours should represent a substantial fraction. The IHPS data is analysed at individual level for hours spent on all economic activities by the household head. Furthermore, the IHPS also provides data for the primary and secondary jobs within a household. An examination of the data revealed that the allocation of hours to secondary employment relative to the primary sector of employment is notably limited.

1.2.6 Household Demographics

The controls for household demographics include the household size and the following characteristics of the household head, namely, age, gender (with male as the reference sex), educational qualification and marital status. Household size ranges from a minimum of 1 to a maximum of 19, 17 and 21 in respective years of 2010, 2013 and 2016. The average household size is about 5 members. With regards to gender, 25 percent of the household heads are female headed whilst 75 percent are male headed in 2016, this is from a base of 20 percent and 80 percent in 2010. Education has six categories: (1) None; (2) Primary Education; (3) Secondary Education; (4) Diploma; (5) University Degree; and (6) Post Graduate Degree. Most of the household heads have no formal education followed by a few with some primary or secondary school education. The marital status of the head of household is also included with five categories, namely, married, separated, divorced, widowed and never married. Interms of background characteristics, 75 percent of the population reside in rural areas whilst 25 percent reside in urban areas. Being an agro-based economy, a large proportion of the population is involved in agriculture for subsistence and as a source of livelihood. The data shows that the average proportion of households involved in agriculture moved from about 82 percent in 2010 and the number had risen risen to about 84 percent in 2016. Throughout the period under review, the proportion of rural based households remained around 80 percent whilst urban based households were about 20 percent.

1.2.7 Rainfall

A rainfall shock variable is included to control for the effect of rainfall variation on demand for labour in agriculture. Ngongondo et al. (2011) notes that Malawi's climate is tropical wet and dry, also known as Savanna with the main rainy season running from November to April and the dry season from May to October. He further notes that some areas experience sporadic winter rains (locally called chiperoni) between May and August. Given that agriculture in Malawi is predominantly rainfed, rainfall corresponding to a complete wet season from November to April (rather than annual or chiperoni) is closely related to crop production (Mussa, 2017). The analysis therefore focuses on variation in precipitation, although it may be important to consider other conditions such as temperature. This is because it is recognised that apart from labour, too much or too little rainfall is critical in subsistence farming.

Literature (Amare et al., 2018, Grimard and Hamilton, 1999, Jensen, 2000, Riley,

2018) defines a conventional measure of a shock as more than one standard deviation in absolute values from the long-term mean during the wet season:

$$\text{RS}_{it} = \frac{(\overline{R}_i - R_{it})}{R_i^{\text{SD}}} \tag{1.1}$$

where RS_{it} is the rainfall shock for household i for the year t; $\overline{R}_i$ is the historical 20 year average rainfall during the wet season in the district of household i; R_{it} is the rainfall during the wet season in the district of household i for the year t; and R_i^{SD} is the standard deviation from the historical average rainfall during the wet season in the district of household i.

The rainfall indicator is constructed based on the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) for the period 1989-2015. The cumulative precipitation is calculated for six consecutive months from November to April in every year and the long-term mean is calculated over a 20-year period for each district. Since the IHPS data also includes a district variable it is used to merge the household level data with the rainfall data.

As further noted in the aforementioned literature, any deviation from the long-term mean does not inherently imply a sudden or unexpected occurrence, so the unfavourable weather is measured as a dummy variable. Normal rainfall is set to zero when the outcome is within a standard deviation of the long-term mean. A positive or negative rainfall shock is set to one when the outcome is a standard deviation above or below the long-term mean, respectively.

$$\text{NRS}_{it} = \begin{cases} 1 & \text{if } \frac{(\overline{R}_{it} - R_{it})}{R_i^{\text{SD}}} < -0.5 \\ 0 & \text{otherwise} \end{cases} \tag{1.2}$$

$$\text{PRS}_{it} = \begin{cases} 1 & \text{if } \frac{(\overline{R}_{it} - R_{it})}{R_i^{\text{SD}}} > 0.5 \\ 0 & \text{otherwise} \end{cases} \tag{1.3}$$

where NRS_{it} is a negative rainfall shock for household i for the year t; PRS_{it} is a positive rainfall shock for household i for the year t; $\overline{R}_{it}$ is the historical 20 year average rainfall during the wet season in the district of household i for the year t; R_{it} is the rainfall during the wet season in the district of household i for the year t; and R_i^{SD} is the standard deviation from the historical average rainfall during the wet season in the district of household i.

Table 1.1: Descriptive Statistics: Full Sample of Households

	2010			2013			2016		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Household Real Annual Consumption (LCU)	398,238	774,831	945	397,672	593,466	945	278,713	294,988	945
National Annual Private Consumption (LCU)	4,452,231	0.00	945	2,922,823	0.00	945	1,771,646	0.00	945
Household Real Annual Income per Household (LCU)	129,901	329,678	945	171,930	522,467	945	95,357	540,140	945
Weekly Hours Worked in Agriculture	6.22	13.57	945	5.85	13.74	945	6.35	14.35	945
Weekly Hours Worked in Industry	0.30	3.07	945	0.82	6.35	945	0.28	3.37	945
Weekly Hours Worked in Services	2.59	10.53	945	2.91	12.14	945	2.02	9.61	945
Agriculture Employment	0.82	0.38	456	0.76	0.43	377	0.84	0.36	381
Industry Employment	0.03	0.17	456	0.06	0.23	377	0.02	0.15	381
Services Employment	0.15	0.36	456	0.18	0.39	377	0.13	0.34	381
Urban Resident	0.22	0.41	945	0.21	0.41	945	0.20	0.40	945
Rural Resident	0.78	0.41	945	0.79	0.41	945	0.80	0.40	945
Household Size	5.16	2.24	945	5.41	2.29	945	5.51	2.36	945
Male Head of Household	0.81	0.39	945	0.81	0.39	945	0.75	0.43	945
Female Head of Household	0.19	0.39	945	0.19	0.39	945	0.25	0.43	945
Age of Household Head	42.07	14.68	945	44.38	14.23	945	47.45	13.99	905
Head of Household has No Education	2.79	1.86	945	3.21	1.95	945	3.43	2.07	937
Head of Household has Primary Education	0.32	0.62	945	0.37	0.66	945	0.37	0.62	937
Head of Household has Secondary Education	0.45	0.94	945	0.49	0.91	945	0.51	0.91	937
Head of Household has Diploma	0.03	0.20	945	0.03	0.22	945	0.05	0.28	937
Head of Household has University Degree	0.00	0.06	945	0.01	0.15	945	0.01	0.13	937
Head of Household has Post Graduate Degree	0.00	0.07	945	0.00	0.00	945	0.00	0.08	937
Head of Household is Married	0.83	0.38	945	0.82	0.38	945	0.79	0.41	945
Head of Household is Separated	0.04	0.19	945	0.04	0.19	945	0.04	0.20	945
Head of Household is Divorced	0.04	0.20	945	0.03	0.18	945	0.04	0.19	945
Head of Household is Widowed	0.09	0.28	945	0.10	0.31	945	0.12	0.33	945
Head of Household has Never Married	0.01	0.10	945	0.01	0.07	945	0.01	0.08	945

1.3 Empirical Strategy

The model is a balanced three period panel data set. A two step process is adopted with a baseline regression (exponential and power utility) and a DID evaluation. Prior to the DID, the data is first matched using PSM with the Mahalanobis matching estimator. The first step tests the theory of complete consumption insurance. This is important as it helps us to ascertain the presence of risk sharing from the observed data. The second step enables the estimation of the heterogeneous effects on household consumption due to an aggregate shock. This will help determine the degree or risk sharing across households.

1.3.1 Baseline Regression Models

For the baseline, the work of Mace (1991) is followed by analysing the risk sharing problem in the context of maximizing individual household expected utility subject to an aggregate resource constraint. Two specifications of homothetic preferences, namely, exponential utility (first differences of consumption) and power utility (growth rates of consumption) are modelled.

These specifications are modelled by: (i) changes in levels of consumption and earnings and (ii) growth rate of consumption and earnings. The tests are on observations on consumption and income at the household level as well as aggregate consumption which does not vary across individuals at each point in time.

The hypothesis is that changes in household consumption are determined by changes in aggregate consumption, independent of other idiosyncratic variables such as changes in household income. Model specifications tested are as follows:

1) Change in levels of consumption and income

$$\Delta C_t^h = \beta_0 + \beta_1 \Delta C_t^a + \beta_2 \Delta y_t^h + B_3 \Delta X_t^h + \mu_t^h \tag{1.4}$$

where ΔC_t^h is the change in household consumption; ΔC_t^a is the change in aggregate consumption; Δy_t^h is the change in household income; and ΔX_t^h is a vector of control variables which include a rainfall shock, month of interview, household size and household head characteristics such as age, gender, level of education and marital status. μ_t^h is the error term that includes time varying components of household and aggregate preference shocks. The βs are the estimated coefficients from the regression.

2) Growth rate of consumption and income

$$\Delta \log C_t^h = \beta_0 + \beta_1 \Delta \log C_t^a + \beta_2 \Delta \log y_t^h + B_3 \Delta \log X_t^h + \mu_t^h \tag{1.5}$$

where $\Delta \log C_t^h$ is the logarithmic growth rate of household consumption; $\Delta \log C_t^a$ is the logarithmic growth rate of aggregate consumption; $\Delta \log y_t^h$ is the logarithmic growth rate of household income; and $\Delta \log X_t^h$ is a vector of control variables which include a rainfall shock, month of interview, household size and household head characteristics such as age, gender, level of education and marital status. μ_t^h is the error term that includes time varying components of household and aggregate preference shocks. The βs are the estimated coefficients from the regression.

1.3.2 Propensity Score Matching

The PSM is in itself a popular method used to estimate casual inferences (Caliendo and Kopeinig, 2008, Cunningham, 2021, Gertler et al., 2016, Rosenbaum and Rubin, 1983). It is also common practice to combine it's use with other impact evaluation methods as it addresses selection bias.

The control group created from this approach is as close as possible in terms of observed covariates to the treated thereby making the identification more credible as treatment effects are due to intervention rather than selection bias. It is for this reason that it is used in this paper to combine with the DID for more robust results on our causal effects. The Mahalanobis matching estimator is used as a distance measure between treated households and control households in the PSM approach.

The estimated propensity score is thus the probability of a household being assigned to a treatment group, conditional on observed characteristics. This is estimated as follows:

$$E(Y_i^T - Y_i^C \mid T_i = 1, X_i) = E(Y_i^T \mid T_i = 1, X_i) - E(Y_i^C \mid T_i = 1, X_i) \tag{1.6}$$

Propensity scores are estimated separately for the employment and residence groups. Y_i represents household consumption. It is denoted as Y_i^T for those households that are employed in industry or services for the employment group and those in urban areas for the residence group. Y_i^C represents the households employed in agriculture for employment group and those residing in rural areas for residence group. T_i is the treatment status where $T_i = 1$ represents a household employed in industry or services and households residing in urban areas in respective groups. $T_i = 0$ represents households employed in agriculture or households residing in rural areas in the respective groups. X_i represents observable characteristics which include gender, age, household income, household size, education and marital status.

$E(Y_i^T \mid T_i = 1)$ is observed, and $E(Y_i^C \mid T_i = 1)$ is the counterfactual that needs to be constructed using propensity score matching. This will help us to identify households in the control group that are as close as possible to the those in the treated group based on their propensity scores.

Figure 1.1: Distribution of Propensity Scores across Treated and Control - Employment Group

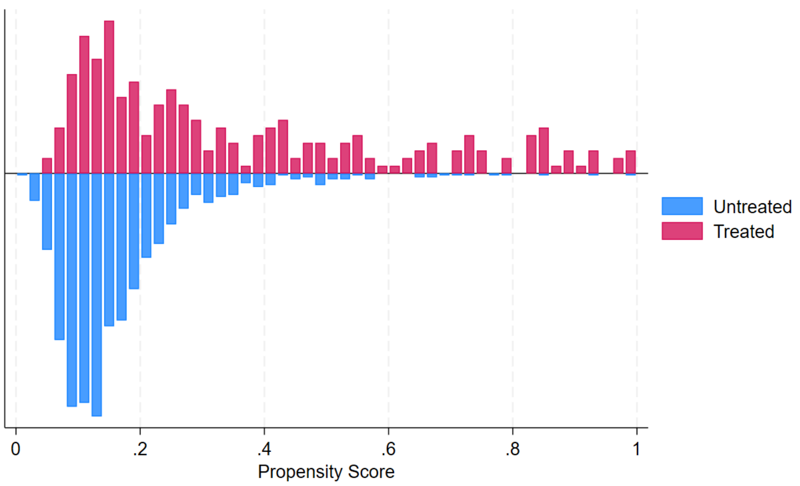
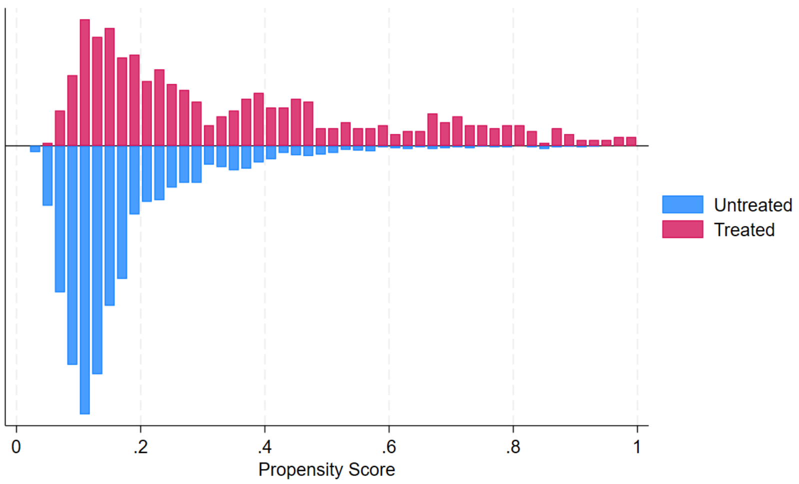


Figure 1.2: Distribution of Propensity Scores across Treated and Control - Residence Group



A visual inspection of Figure 1.1 shows an overlap of the propensity scores for the control(employed in agriculture) and the treated (employed in industry or services). Figure 1.2 also displays common support of the propensity scores for the control(rural residents) and the treated (urban residents). Graphical depiction of the quality of matching on covariates is presented in Appendix 1.

1.3.3 Difference in Differences

The DID is one of the most commonly used program evaluation methods (Angrist and Pischke, 2009, Ashenfelter, 1978, Ashenfelter and Card, 1985, Card and Krueger, 1993, Heckman and Robb Jr, 1985). In this paper there are two outcomes of interest - the logarithmic transformations of real household annual consumption and the number of hours spent in agriculture sector relative to industry and services. The differences are observed within and across the three sectors of employment as well as rural and urban households before and after the devaluation. This is to test whether there is evidence of a heterogeneous effect of an exchange rate shock on household consumption.

1.3.3.1 Parallel Trends

A key identifying assumptions of the DID is that of parallel trends. This implies that trends would be the same in the treated and control groups in the absence of the policy intervention. It is, therefore, imperative that it is ascertained whether the treatment and control groups had parallel trends before the policy intervention. However, this requires having at least two periods of pre-treatment outcome data. In our case, however, we only have one round of survey data before the shock. This paper thus considered alternative approaches to show that the key identifying assumption had been satisfied to establish causality.

One approach suggested in the literature (Becker and Hvide, 2013, Ichino et al., 2007, Mckenzie, 2023) is to match households before applying the DID. The premise is that the comparison will be on households that have similar baseline characteristics. This renders credibility to the identification strategy (see Section 1.3.2).

Further to matching, the rule of thumb suggested by Crump et al. (2009) is to discard all units with estimated propensity scores outside the range [0.1,0.9]. In our analysis, all the units had propensity scores within this range affirming that the households in the sample were similar to a greater extent.

1.3.3.2 Estimation of the DID model

In this approach, the outcomes are observed for the two groups in the period before the devaluation in 2010 and the post treatment period being 2013. The first group is based on sector of employment of the household head in primary (agriculture); secondary (industry) or tertiary (services) sectors. The second comparison group is whether the household resides in a rural or urban area.

It is important to note that there are separate dummy variables for industry and services sectors, with agriculture being the omitted category. This distinction allows for a more nuanced understanding of the effects of different sectors on consumption. This approach enables the capturing of distinct characteristics and dynamics associated with the industry and services sectors separately.

Before estimating the DID model on consumption, a similar specification was run on household income as an outcome variable. The idea was to establish whether households employed in agriculture saw an increase in household income relative to those employed in services and industry:

$$y = \alpha + \delta_0 dT + \delta_1 dGEmpl + \delta_2 dT \cdot dGEmpl + \delta_3 Z + \varepsilon \tag{1.7}$$

where y is the outcome of interest (household income); the δs are the estimated coefficients; the time dummy dT indicates the year of intervention with a value of 0 in 2010 and 1 in 2013. It captures aggregate factors that would cause changes to consumption even in the absence of the policy shock; dummy variable group *dGEmpl* captures possible differences between household heads employed in agriculture ($= 0$), industry ($= 1$) or services ($= 2$) before and after policy change; *dT.dGEmpl* is the interaction between time and employment group which captures the DID estimate; Z is a vector of control variables which include household head characteristics such as age, gender, level of education and marital status. The model also controls for household size, rainfall variation and month of interview; and ε is the error term.

Similarly, a specification with household income as an outcome was run on the residence group:

$$y = \alpha + \delta_0 dT + \delta_1 dGRes + \delta_2 dT \cdot dGRes + \delta_3 Z + \varepsilon \tag{1.8}$$

where y is the outcome of interest (household income); the δs are the estimated coefficients; the time dummy dT indicates the year of intervention with a value of 0 in 2010 and 1 in 2013. It captures aggregate factors that would cause changes to consumption even in the absence of the policy shock; dummy variable group *dGRes* captures possible differences between rural households ($= 0$) and urban households ($= 1$) before and after policy change; *dT.dGRes* is the interaction between time and residence group which captures the DID estimate; Z is a vector of control variables which include household head characteristics such as age, gender, level of education and marital status. The model also controls for household size, rainfall variation and month of interview; and ε is the error term.

Equation 1.9 represents the regression estimated for the employment group with household consumption as the dependent variable:

$$c = \alpha + \delta_0 dT + \delta_1 dGEmpl + \delta_2 dT \cdot dGEmpl + \delta_3 Z + \varepsilon \tag{1.9}$$

where c is the outcome of interest (household consumption); the δs are the estimated coefficients; time dummy dT indicates the year of intervention with a value of 0 in 2010 and 1 in 2013. It captures aggregate factors that would cause changes to consumption even in the absence of the policy shock; dummy variable group $dGEmpl$ captures possible differences between household heads employed in agriculture (= 0), industry (= 1) or services (= 2) before and after policy change; $dT.dGEmpl$ is the interaction between time and employment group which captures the DID estimate; Z is a vector of control variables which include household head characteristics such as age, gender, level of education and marital status. The model also controls for household income, household size, rainfall variation and month of interview; and ε is the error term.

Equation 1.10 represents the regression estimated for the rural and urban households with consumption as the dependent variable:

$$c = \alpha + \delta_0 dT + \delta_1 dGRes + \delta_2 dT \cdot dGRes + \delta_3 Z + \varepsilon \tag{1.10}$$

where c is the outcome of interest (household consumption); the δs are the estimated coefficients; time dummy dT indicates the year of intervention with a value of 0 in 2010 and 1 in 2013. It captures aggregate factors that would cause changes to consumption even in the absence of the policy shock; dummy variable group $dGRes$ captures possible differences between rural households (= 0) and urban households (= 1) before and after policy change; $dT.dGRes$ is the interaction between time and residence group which captures the DID estimate; Z is a vector of control variables which include household head characteristics such as age, gender, level of education and marital status. The model also controls for household income, household size, rainfall variation and month of interview; and ε is the error term.

Equation 1.11 represents the regression estimated for the employment group with hours worked in agriculture as the dependent variable:

$$h_{ag} = \alpha + \delta_0 dT + \delta_1 dGEmpl + \delta_2 dT \cdot dGEmpl + \delta_3 Z + \varepsilon \tag{1.11}$$

where h_{ag} is the outcome of interest (hours worked in the agriculture sector); the δs are the estimated coefficients; the time dummy dT indicates the year of intervention with a value of 0 in 2010 and 1 in 2013; dummy variable group $dGEmpl$ captures possible differences between household heads employed in agriculture (= 0), industry (= 1) or services (= 2) before and after policy change; $dT.dGEmpl$ is the interaction between time and employment group which captures the DID estimate; Z is a vector of control variables which include household head characteristics such as age, gender, level of education and marital status. The model also controls for household income, household size, rainfall variation and month of interview; and ε is the error term.

1.4 Results

Table 1.2 presents the results obtained from the exponential (first differences) and power utility (growth rates) models. These coefficients were estimated through ordinary least squares (OLS), as depicted in Equation 1.4 and Equation 1.5. According to Mace (1991), in a model of perfect risk sharing, the coefficients are expected to be $\beta_1 = 1$ for aggregate consumption and $\beta_2 = 0$ for household income.

The analysis from the first differences model indicates that $\beta_1 = 1.14$ ($p < 0.01$) and $\beta_2 = 0.01$ ($p > 0.10$). Similarly, the growth rates model produces comparable results with $\beta_1 = 0.99$ ($p < 0.02$) and $\beta_2 = 0.01$ ($p > 0.10$). These findings are in alignment with the theoretical predictions of the theory of full consumption insurance and existing literature.

The consistency between the empirical results and the benchmark model of full consumption insurance suggests that changes in household consumption are primarily influenced by shifts in aggregate consumption rather than by idiosyncratic risks such as variations in household income. This implies a high degree of consumption smoothing across households, as fluctuations in overall consumption can be mitigated through both formal and informal mechanisms such as inter-household transfers, micro finance and savings groups, social safety nets and financial markets, amongst others. Consequently, the observed responsiveness of household consumption to changes in aggregate consumption underscores the efficacy of risk-sharing mechanisms in buffering against shocks and improving resilience of the economy as a whole.

Table 1.2: Baseline Regression Models

VARIABLES	(Model 1: First Differences) Change in Household Consumption	(Model 2: Growth Rates) Log Household Consumption
Aggregate Consumption	1.140***	0.991***
	(0.361)	(0.349)
Household Income	0.0146	0.0188
	(0.0357)	(0.0154)
Household Size	16,177	0.0446**
	(13,446)	(0.0174)
Age of Household Head	-454.6	-0.0605
	(2,556)	(0.0769)
Female	-281,320**	-0.0323
	(128,232)	(0.0276)
Head of Household is Separated	25,754	-0.0582
	(181,257)	(0.0377)
Head of Household is Divorced	233,994	-0.0430
	(196,421)	(0.0393)
Head of Household is Widowed	55,178	-0.0258
	(171,660)	(0.0371)
Head of Household has Never Married	-667,139*	-0.0745
	(340,879)	(0.0652)
Head of Household has Primary Education	69,299	0.00123
	(53,817)	(0.0101)
Head of Household has Secondary Education	69,017	-0.00568
	(57,859)	(0.00956)
Head of Household has Diploma	554,422***	0.0129
	(143,915)	(0.0228)
Head of Household has University Degree	130,004	-0.0696
	(238,614)	(0.0540)
Head of Household has Post Graduate Degree	-	-
	(0.0141)	
Constant	-122,221**	0.0298***
	(59,517)	(0.0108)
Observations	1,828	748

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

Before introducing the DID estimations with household consumption and hours worked in agriculture as outcomes, another model is estimated with changes in household income as a dependent variable. The first estimation is for the employment groups (industry and services workers relative to agriculture sector workers) as depicted in Equation 1.7. The second estimation is on residence (urban households relative to rural households) as shown in Equation 1.8.

The results show a slight drop in household incomes for those employed in the modern sector compared to their counterparts in the traditional sector. Specifically, there is an estimated decline of 0.47 percent ($p < 0.01$) for those employed in the industry sector and 0.75 percent ($p < 0.01$) for those employed in the services sector. This suggests that household heads employed in industry and services sectors experience a relative decrease in household income compared to those employed in the agriculture sector. These results are presented in Table 1.3.

The results also show a minuscule disparity in household income between urban and rural households, with urban households experiencing a decline of 0.02 percent ($p < 0.01$) relative to their rural counterparts. This indicates that households residing in urban areas were affected more by the devaluation, leading to a decrease in income compared to those in rural areas. The results are shown in Table 1.4.

Despite the subtle differences observed, these findings offer insights into the intricacies of income dynamics among households employed across the three sectors and residing in different areas. Such granular understanding is imperative for formulating targeted policy interventions designed to mitigate income disparities and facilitate economic growth and stability across heterogeneous segments of the population.

Table 1.5 presents the DID results with employment group on household consumption as an outcome variable as estimated in Equation 1.9. Although the results show a decline in household consumption for those employed in industry and services, the observed decreases are minimal estimated at 0.02 percent ($p < 0.10$) and 0.12 percent ($p < 0.05$), respectively.

These findings align with the theory of full consumption insurance. While it was anticipated that the devaluation would have a more pronounced impact on households employed in the industry and services sectors, the observed effects are not significantly different from zero. Consequently, it can be inferred that the impact of the exchange rate shock was relatively uniform across all households, irrespective of their employment sector.

Table 1.3: DID Model: Household Income and Employment Group

VARIABLES	(No Controls) Log Household Income	(Controls) Log Household Income
Time	1.387***	1.380***
	(0.196)	(0.211)
Industry Employment	1.274***	1.068***
	(0.359)	(0.401)
Services Employment	1.209***	0.831***
	(0.207)	(0.201)
Time#Industry- Employment	-2.065***	-1.849***
	(0.494)	(0.518)
Tine#Services Employment	-2.309***	-2.133***
	(0.306)	(0.303)
Log Household Income		0.0212
		(0.185)
Log Household Size		-1.288***
		(0.248)
Log Age of Household Head		-1.288***
		(0.248)
Female		-0.161
		(0.391)
Head of Household is Separated		-0.0641
		(0.584)
Head of Household is Divorced		0.386
		(0.539)
Head of Household is Widowed		0.221
		(0.508)
Head of Household has Never Married		0.636
		(1.173)
Head of Household has Primary Education		0.116
		(0.118)
Head of Household has Secondary Education		0.233***
		(0.0645)
Head of Household has Diploma		0.789***
		(0.270)
Head of Household has University Degree		0.118
		(0.226)
Head of Household has Post Graduate Degree		4.183***
		(0.208)
Constant	10.32***	14.58***
	(0.119)	(1.174)
Observations	697	695

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

Table 1.4: DID Model: Household Income and Residence Group

VARIABLES	(No Controls) Household Income	(Controls) Household Income
Time	1.053***	1.020***
	(0.187)	(0.203)
Urban Residence	1.413***	1.156***
	(0.200)	(0.225)
Time#Urban Residence	-1.221***	-1.041***
	(0.325)	(0.324)
Log Household Size		0.391**
		(0.189)
Log Age of Household Head		-0.983***
		(0.260)
Female		-0.0977
		(0.369)
Head of Household is Separated		-0.414
		(0.571)
Head of Household is Divorced		-0.0505
		(0.573)
Head of Household is Widowed		-0.0623
		(0.440)
Head of Household has Never Married		1.378
		(1.161)
Head of Household has Primary Education		-0.107
		(0.124)
Head of Household has Secondary Education		0.117*
		(0.0657)
Head of Household has Diploma		0.360
		(0.228)
Head of Household has University Degree		-0.501*
		(0.299)
Head of Household has Post Graduate Degree		2.242***
		(0.376)
Constant	10.24***	13.13***
	(0.121)	(1.200)
Observations	710	709

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

Such insights shed light on the underlying mechanisms governing household consumption dynamics amidst economic shocks. Understanding these nuanced responses of households to external shocks not only enriches theoretical frameworks but also informs policymakers in designing targeted interventions to bolster resilience and mitigate adverse effects on household welfare.

A comparison of the results with household income and household consumption as outcomes variables, demonstrate support for the permanent income hypothesis. The empirical evidence suggests that fluctuations in household consumption are less responsive to short-term variations in household income but more closely aligned with permanent alterations in income levels. Notably, the observed effect sizes indicate a greater magnitude of response to changes in household income compared to changes in consumption levels. This supports the notion that household consumption decisions are primarily driven by long-term income considerations rather than immediate fluctuations.

Table 1.6 presents the results from the DID model with residence group on household consumption (Equation 1.10). Urban households experienced a decline in consumption relative to rural households by 0.10 percent ($p < 0.01$). The results are once again consistent with the model of full insurance. While urban households experience a slight drop in consumption, it is important to note that this effect is not significantly different from that observed in households residing in rural areas.

This nuanced understanding sheds light on the resilience inherent in households across different residential settings, suggesting risk sharing in response to economic fluctuations. Such insights can guide policymakers in designing targeted interventions to support household welfare and promote economic stability across heterogeneous households based on residence.

Table 1.7 presents the results from the DID model with employment group having total hours worked in agriculture as an outcome variable (Equation 1.11). The results show a fall in the weekly hours worked for households employed in the modern sector relative to those in the traditional sector. Households employed in industry and services saw their respective weekly hours drop by 0.96 percent ($p < 0.05$) and 0.77 percent ($p < 0.05$) relative to hours worked in the agriculture sector. These results appear to suggest that, following the devaluation, a shift is observed in working hours with households potentially reducing their hours worked in the modern sector and increasing time spent in the traditional sector.

Table 1.5: DID Model: Household Consumption and Employment Group

VARIABLES	(No Controls) Log Household Consumption	(Controls) Log Household Consumption
Time	0.147***	0.123**
	(0.0358)	(0.0509)
Industry Employment	0.302**	0.248**
	(0.126)	(0.116)
Services Employment	0.660***	0.403***
	(0.0858)	(0.0758)
Time#Industry Employment	-0.102**	-0.0986*
	(0.193)	(0.176)
Time#Services Employment	-0.377***	-0.244**
	(0.0950)	(0.0957)
Log Household Income		0.0193**
		(0.00965)
Log Household Size		0.306***
		(0.0483)
Log Age of Household Head		0.0142
		(0.0663)
Head of Household is Separated		-0.0984
		(0.130)
Head of Household is Divorced		-0.0873
		(0.0832)
Head of Household is Widowed		-0.0685
		(0.0689)
Head of Household has Never Married		0.449*
		(0.248)
Head of Household has Primary Education		0.106***
		(0.0288)
Head of Household has Secondary Education		0.183***
		(0.0210)
Head of Household has Diploma		0.547***
		(0.126)
Head of Household has University Degree		0.379***
		(0.0902)
Head of Household has Post Graduate Degree		1.285***
		(0.0664)
Constant	13.16***	12.48***
	(0.0292)	(0.327)
Observations	833	695

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

Table 1.6: DID Model: Household Consumption and Residence Group

VARIABLES	(No Controls) Log Household Consumption	(Controls) Log Household Consumption
Time	0.147***	0.167***
	(0.0231)	(0.0343)
Urban Residence	0.539***	0.260***
	(0.0521)	(0.0437)
Time#Urban Residence	-0.265***	-0.265***
	(0.0461)	(0.0546)
Log Household Size		0.344***
		(0.0366)
Log Household Income		0.0382***
		(0.00701)
Log Age of Household Head		0.0874*
		(0.0493)
Female		-0.0331
		(0.0658)
Head of Household is Separated		-0.0512
		(0.0925)
Head of Household is Divorced		-0.0848
		(0.0886)
Head of Household is Widowed		-0.0764
		(0.0808)
Head of Household has Never Married		0.279*
		(0.153)
Head of Household has Primary Education		0.0840***
		(0.0199)
Head of Household has Secondary Education		0.187***
		(0.0161)
Head of Household has Diploma		0.454***
		(0.0785)
Head of Household has University Degree		0.388***
		(0.0829)
Head of Household has Post Graduate Degree		0.484***
		(0.122)
Constant	13.14***	12.08***
	(0.0219)	(0.238)
Observations	1,890	1,379

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

Table 1.7: DID Model: Hours in Agriculture and Employment Group

VARIABLES	(No Controls) Weekly Hours in Agriculture	(Controls) Weekly Hours in Agriculture
Time	3.162**	6.090***
	(1.338)	(2.087)
Industry Employment	-16.93***	-17.54***
	(1.326)	(1.457)
Services Employment	-16.16***	-17.92***
	(0.982)	(1.277)
Time#Industry Employment	-1.503	-5.135**
	(1.642)	(2.487)
Time#Services Employment	-2.961**	-5.325**
	(1.343)	(2.084)
Log Household Size		-2.914*
		(1.523)
Log Household Income		1.069***
		(0.295)
Log Age of Household Head		-0.643
		(1.973)
Female		-1.202
		(2.314)
Head of Household is Separated		1.180
		(4.379)
Head of Household is Divorced		-1.327
		(3.085)
Head of Household is Widowed		-0.958
		(3.284)
Head of Household has Never Married		9.177
		(6.453)
Head of Household has Primary Education		-1.364*
		(0.790)
Head of Household has Secondary Education		0.198
		(0.676)
Head of Household has Diploma		-0.721
		(1.180)
Head of Household has University Degree		0.347
		(0.526)
Head of Household has Post Graduate Degree		-12.50***
		(2.177)
Constant	15.90***	-0.789
	(0.917)	(9.691)
Observations	833	695

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

It is imperative to approach the interpretation of these findings with caution due to the complexities involved in labour allocation dynamics. Changes in labour allocation between sectors (extensive margin) may not precisely indicate sector reallocation of labour as distinct from within sector (intensive margin) changes in hours worked. For instance, individuals serving as household heads across multiple sectors might redistribute more time towards agricultural activities and/or seek more casual employment in industry and services. Consequently, there is a need for additional research to delve deeper into these intricacies. This could provide a more comprehensive understanding of the factors that drive both the intensive and extensive margins in sectoral labour reallocation.

1.5 Conclusion

This study initially tested the theory of perfect consumption insurance which was not rejected. This is the benchmark model of full consumption insurance. Changes in household consumption are responsive to changes in aggregate consumption and not idiosyncratic risks such as changes in household income. The evidence is consistent with some literature that analysed observed data and showed perfect risk sharing. As Mace (1991) put it, these results do not necessarily prove that all markets are perfect but rather that market imperfections or lack of completeness may not be the key feature in explaining consumption allocations.

The findings from the estimation of the differential impact of the currency devaluation provide further evidence that aligns to the full insurance model. Households employed in the traditional sector were relatively better off compared to those employed in the modern sector. The latter households saw both their consumption and income levels drop relative to their counterparts in agriculture. However, the size of the effect is almost zero. The devaluation also led to a drop in hours worked in industry and services sectors compared to the agrarian sector. The estimated impact is almost a 1 percent fall in weekly hours for both sectors relative to the agriculture sector. Urban households were marginally more affected than rural households. The effect, however, is not different from zero.

The evidence from this paper suggests that the exchange rate shock did not result in significantly different impacts across the heterogeneous households, as indicated by the size of coefficients. However, there appears to be a slightly higher coefficient for rural-urban differences as compared to the employment sectors. This implies potentially less risk-sharing in urban households compared to their rural counterparts.

These nuanced disparities underscore the importance of considering diverse household characteristics in policy making. It suggests that while some households may possess inherent resilience against certain shocks, others may require additional support. For instance, this implies that alongside devaluation policies, it is crucial to implement supportive measures or interventions such as safety nets targeted at vulnerable groups like urban poor households. In essence, understanding and addressing these disparities can enhance the effectiveness and equity of policy interventions, ensuring that all households are adequately supported and insulated against economic shocks.

The findings also shed light on potential dynamics of labour migration between traditional and modern sectors, with policy implications for the broader economy. This is particularly important in the context of productivity growth and structural change in developing countries like Malawi. However, it is crucial to exercise caution when interpreting the results on shifts in labour hours. These shifts may not necessarily indicate a reallocation of labour between sectors (extensive margin) but could rather reflect changes in hours within sectors (intensive margin). Further research is imperative to delve deeper into these dynamics and identify the comprehensive factors driving sectoral labour reallocation.

Chapter 2

Consumption Smoothing and Welfare Effects: *Mtukula Pakhomo* Social Cash Transfer Program

2.1 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, 2006, Chetty and Finkelstein, 2013, Gruber, 1997). 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

[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

(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.

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 (Abdoulayi et al., 2014, 2016, Bastagli et al., 2019, Handa et al., 2015, World Bank, 2018a,b). 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

[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).

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 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).

In this study, a theoretical framework is constructed to optimize social insurance benefits while addressing moral hazard, where individuals may adjust their behaviour in response to insurance incentives. Empirically, the propensity score matching (PSM) is employed to estimate coefficients, with robust statistical inferences. Subsequently, the sufficient statistic approach is applied to evaluate the welfare implications of the *Mtukula Pakhomo* social cash transfer program, using coefficients obtained from the PSM to use the formula for optimal social insurance from the model to ascertain whether the program is scaled optimally.

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 and unemployment insurance in developed countries. 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 *Mtukula Pakhomo* program. 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 2.2. Data and methodology are presented in Section 2.3. The methodology includes both structural (theoretical) and reduced form (program evaluation) approaches which have been combined to present a sufficient statistic approach. Results and analysis are discussed in Section 2.4. The conclusions are drawn in Section 2.5.

2.2 *Mtukula Pakhomo* Program

2.2.1 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 2.1). 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

[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)

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 (Abdoulayi et al., 2014, 2016, Baird et al., 2011, Brugh et al., 2018, Handa et al., 2015, Miller et al., 2011, Ralston et al., 2017) 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 2.1.

2.2.2 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 2.2). This stratification is based on the decision table and cut-off points from a proxy means test (PMT) model (Table 2.2).

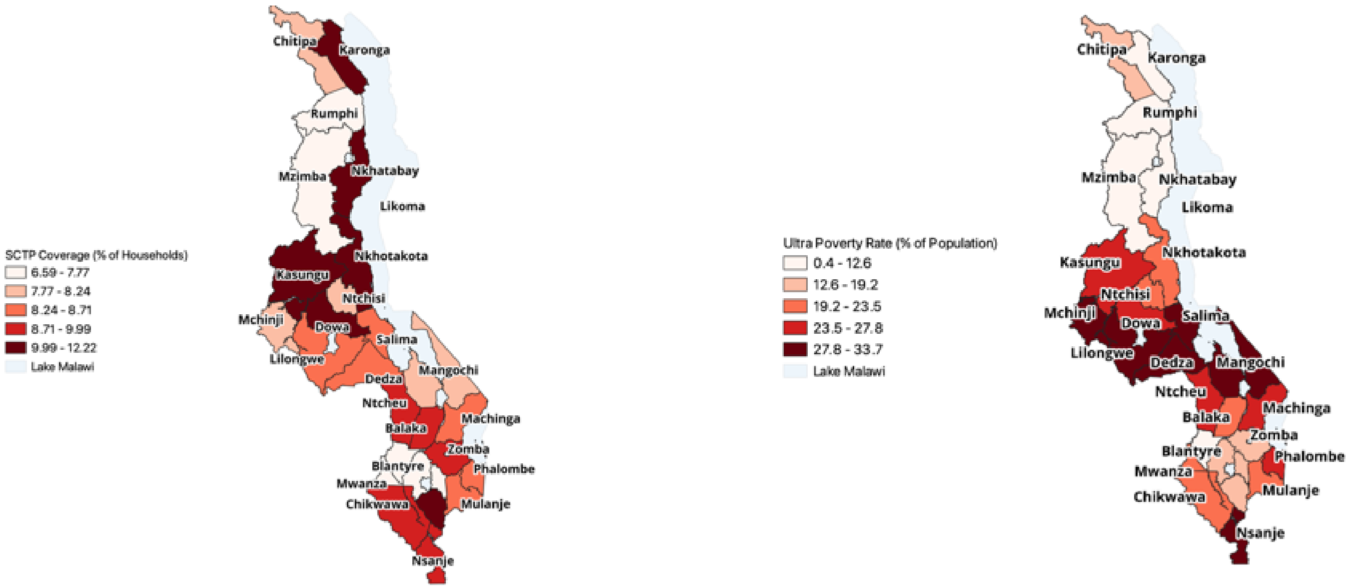
The Ministry of Finance, Economic Planning and Development is responsible for the development of the PMT formula. The current PMT score is based on the fourth Integrated Household Survey (IHS4) conducted by the National Statistical Office. Social Support Programs by Government use the harmonized data 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].

[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. The final selection of eligible households is done at the VC level.

Figure 2.1: 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. It is worth noting that other variations in poverty rates across districts could stem from differences in the timing of household enrolment, potentially leading to improved poverty rates over time for districts that were amongst the early ones to have the program rolled out.

Table 2.1: 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)

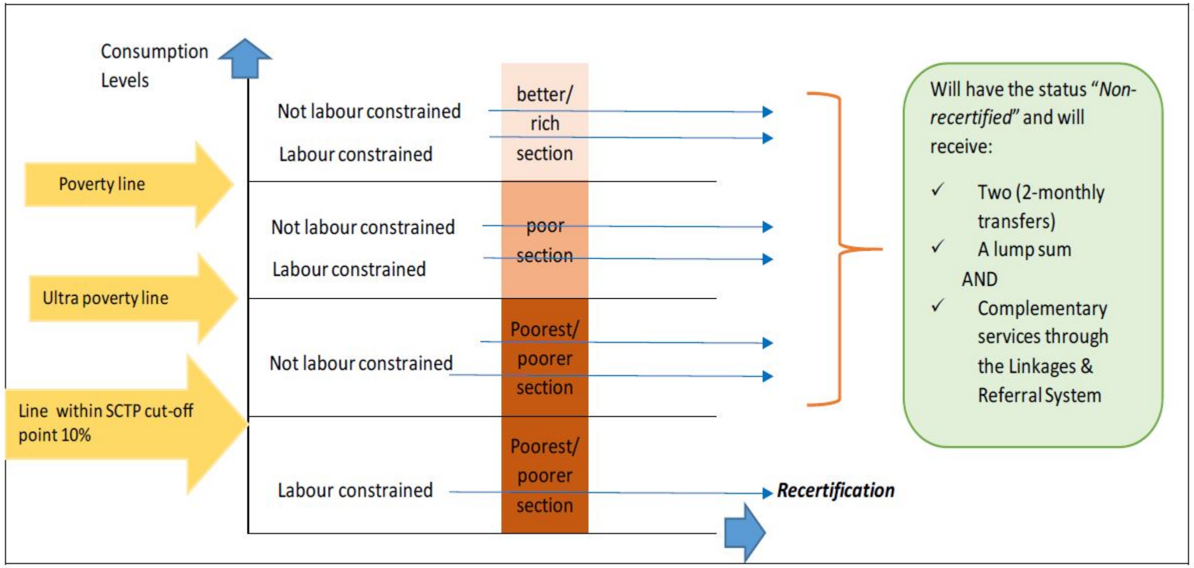
Notes: Conversion from Malawi Kwacha (MWK) to United States Dollar ($) based on Reserve Bank of Malawi exchange rate data

Table 2.2: 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 2.2: Recertified and Non-Recertified Households



Source: Government of Malawi (2020a)

Notes: See Table 2.3 for definition of recertified and non-recertified households

2.2.3 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 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 2.3 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 first two eligibility criteria (ultra poor and labour constrained) are clear, the third requirement that SCTP enrollment should be within the 10 percent cut off point of a selected geographical area (regardless of the poverty score) presents a challenge. It therefore means 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 2.3: 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)

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. The control group only encompasses the newly eligible but not enrolled but excludes the pre-eligible but not enrolled due to lack of baseline data.

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 screened by a screening officer and household oriented by orientation officer. Their data is then uploaded in the MIS by an enrollment officer using their household code as indicated on their UBR receipt.

2.3 Data and Methodology

2.3.1 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

[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.

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 2.3). 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 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 2.4 and Table 2.5. The gender disaggregated summary statistics are presented in Table 2.6 and Table 2.7 for female headed households. Male headed households summary statistics are presented in Table 2.8 and Table 2.9.

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 2.4: 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 Separated	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	594	0.06	0.24	474
Household Member has Chronic Illness	0.15	0.36	973	0.16	0.37	594	0.14	0.35	474
Household Dependency Ratio	3.07	2.44	973	3.39	2.51	594	2.64	2.27	474

Table 2.5: 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 Separated	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	3404	0.08	0.27	6839
Household Member has Chronic Illness	0.19	0.39	7922	0.21	0.41	3404	0.17	0.38	6839
Household Dependency Ratio	2.58	2.35	7922	2.21	2.53	3404	2.78	2.23	6839

Table 2.6: *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 Separated	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	463	0.05	0.21	283
Female Headed Household Member has Chronic Illness	0.17	0.38	688	0.18	0.38	463	0.16	0.37	283
Female Headed Household Dependency Ratio	3.25	2.48	746	3.42	2.52	463	2.96	2.39	283

Table 2.7: ***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 Separated	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	2543	0.08	0.28	3739
Female Headed Household Member has Chronic Illness	0.21	0.41	5093	0.22	0.42	2543	0.20	0.40	3739
Female Headed Household Dependency Ratio	2.72	2.53	6282	2.35	2.65	2543	2.98	2.41	3739

Table 2.8: 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 Separated	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	320	0.16	0.37	117	0.08	0.28	191
Male Headed Household Member has Chronic Illness	0.11	0.32	320	0.12	0.33	117	0.11	0.31	191
Male Headed Household Dependency Ratio	2.87	2.27	320	3.43	2.57	129	2.49	1.96	191

Table 2.9: 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 Separated	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	3958	0.15	0.36	640	0.07	0.26	3100
Male Headed Household Member has Chronic Illness	0.15	0.35	3958	0.18	0.38	640	0.14	0.35	3100
Male Headed Household Dependency Ratio	2.90	2.13	3958	2.70	2.50	858	2.96	2.02	3100

2.3.2 Theoretical Model

A static model is considered with 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 [8]. Assume individuals enter the model with exogenously determined assets A.

Consumption by the ultra poor is denoted as:

$$c_0 = A + w_0 + b \tag{2.1}$$

Consumption by the non ultra poor is denoted as:

$$c_1 = A + w_1 - \tau(b) \tag{2.2}$$

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:

$$\max V(e) = evc_1 + (1-e)uc_0 - \psi(e) \tag{2.3}$$

[8] While it might seem plausible to remove the tax on the non-poor in the model if the program is financed by development partners, there are significant implications to consider. Even if fiscal resources are sourced externally, the government still bears an opportunity cost. By not taxing the non-poor domestically, the government would forego an opportunity to raise revenue, which could be allocated to finance other essential programs not covered by external funding sources. Thus, taxing the non-poor is crucial not only for ensuring the financial viability of the program but also for enabling the government to address broader socio-economic challenges and meet the diverse needs of its population.

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

$$vc_1 - uc_0 = \psi'(e) \tag{2.4}$$

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

$$\begin{aligned} &\max_b W(b) = ev(A + w(_1 - \tau(b)) + (1-e)u(A + w_0 + b) - \psi(e) \\ &\text{s.t. } e = e(b) \end{aligned} \tag{2.5}$$

Differentiating 2.5 and using the FOC for e in 2.4 yields[9] :

$$\begin{aligned} \frac{dW(b)}{db} &= (1-e)u'(c_0) - \left[\frac{d\tau}{db}\right] ev'(c_1) \\ &= (1-e)\left[u'(c_0) - \left(\frac{\varepsilon_{1-e,b}}{e} + 1\right)v'(c_1)\right] = 0 \end{aligned} \tag{2.6}$$

2.3.3 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:

$$\frac{u'(c_0) - v'(c_1)}{v'(c_1)} \tag{2.7}$$

[9]See Appendix 2 for details

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

$$\frac{\varepsilon_{1-e,b}}{e} \tag{2.8}$$

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:

$$\frac{u'(c_0) - v'(c_1)}{v'(c_1)} = \frac{\varepsilon_{1-e,b}}{e} \tag{2.9}$$

Allowing for state dependent utility yields the following:

$$\frac{u'(c_0) - v'(c_1)}{v'(c_1)} = \gamma \frac{\Delta c}{c_1}(b) \tag{2.10}$$

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

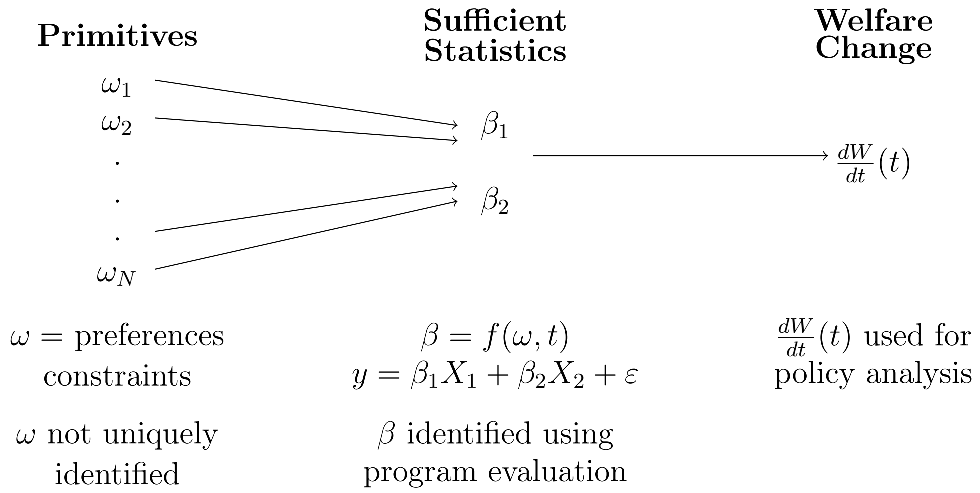
The benefit of the transfer program can be obtained by plugging equation 2.10 into equation 2.9:

$$M_W(b) = \gamma \frac{\Delta c}{(c_1)}(b) - \frac{\varepsilon_{1-e,b}}{e} \tag{2.11}$$

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.

The central concept of the sufficient statistic approach is to derive formulas (as illustrated in Figure 2.3) 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 (W), 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. The coefficients (βs) derived from analysis of treatment effects using PSM (discussed in the next section) will then be used in the sufficient statistic approach in this paper.

Figure 2.3: 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.

2.3.4 Empirical Strategy

2.3.4.1 Propensity Score Matching

The empirical approach adopts a casual inference method. 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 (see sub section 2.2.3 under data analysis and classification). This, therefore, renders the use of methodologies such as the Regression Discontinuity Design difficult. The unavailability of baseline data 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:

$$E(Y_i^T - Y_i^C \mid T_i = 1, X_i) = E(Y_i^T \mid T_i = 1, X_i) - E(Y_i^C \mid T_i = 1, X_i) \tag{2.12}$$

$E(Y_i^T \mid T_i = 1)$ 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 households had they not received the transfer. T_i is the treatment status where $T_i = 1$ represents a household receiving a transfer and $T_i = 0$ represents households not receiving the transfer. X_i represents observable characteristics which include PMT score, age, gender, marital status and education.

2.3.4.2 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).

$$(Y_i^T, Y_i^C) \perp T_i \,|\, X_i \tag{2.13}$$

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).

$$0 < \Pr(T_i = 1|X_i) < 1 \tag{2.14}$$

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.

2.3.4.3 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 as it has a count dependent variable (number of meals taken by 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 check if the equidispersion assumption holds and if not whether alternative count models were more appropriate. 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 (Dehejia and Wahba, 1999, Heckman et al., 1997). 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 (Cunningham, 2021, Gertler et al., 2016, Imbens, 2015). 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, Garrido et al., 2014, Leuven and Sianesi, 2018, 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 2.10 and Table 2.11). To account for uncertainty in treatment effect standard errors, the bootstrapped and Abadie-Imbens standard errors (Abadie and Imbens, 2016, Sianesi, 2004) 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 2.12 - Table 2.17, 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 [10]. 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 2.4 and Figure 2.5). As depicted in the density plots and boxes in Panels A and B of Figure 2.6 and Figure 2.7, 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 2.6 and Figure 2.7.

[10] 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 (Austin, 2009, Imai et al., 2008). However, this is simply complementing the diagnostic results from the standardized mean differences.

Table 2.10: *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 2.11: 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 2.12: Balance of Covariates Before and After Matching - Full Sample (Poorest)

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Untreated	%bias	|bias|	t	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 2.13: Balance of Covariates Before and After Matching - Female Headed Households (Poorest)

Variable	Unmatched	Mean			%reduct	t-test	
	Matched	Treated	Untreated	%bias	|bias|	t	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 2.14: 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 2.15: Balance of Covariates Before and After Matching - Full Sample (Poorer)

Variable	**Unmatched Matched**	**Mean**		**%bias**	**%reduct**	**t-test**	
		Treated	**Untreated**		**|bias|**	**t**	**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 2.16: 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 2.17: Balance of Covariates Before and After Matching - Male Headed Households (Poorer)

Variable	**Unmatched**	**Mean**			**%reduct**	**t-test**	
	Matched	**Treated**	**Untreated**	**%bias**	**$\lvert$bias$\rvert$**	**t**	**$p>\lvert t\rvert$**
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 2.4: Distribution of Propensity Score across Treatment and Comparison Groups - Poorest

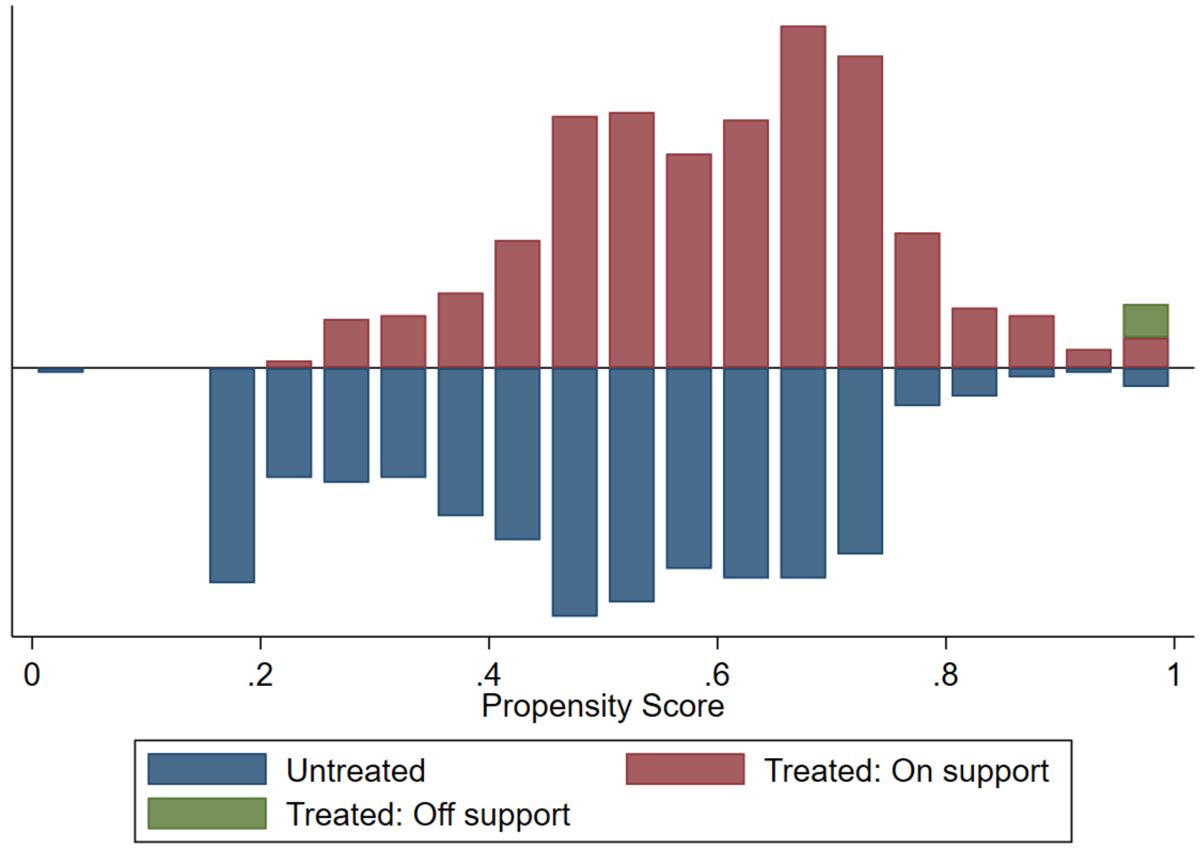


Figure 2.5: Distribution of Propensity Score across Treatment and Comparison Groups - Poorest

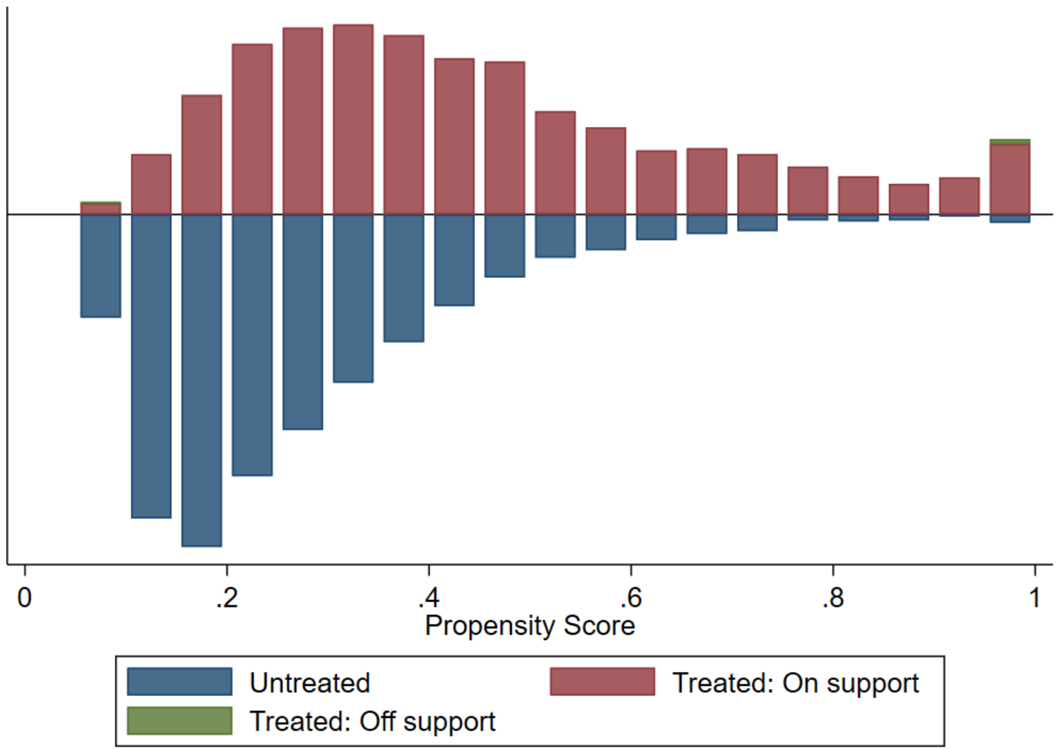


Figure 2.6: Assessing Matching Quality - Poorest

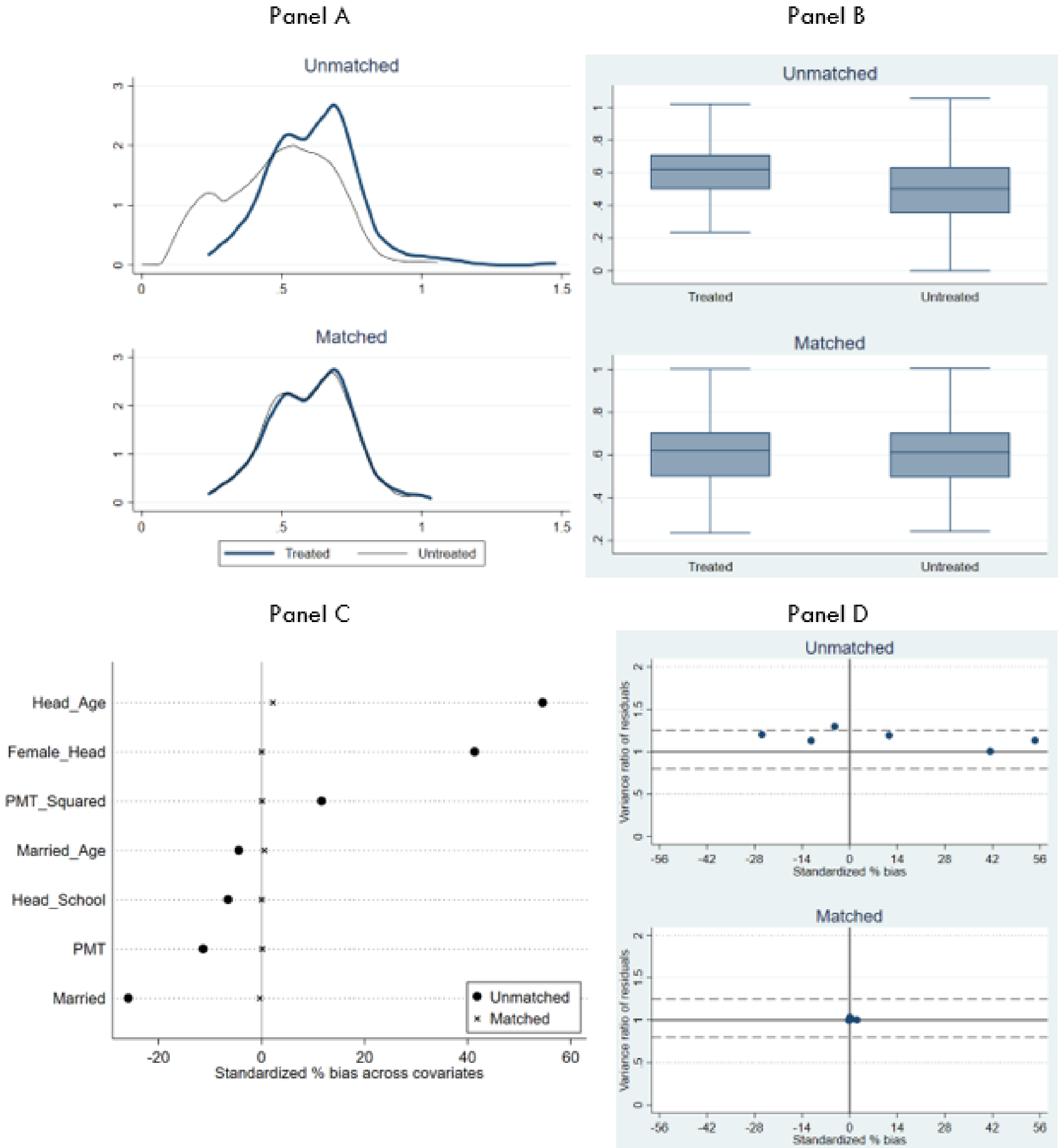
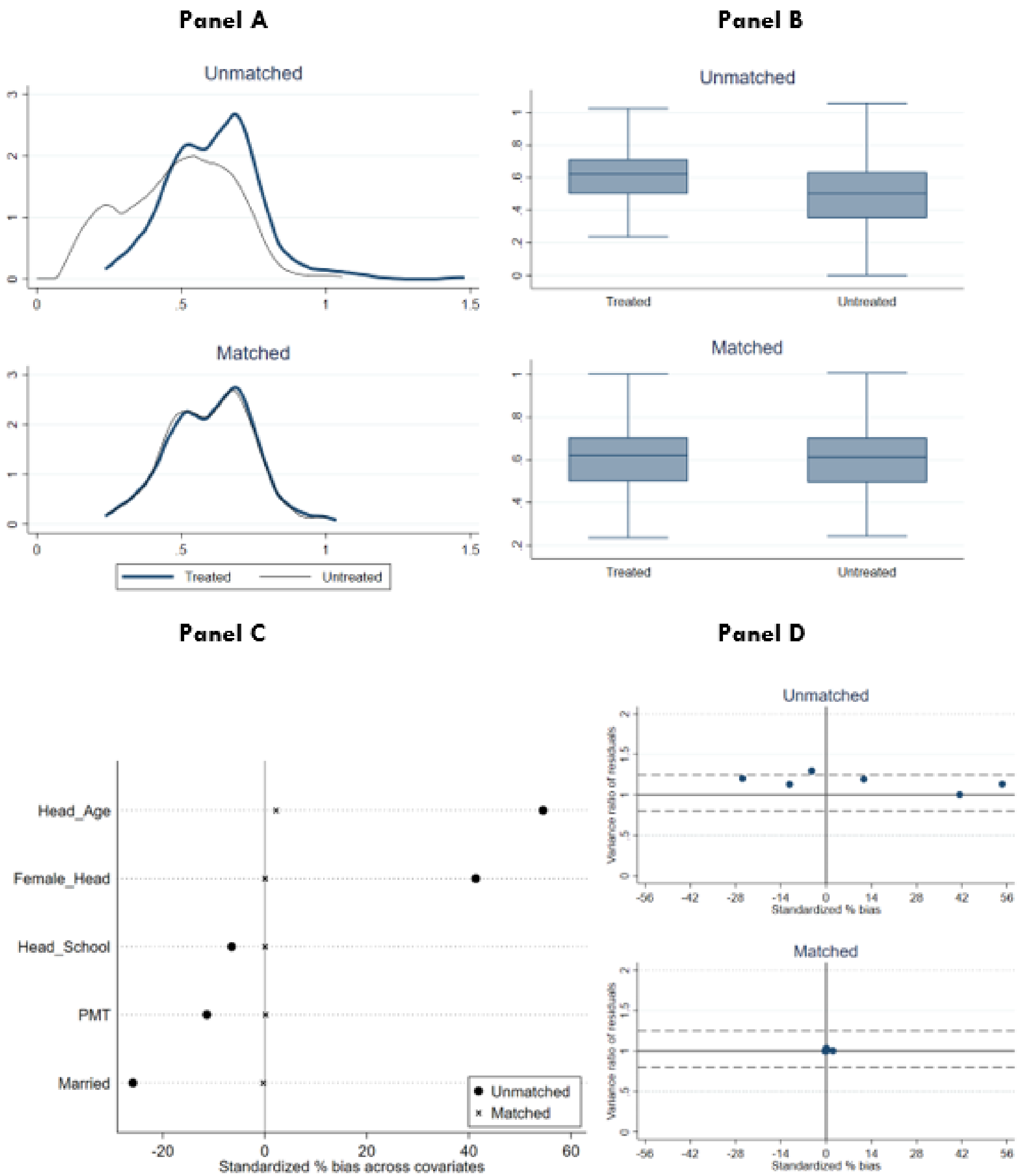


Figure 2.7: Assessing Matching Quality - Poorer



2.4 Results

2.4.1 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 households headed by females and males. The aim is to investigate potential gender disparities in the impact of the program.

For households overall, the hypothesis posits that participation in the program leads to an increase in the average number of daily meals consumed. For female headed households, the assumption is that if the cash transfer program begins to address gender disparities that disproportionately affect women, the effect of the program will likely be more pronounced. This expectation reflects the anticipation that female headed households, which may be more vulnerable to gender related inequalities, will experience a greater improvement in daily meal consumption as a result of the program.

The results for the poorest households are detailed in Table 2.18. For an intuitive interpretation of the poisson regression coefficient, it is common practice to exponentiate the estimated coefficient, yielding the incidence rate ratio (IRR). In this context, the results suggest that a unit increase in the cash transfer is associated with a 1.21 times higher expected count of average meals consumed by households, for the treated poorest households. In other words, a one percent increase in the cash transfer is estimated to correspond to a 21 percent ($p < 0.01$) increase in the average number of meals consumed by households.

Furthermore, when disaggregating households by gender, the analysis reveals differential effects. Female headed households exhibit a higher increase, estimated at 1.23 times more, in the expected count of average meals consumed compared to male headed households, which show a lesser increase, estimated at 1.16 times more. Stated differently, a one percent increase in the cash transfer is estimated to correspond to a 23 percent ($p < 0.01$) increase in meals eaten for female headed households, and a 16 percent ($p < 0.01$) increase in meals eaten for male headed households. These findings underscore the differential impact of the cash transfer program on household food consumption with regards to gender disparities.

The findings for treated poorer households, as presented inTable 2.19, reveals that among all households in the treated poorer category, a one percent rise in the cash transfer corresponded to a 15 percent ($p < 0.01$) increase in the expected count of average meals consumed. Similarly, for female headed households within this group, the increase was slightly higher, reaching 16 percent ($p < 0.01$). Male headed households experienced a slightly lower increase of 12 percent ($p < 0.01$) in the expected count of average meals consumed. These findings underscore the significant impact of the cash transfer program on enhancing food consumption among treated poorer households. Moreover, the differential effects observed between female and male headed households highlight the importance of considering gender dynamics in social welfare interventions.

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. Similar conclusions were drawn by Abdoulayi et al. (2014), Handa et al. (2015) and Abdoulayi et al. (2016), who conducted a comprehensive assessment of the Malawi SCTP through baseline, midline, and endline randomized control experiments. 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 [11] 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 percent. Similarly, this suggests that impacts are likely to be larger among the poorest households.

The analysis conducted in this paper reveals compelling evidence of the effectiveness of the evaluated program. The results indicate significant impacts not only among the poorest households but also across all households, including those categorized as poorer. This finding is consistent with prior studies (Abdoulayi et al., 2016, Handa et al., 2015), which also underscored the program's broad-reaching impact.

Moreover, our analysis delves deeper into these findings, examining the positive outcomes among the two aforementioned groups separately. Additionally, the impact is further assessed on the basis of the gender of the household head, providing nuanced insights into the effectiveness of the program across different demographic segments.

[11] 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

Research in the literature on social protection programs in other African countries has yielded comparable findings regarding the impact on consumption and food security among beneficiaries. For instance, Ralston et al. (2017) reported a substantial increase in both total consumption (24 percent) and food consumption (23 percent). Similarly, Brugh et al. (2018) found that the program was linked to an average 11 percentage point increase in the likelihood of consuming more than one meal. These studies contribute to a growing body of evidence highlighting the positive effects of social protection interventions on household well-being across various contexts in Africa.

This paper diverges from the conventional scope of prior studies on *Mtukula Pakhomo*, which mainly centered on evaluating the program's impact on consumption levels. By using the sufficient statistic approach, the analysis delves deeper in not only understanding the dynamics of consumption smoothing resulting from program participation. It further offers a comprehensive assessment of the broader welfare implications for beneficiary households, thereby providing a more holistic understanding of the impact beyond mere consumption outcomes and whether or not the scale is optimal.

2.4.2 Sensitivity Analysis

As a robustness check, the sample of ultra-poor households (encompassing both the poorest and the poorer categories) was pooled into a single group, a method commonly employed in most studies evaluating the SCTP (Abdoulayi et al., 2014, 2016, Baird et al., 2011, Brugh et al., 2018, Handa et al., 2015, Miller et al., 2011, Ralston et al., 2017). The results in Table 2.20, remain consistent across these different methodological approaches. Specifically, they indicate an average increase in meals consumed by treated households of 15 percent ($p < 0.01$) for all households, 16 percent ($p < 0.01$) for female headed households, and 12 percent ($p < 0.01$) for male headed households. These findings underscore the robustness of findings and validates the positive impact of the SCTP on consumption, regardless of the sampling approach.

Another variation in our analysis involved examining the data from the two districts individually. Despite differences in magnitude, the results obtained at the district level remained consistent with those from the pooled analysis.

Table 2.18: 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 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 2.19: 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 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 2.20: 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 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.

2.4.3 Welfare Gain from Social Insurance

The welfare gain can be calculated from Equation 2.11 in Section 2.3.3 and the coefficient that has been estimated in Table 2.18, Table 2.19 and Table 2.20 in Section 2.4.1.

Restating Equation 2.11

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

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 2.18, Table 2.19 and Table 2.20. Panel A in Table 2.21 for all households, Table 2.22 for female headed households and Table 2.23 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 2.21, Table 2.22 and Table 2.23. As γ increases, it means that the household is more risk averse hence a higher value is placed on the provision of social insurance.

For estimating the cost of the program, a simple yet practical approach is adopted. Leveraging data on ultra-poverty rates prior to the full roll out across all districts, a comparison is made of the incidence of poverty between districts with and without the program. This serves as a proxy for moral hazard due to potential of households to take on more risk or reduce effort due to absence of the social cash transfer. It reflects the essence of the targeted selection process of the program, which is non-random and tends to prioritize areas with higher ultra-poverty rates. While this method may skew the estimate of moral hazard upward, it is worth noting that even under very low levels of risk aversion (γ), the marginal benefit remains positive so it does not change the interpretation of the results. Furthermore, it is recognized that this approach captures the inherent nature of the program, whose aim is to address poverty where it is most prevalent.

To quantify the effort required for program participation ($\varepsilon_{1-e,b}$), an OLS regression is estimated. In the model ultra-poverty incidence is employed as the dependent variable and a binary indicator of program presence in the respective districts as the independent variable. Additionally, district level factors are controlled for. These are region (north, centre and south), population, proportion of employed households, and tribe (chewa, lambya, lomwe, ngoni, nyanja, sena, tonga, tumbuka and yao). The coefficient estimated from this regression (Table A.1 in Appendix 2) serves as our measure of the program's cost in terms of effort expended.

Taking into account risk aversion, observed changes in consumption, and the effort required, a sufficient statistic for evaluating the welfare implications of the program is obtained. The positive difference between the simulated benefit and the estimated moral hazard cost indicates a tangible enhancement in the welfare of households benefiting from the SCTP. This underscores the effectiveness of the program in improving the overall welfare of targeted households. It can be further inferred that the level of benefit as currently estimated is actually far from optimal. The analysis thus highlights the imperative for further optimization and refinement of the program to ensure it attains maximal efficacy in alleviating poverty and enhancing the welfare of vulnerable households.

Table 2.21: 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 ($\Delta c/c$)				
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 ($\gamma\Delta c/c$)				
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 ($\varepsilon 1\text{-}e,b/e$)				
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.

Table 2.22: 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 (Δc/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 (γΔc/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 (ε1-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 2.23: 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 (Δc/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 (γΔc/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 (ε1-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.

2.5 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.

Chapter 3

More Money for Health: Projecting Fiscal Space for Health

(Co-author: Paulo Santos Monteiro)

3.1 Introduction

Most developing countries are faced with the challenge of matching limited resources against competing priorities. Literature Mcintyre et al. (2017), World Health Organization (2001, 2010) suggests that government health spending in Low and Lower Middle Income Countries (LLMICs) should be at least 5 percent of the Gross Domestic Product (GDP) for the country to progress towards Universal Health Coverage (UHC). However, existing data shows that for most LLIMCs (especially in Sub Saharan Africa), spending on health over the past two decades averaged about 2 percent of GDP. Considering the macroeconomic and fiscal realities of countries, policy dialogue on health financing is critically important.

As highlighted by the World Health Organisation World Health Organization (2001), improving health contributes fundamentally to economic development, particularly for the poor. This connection, often underestimated, is a powerful means for achieving various development goals, including poverty reduction Barro and Sala-i Martin (2004), Bloom et al. (2001), Easterly and Levine (1997), Hsiao and Heller (2000), Mankiw et al. (1992), Sachs and Warner (1995), World Bank (2004), World Health Organization (1978). Despite its qualitative and quantitative significance, research establishing a causal role for improved health in economic growth remains limited World Health Organization (2001).

This paper, therefore, estimates a panel Structural Vector Autoregressive (SVAR) model with macro-fiscal and health blocks to study how structural shocks jointly affect the macroeconomy and health outcomes in the short run. The analysis is underpinned by a framework that establishes causal relationships between public expenditure, health and human capital dynamics, and macroeconomic outcomes. The model is estimated for Eswatini, Malawi, Mauritius, and Zambia using annual data over a 20-year period from 2000 to 2020. These countries were the selected East, Central and Southern Africa (ECSA) focus member states that were to inform African Union led health financing dialogues between Ministries of Finance and Health. It is noted that Mauritius is different from the other countries in several significant aspects. It boasts a more diversified economy, with a strong emphasis on services like tourism and financial services, whereas the other countries rely predominantly on agriculture. Additionally, Mauritius has historically experienced higher and more consistent economic growth rates, attracted more foreign investment, and maintained relatively prudent fiscal and monetary policies, leading to lower public debt levels and greater stability. In contrast, Eswatini, Malawi and Zambia have often struggled with fiscal deficits and high debt burdens, alongside higher inflation rates and currency volatility.

This study aims to answer four research questions, namely: (i) how health expenditure and the macroeconomy are intertwined; (ii) the effects of macro structural shocks on health outcomes; (iii) whether health expenditure and other components of government spending are rival competitors for fiscal capacity; and (iv) how external shocks affect macroeconomic and health outcomes. It provides contextual evidence on the macroeconomic and fiscal developments of the four countries over the last two decades [1]. These are also described in relation to outcomes on health and incidence of poverty. The dynamic panel model that is considered includes child mortality (under 5 mortality per 1,000 live births) as a proxy for health outcomes.

Fiscal multipliers, which show the ratio of output change to an exogenous change in the fiscal deficit compared to their baselines, are identified for various public expenditure components. Put simply, they measure how changes in public spending affect the economy. This allows the construction of counterfactual scenarios, making it possible to examine diverse fiscal policy plans and their potential impacts on both macroeconomic and health outcomes. In essence, these multipliers measure the immediate effects of discretionary fiscal policy on output Batini et al. (2014).

The main approaches to estimate fiscal multipliers highlighted by Kraay Kraay (2012) and Spilimbergo et al Spilimbergo et al. (2009) are: (i) the vector auto-regression (VAR) based identification schemes with Blanchard and Perotti Blanchard and Perotti (2002) as a leading example; (ii) case studies that isolate a sub-component of spending or taxes that is likely to be uncorrelated with contemporaneous economic shocks such as Barro Barro (1981) or identify an external source of variation in government spending unlikely to be correlated with contemporaneous macroeconomic events such as Romer and Romer Romer and Romer (2010); (iii) Model simulations with an underlying ISLM structure; and (iv) econometric studies of consumer behavior in response to fiscal shocks.

[1] See Appendix 3

While acknowledging the merits of each approach, the VAR method is typically preferred for estimating fiscal multipliers due to its strong empirical foundation, ability to capture dynamic interactions among variables, adaptable model specification, and robust identification schemes for mitigating endogeneity concerns. In this paper, the VAR approach is selected based on these strengths and its alignment with the research questions, considering the availability of data and the underlying assumptions guiding the analysis.

It has been shown that the size of the fiscal multiplier is country, time, and circumstance specific. On the one hand, in Low Income Countries (LICs), the cross-country VAR estimates of fiscal multipliers range from negative to 0.5. This is partly due to higher fiscal sustainability concerns. Nonetheless, it is recognized that these estimates can be downward biased as a result of lack of accurate data leading to attenuation bias Spilimbergo et al. (2009). On the other hand, evidence from most developed economies has presented an array of estimates ranging from ranging from zero (and even negative) to well above one Kraay (2012). This is also evident in the study by Ilzetzki et al Ilzetzki et al. (2013) who found that the output effect of an increase in government consumption is larger in industrial than in developing countries and that fiscal multipliers in high-debt countries can be negative.

Our identification strategy follows the traditional use of SVAR models to identify fiscal shocks. It follows Blanchard and Perotti Blanchard and Perotti (2002) who used a mixed structural VAR and event study to characterize the dynamic effects of shocks in government spending and taxes on US activity in the post war period. Their results were consistent with standard wisdom showing a positive government spending shocks having a positive effect on output whilst positive tax shocks had a negative effect. The multiplier, however, was small - often close to one. This was explained by the crowding out effect of different components of output.

The results from our analysis reveal four main findings related to the research questions. Firstly, increased public health spending is associated with improved health outcomes, even in the short run. Secondly, the short run impact of negative macroeconomic shock puts adverse pressure on resources available in health. Thirdly, evidence of rivalry for fiscal capacity across components of public spending is also shown. Lastly, investing in health is particularly vulnerable to exogenous shocks such as fluctuations in the ease of access to international liquidity.

The rest of this chapter is organised as follows: Section 3.2 provides the methodolody adopted. Section 3.3 presents the data used in this paper. Section 3.4 presents the key findings. Section 3.5 concludes the chapter drawing on the empirical results.

3.2 Empirical Dynamic Model

A panel Structural Vector Autoregressive (SVAR)[2] is estimated jointly for Eswatini, Malawi, Mauritius, and Zambia, using annual data over a 20-year period from 2000 to 2019. The aim is to study how structural shocks to the output, different sub-components of public expenditure (notably, health expenditure) and exogenous financial shocks jointly affect the macroeconomy and health outcomes in the short-run[3].

3.2.1 Model Specification

A generalized method of moments (GMM) model is estimated by pooling together the data on all four countries. This is similar to, for example, Ravn et al. (2012) who also propose a panel SVAR model to estimate the response of economic activity, inflation rates and real exchange rates using a panel of four industrialized countries.

As in the traditional VAR all variables enter the model endogenously except for one variable. This is the external financial shocks proxied by the measure of stress in emerging market corporate bonds markets.

The model is estimated as follows:

$$X_{it} = \alpha_{it} + \sum_{s=1}^{p} X'_{it-s}\beta + C_i + T_{i,t} + \varepsilon_{it} \tag{3.1}$$

where α_{it} contains the deterministic trend components and, possibly, additional exogenous variables. The number of lags included in the model is set at $p = 2$[4]. C_i are country fixed effects and $T_{i,t}$ are country time effects. $\varepsilon_{it} = Be_{it}$ denotes the vector of reduced form residuals which is given by a combination of the structural shocks. X_{it} is the vector of endogenous variables at time t for each country i and is given by:

[2] A Vector Autoregressive (VAR) is an n-equation, n-variable linear model in which each endogenous variable is in turn explained by its own lagged values, plus current and past values of the remaining variables (Stock and Watson, 2001). When additional restrictions are imposed on the contemporaneous links among the variables (identification restrictions) we obtain a structural VAR, and it becomes possible to identify structural shocks

[3] The short-run is referring to business cycle and higher frequencies, with the typical business cycles corresponding to periodicities of 6 years

[4] As in (Bernanke and Mihov, 1998) we determine the number lags estimating different lags until the last lag was statistically insignificant

$$X_{it} = \begin{bmatrix} \text{change in government expenditure} \\ \text{real GDP growth} \\ \text{share of health expenditure} \\ \text{change in child mortality (\% live births)} \\ \end{bmatrix}$$

The model is estimated on stationary data and to achieve stationarity we consider the growth rate of GDP and the changes in the share of government expenditure and in child mortality instead of their levels. Moreover, any deterministic trends are estimated and removed.

To address the concern around correlation between fixed effects and the covariates leading to biased estimates (Holtz-Eakin et al., 1988) the model uses a GMM to fit a multivariate panel regression of each dependent variable on own it's lags and those of all other dependent variables (Abrigo and Love, 2016).

3.2.2 Identification of Shocks

The structural shocks are identified by ordering the variables such that government spending is not affected contemporaneously by any shock other than the structural shock to government spending. GDP growth is allowed to vary contemporaneously with the government expenditure shock and an economic activity shock. A third structural shock that we identify is to the share of expenditure in health as a share of total government outlays. Fiscal multipliers associated with different sub-components of public expenditure are identified. This allows construction of counterfactual scenarios regarding different fiscal policy plans and macroeconomic and health outcomes.

Ordering government expenditure before GDP follows the tradition in the empirical studies of fiscal multipliers using VAR models (Bernanke and Mihov, 1998, Blanchard and Perotti, 2002, Gordon and Leeper, 1994). In this paper it is justified by both theoretical and empirical considerations. The causal directionality assumed in economic models positions government spending as an exogenous variable that directly influences GDP, reflecting the focus on understanding the impact of fiscal policy actions on economic output. This ordering facilitates the estimation of fiscal multipliers, crucial for assessing the effectiveness of government spending policies, by capturing the immediate effects of expenditure shocks on GDP. Additionally, adhering to empirical conventions established in prior research ensures consistency with widely accepted practices in the estimation of fiscal multipliers using VAR models.

3.2.3 Impulse Response Functions

The Cholesky decomposition proposed by Sims (1980) imposes a recursive structure on a VAR. However, the decomposition is not unique but depends on the ordering of variables (Abrigo and Love, 2016). It is the commonly used decompostion of the variance-covariance matrix of residuals to compute impulse-response functions. The IRFs are then computed based on the ordering described above.

3.3 Data Description

The dynamic panel model is estimated with macro-fiscal and health blocks. Endogenous variables are sourced from the World Development Indicators database (World Bank, 2022b) whilst exogenous variables are from the Federal Reserve Economic Data database (Federal Reserve Economic Data, 2022). It covers the period 2000 to 2020.

3.3.1 Macro-Fiscal Variables

The macroeconomic and aggregate fiscal variables included in the macro block of the SVAR model are the percentage change in a country's real GDP, and the change in total government expenditure as a proportion of GDP. On the one hand, Real GDP growth serves as a fundamental indicator of economic performance, reflecting the overall expansion or contraction of the economy over time. On the other hand, the change in total government expenditure as a share of GDP offers crucial information about the fiscal stance of the government and its role in influencing aggregate demand and economic outcomes. By examining the interaction between these variables within the SVAR framework, we can analyze the dynamic effects of fiscal policy shocks on economic activity, government spending behavior, and the overall macroeconomic environment. This comprehensive approach enables a deeper understanding of the interplay between fiscal policy, economic growth, and broader macroeconomic conditions, thereby informing policy decisions and shaping future economic strategies.

3.3.2 Health Variables

In the health block of the model, we include health expenditure as a share of total government expenditure and the rate of change in child mortality (under 5 mortality per

100,000 live births). This latter variable is chosen as our proxy for health outcomes because this is a variable which is likely to respond more quickly to changes in health expenditure and macroeconomic conditions compared to other more slow-moving health outcomes, such as chronic diseases. It should be noted that the analysis in this paper focuses on government spending specifically allocated within the national budget toward the health sector. This focus is somewhat constrained due to challenges in accessing off-budget data, particularly concerning external aid or donor-financed contributions not channelled through the government budget. However, despite this constraint, the exclusion of off-budget data does not diminish the significance of understanding the fiscal impact and effectiveness of health expenditures. By concentrating on health funding provided on budget, this approach allows for a more direct examination of the relationship between health spending and broader fiscal dynamics, thus highlighting its crucial importance within the national budgetary framework.

3.3.3 Finance Variable

The external finance premium serves as an exogenous shock, representing the additional cost or risk premium incurred by firms when obtaining external financing, such as through bond issuance or borrowing from financial markets. This premium is proxied by the corporate spread observed in emerging markets across Europe, Africa, and the Middle East. The corporate spread denotes the disparity between interest rates on corporate bonds and government bonds with comparable maturities, reflecting the supplementary yield demanded by investors for holding corporate bonds over government securities.

3.3.4 Short Run Dynamics

Although this is a pooled analysis thereby offering valuable insights into broad trends and patterns, it is important to examine the short run dynamics in the individual countries. This provides deeper insights into the specific contexts, drivers, and implications of the observed phenomena. All the endogenous variables for each country included in the panel SVAR model are thus shown in Figures 3.1 - 3.4. Some of the main data trends described in Appendix 3 for each country are placed in evidence. The following focuses on some of the short-run dynamics in each of the four countries during the period 2000 to 2020.

In Eswatini (Figure 3.1), the deep fiscal contraction following the global financial crisis around 2010 is very salient. The fiscal retrenchment had a detrimental impact on the level of public investment in health spending, which also appears to have halted some of the progress made in relation to health outcomes. This is evident in the dramatic slowdown in the decline in child mortality since 2010.

In Malawi (Figure 3.2), despite macroeconomic volatility, there have not been large fiscal contractions. Average GDP growth has been strong and at the same time, the share of expenditure in health as a share of total government outlays has increased. This has led to improvements in health outcomes, noticeably with regards to child mortality. Although there are concerns about fiscal capacity and fiscal space, there seems to have been a sustained effort to improve human development outcomes.

Until the COVID 19 pandemic, Mauritius had enjoyed a stable macroeconomic outlook. It had also achieved significant gains in relation to improving its healthcare sector with significant increases in health expenditure as a share of total government outlays (Figure 3.3). But the Mauritius economy, which is especially dependent on international travel and its tourism industry, has suffered since the 2020 pandemic. As a result, it lost fiscal capacity and remains in a more fragile position compared to earlier years. Unfortunately, health outcomes have also deteriorated in the most recent years. This is despite the successful public health campaign directed at protecting the population from the Covid epidemic[5].

Zambia's macroeconomic outlook has deteriorated since 2010 and the latter period of the decade have been characterized by substantial fiscal retrenchment and weak GDP growth (Figure 3.4). There were big improvements in health outcomes at the start of the century but these have also slowed in recent years.

[5] Mauritius' vaccination campaign covered over 90 percent of the eligible population by May 2022

Figure 3.1: Key Economic and Social Data Eswatini

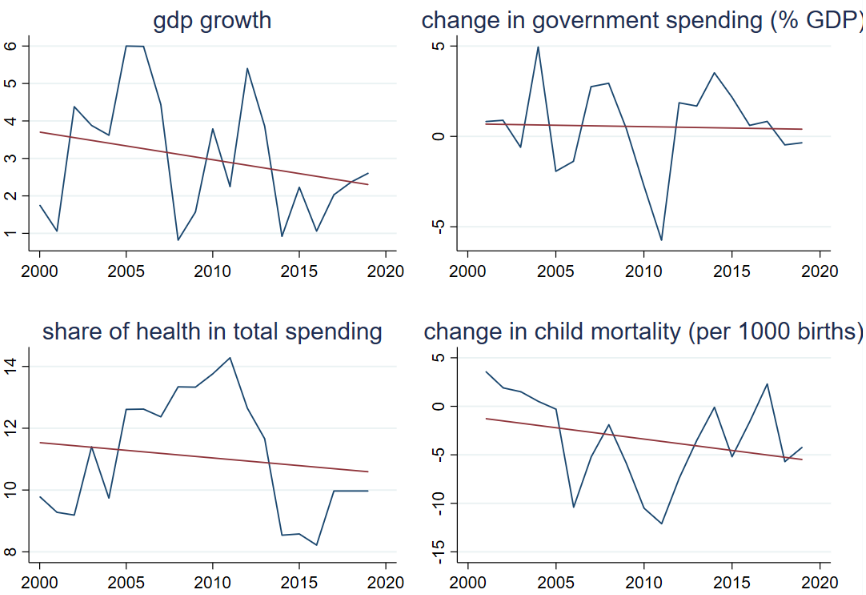


Figure 3.2: Key Economic and Social Data Malawi

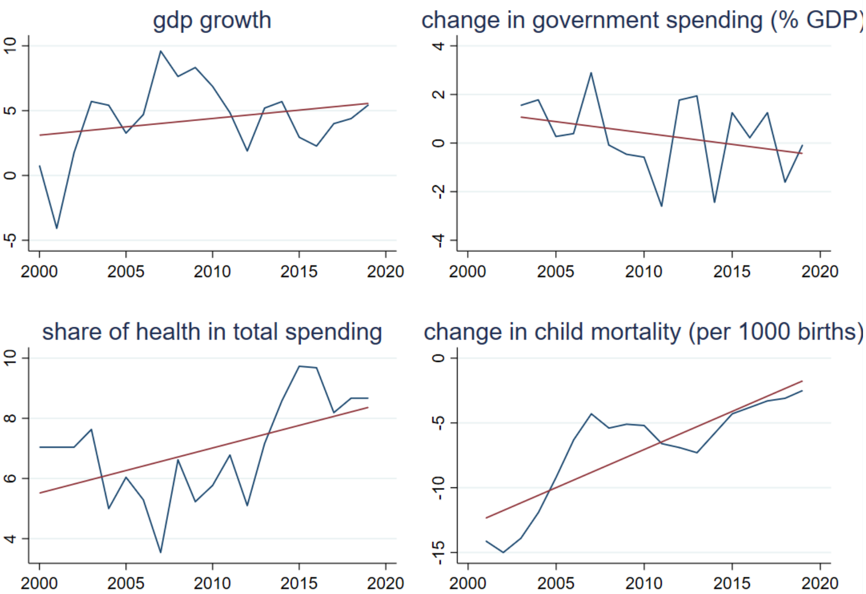


Figure 3.3: Key Economic and Social Data Mauritius

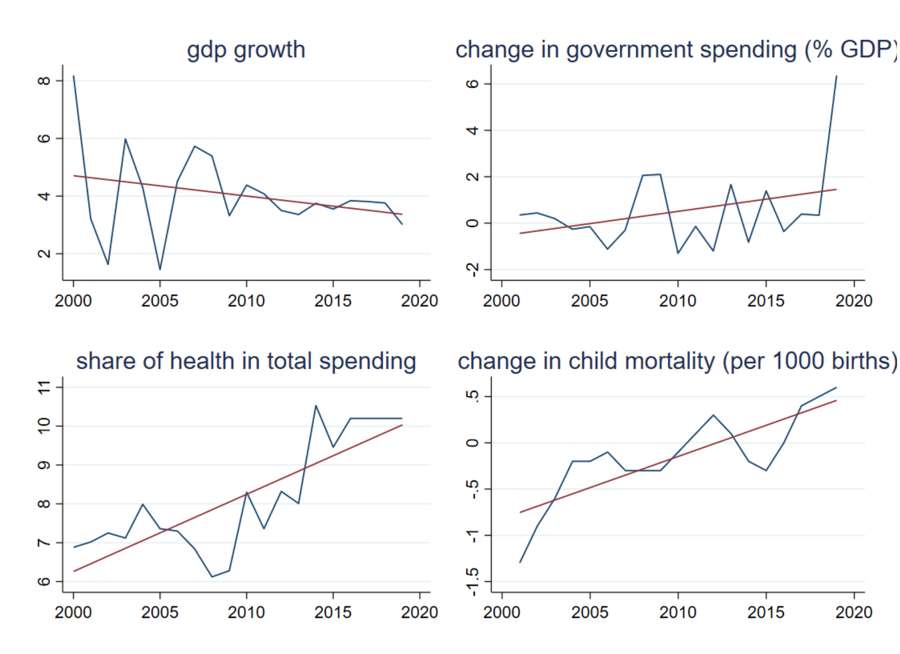
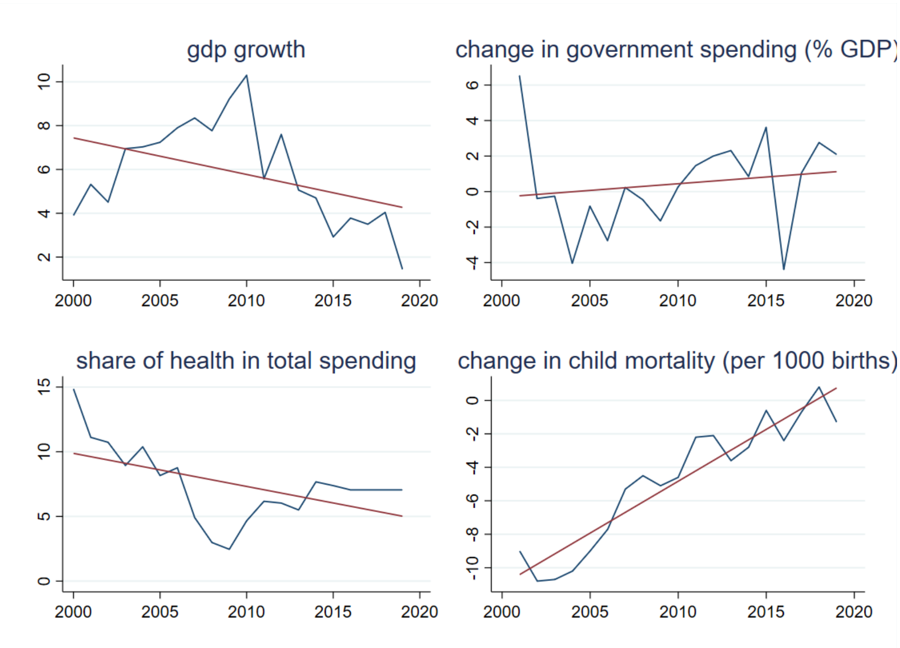


Figure 3.4: Key Economic and Social Data Zambia



3.4 Empirical Results

The structural analysis based on the SVAR model looked at the dynamic transmission of the three identified endogenous structural shocks: government expenditure shock, a GDP growth shock, and health expenditure shock. An exogenous financial shock is also considered. This analysis is conducted using structural IRFs which show the accumulated response of the endogenous variable in the SVAR to each structural shock for a 10 year time horizon.

The IRF are reported alongside the 50 percent confidence intervals, a justifiable size given the relatively small data and resulting low power of the statistical discrimination. (Figure 3.5) reports the IRFs corresponding to a government spending shock. A positive expenditure shock over a 10 year horizon raises the total government expenditure as a share of GDP by roughly 2.5 percentage points. This results in an accumulated change in GDP of roughly 1 percentage points. Thus, the long-run multiplier is estimated to be roughly equal to 0.28, which is in line with some of the consensus fiscal multiplier estimates available in the literature (Ramey and Zubairy, 2018).

The 2.5 percentage points increase in overall government expenditure (as a share of GDP) conditional on the exogenous expenditure shock is found to lower the share of expenditure in health (as a share of total government outlays) by roughly 1.5 percentage points. This finding indicates that the different sub-components of public expenditures are rivalling sources of funding demands. This suggests an environment in which there are binding constraints on fiscal capacity and, thus, in which there are trade-offs confronting the public sector with regards to funding different components of the public sector, including the health sector. The fiscal shock also affects the change in child mortality in a direction which is detrimental to health outcomes. This suggests a connection between overall increasing government expenditure lowering the share of expenditure in health and, thus, worsening health outcomes.

Apart from the rivalry, the observed trend of an increase in government spending coupled with a decrease in the health share could also be attributed, at least in part, to the influence of health aid. In instances where development partners provide substantial support towards health, governments may opt to allocate a smaller share of their own resources to the sector, thereby freeing up funds to address other pressing needs or policy priorities. This strategic reallocation of resources underscores the dynamic interplay between domestic government spending and external assistance, shaping fiscal decisions and resource allocation strategies. Recognizing this is essential in ensuring a nuanced understanding of the factors driving fiscal decision-making and resource prioritization.

The second structural shock we consider is a positive shock to overall economic activity, dubbed a GDP growth shock. The IRFs to a GDP growth shock are reported in (Figure 3.6). The GDP growth shock is one which raises GDP growth by a cumulative amount of 3 percentage points over a 10 year horizon. This shock results in a reduction in the share of government expenditure (as a proportion of GDP) of only 0.5 percentage points. This means that government outlays increase in nominal terms following the increased economic activity, once again suggesting binding constraints to fiscal capacity. The GDP growth shock does not affect the government budgeting across health and the other components of public expenditure, as the share of expenditure in health remains roughly constant. Despite that, a positive shock to economic activity is clearly beneficial to health outcomes. This is consistent with what we would expect if an increase in disposable income, for example, alleviates poverty and improves living conditions.

The third structural shock considered is a shock to health expenditure. This shock is ordered third, implying that a shock to health expenditure is allowed to affect contemporaneously GDP and the government's fiscal outlays but is only allowed to improve health outcomes within at least one year. In other words, while the shock may affect economic variables immediately, its influence on health outcomes is expected to exhibit a delayed response, taking at least one year to materialize. The IRFs for the health expenditure shock are presented in (Figure 3.7). The cumulative impact of the health expenditure shock on the share of health expenditure in total public outlays is substantial (above 5 percentage points). Importantly, the total government expenditure (as a share of GDP) conditional on a health expenditure shock stays constant. This means that an increase in health expenditure is accommodated by reducing spending on other components of public outlays. This reallocation ensures that the government's total expenditure remains constant as a share of GDP, even as priorities shift towards the health sector. Once again it is apparent that the fiscal capacity of the countries in our sample is limited and that there are significant trade-offs faced by the public sector in the allocation of resources.

The health expenditure shock appears to have a negative cumulative impact on GDP growth, which may be associated with the crowding out of components of public expenditure with larger short-run multipliers compared to health expenditure. At the same, the health expenditure shock has a clear positive impact on health outcomes, lowering child mortality considerably over the 10-year horizon. Thus, there is a clear positive health multiplier of increased health expenditure in the short-run, which adds to the clear long-run benefits of improved investment in healthcare. However, the limited fiscal space and severely constrained public finances of the countries studied poses a difficult challenge for policymakers wishing to achieve macroeconomic stability and at the same time fulfil the long-run objectives with regards to public health and human development.

In the countries considered, the availability of resources to invest in health is particularly vulnerable to fluctuations in the ease of access to international liquidity.

To illustrate this phenomenon, we estimate IRFs for each of the four variables in our SVAR to exogenous shocks to the external finance premium in African countries. The estimated IRFs are shown in (Figure 3.8). External liquidity shocks are found to have a substantially negative impact on the expenditure in health as a share of total government expenditure and this is associated with worsening health outcomes.

Figure 3.5: Impulse Response Function: Government Spending Shock

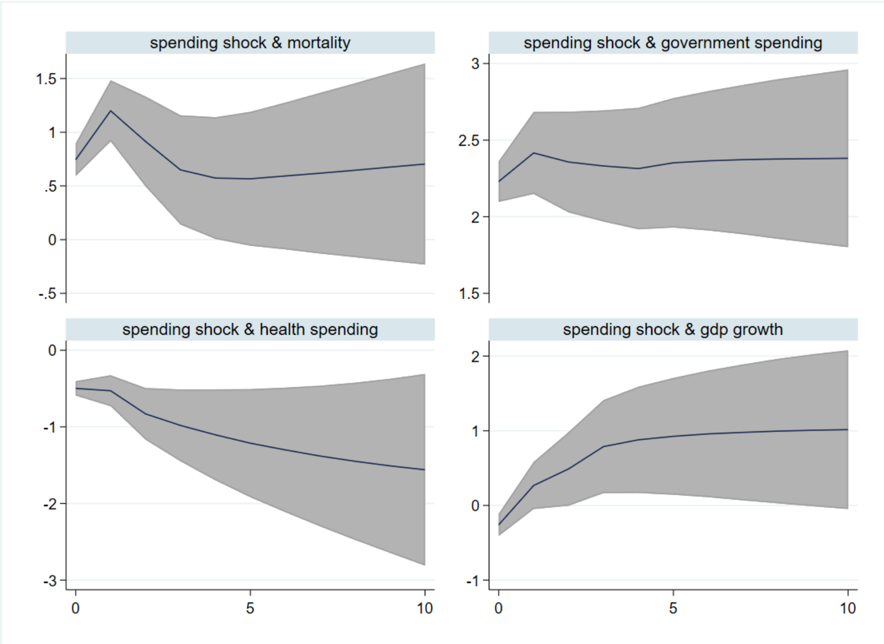


Figure 3.6: Impulse Response Function: GDP Growth Shock

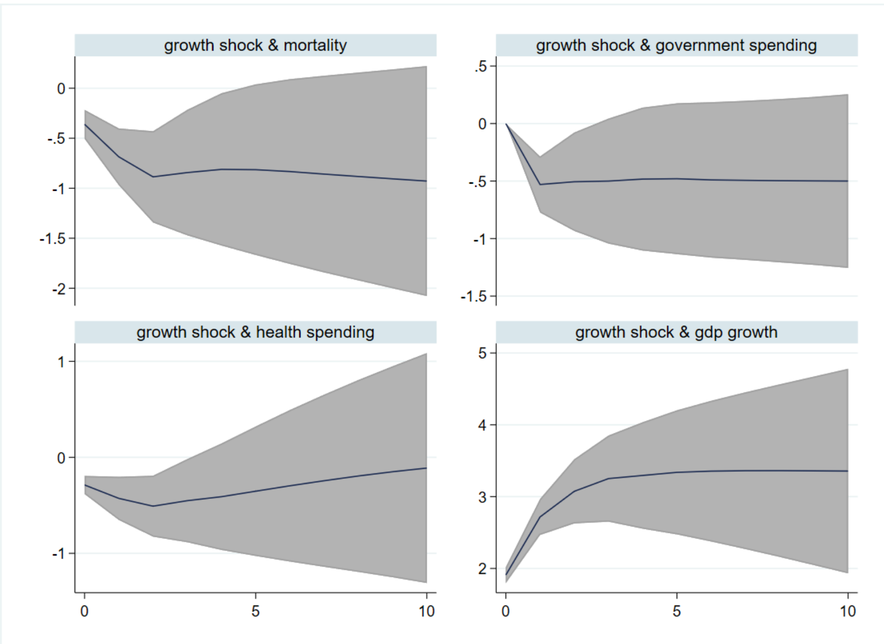


Figure 3.7: Impulse Response Function: Health Shock

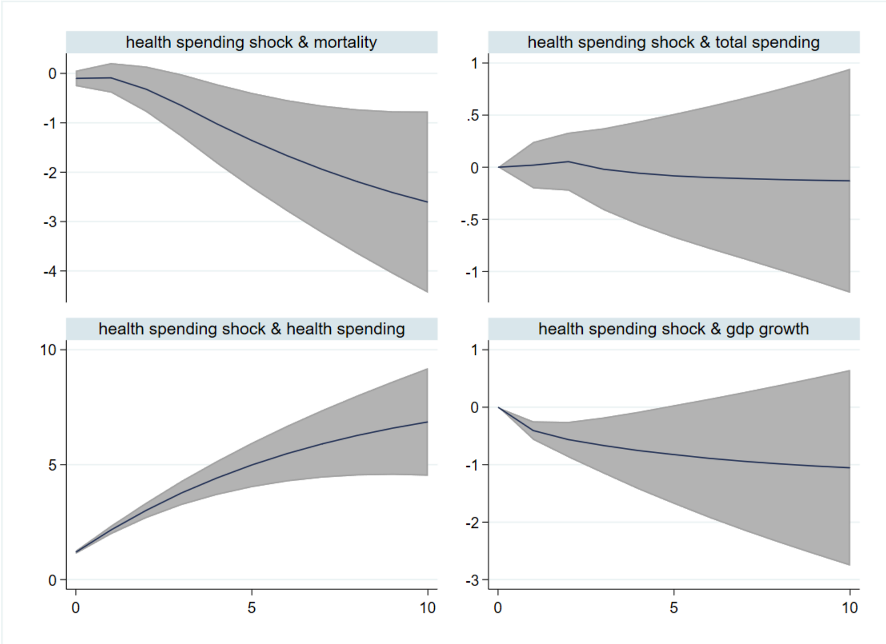
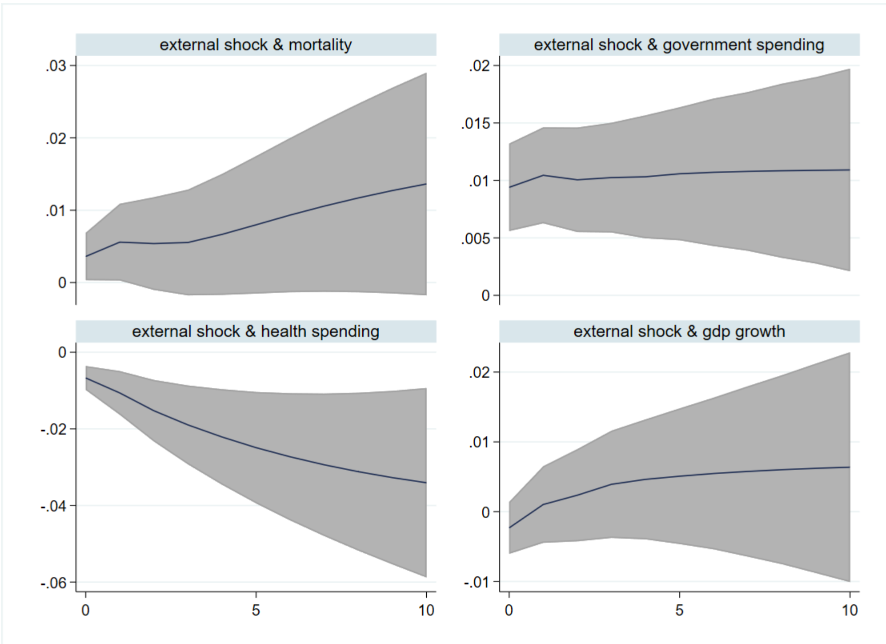


Figure 3.8: Impulse Response Function: External Finance Shock



3.5 Conclusion

The results highlight important public policy challenges for African countries. It is a clear policy priority for African countries to achieve significant improvements in population health and robust healthcare systems. To achieve this public health expenditure is paramount, as it represents the principal source of health finance. However, fiscal space is limited and macroeconomic stability often either hinges on curtailing public expenditure or, even if counter-cyclical fiscal policy stabilization is feasible, there is a clear incentive to favour expenditure on public investments with the largest GDP multipliers in the short run. As seen, this may fail to adequately protect funding to the healthcare system. Easy access to international capital markets and special financing facilities for investment in healthcare may, therefore, be important to alleviate the existing constraints.

Health spending should thus be viewed as an economic investment rather than a cost. It is recognised that the short run economic multiplier effect of health spending is not as large as some other forms of public spending. Nonetheless, the long run implications cannot be ignored. Spending public resources on health leads to improved population health and associated economic returns. This calls for examination of how health expenditure can achieve even greater economic returns and facilitate greater public investments into the sector. Research is still in its infancy, but spending on healthcare inputs that have higher multipliers and aligning health sector and industrial policy objectives could be possible ways. Further research on how to increase the multiplier effects of health spending is desperately sought. A clear policy priority is to achieve improvements in population health and robust healthcare systems. Needless to say, a holistic approach is key in the balance between increased resources for health alongside efficient, effective, and equitable use of those resources to achieve health sector objectives.

Conclusion

This thesis has discussed three chapters that have provided empirical evidence on household and government consumption patterns, macroeconomic shocks and the welfare implications. The studies have not only employed theoretical and empirical strategies but they also used micro-econometric approaches, macroeconomic methods and a combination of both, to address the respective research questions. The evidence generated from this analysis has important implications for policy makers to consider. The first two chapters analyze data from Malawi whilst the third chapter is a cross country analysis of four countries in Sub Saharan Africa - Eswathini, Malawi, Mauritius, and Zambia.

Chapter 1 initially tested the theory of full consumption insurance. The results indicated the presence of perfect risk sharing in our model. This is the benchmark case of the connection between consumption shocks and income shocks and has been described as one polar end of such models. It revealed that household consumption can be explained by changes in aggregate consumption rather than idiosyncratic shocks such as changes in household income. The second step was to assess the impact of an exchange rate devaluation using a DID approach. The aim was to ascertain if an aggregate shock such as a currency devaluation has heterogeneous effects across households depending on their sector of employment or place of residence. The evidence was largely consistent with the model of full consumption insurance as the marginal treatment effects were not significantly different from zero. Although there appeared to be some differences across households based on the sectors of employment or whether they were urban or rural based, the changes in household consumption implied that the devaluation, to a larger extent, affected all sampled households in the same way.

Despite this evidence that aggregate shocks may largely be insurable, the results suggest that risk sharing in response to the devaluation is less in those households employed in industry and services a well as urban households, relative to those employed in agriculture or rural based. From a policy perspective, it is important to take into consideration these relatively nuanced detrimental effects. It underscores the importance of understanding and addressing disparities in order to address risk sharing and consumption smoothing differences across households based on their characteristics. For instance, it may be imperative for the government to consider policies that target the urban poor in the face of adverse shocks such as the devaluation as they may need to be supported. This is because they may face a higher cost of living or they may rely more on particular sectors that are more exposed to imports relative to the rural poor. Similarly, those households transitioning out of industry and services may need support in order to mitigate any impact on incomes regardless of how small it may be. In a broader sense, it is important for policy makers to consider addressing structural challenges the country may have that render the modern sector unproductive for households to spend more hours in the agrarian sector. This has strong implications for the structural transformation process of the country.

It is acknowledged that market imperfections exist and the findings from the first chapter simply demonstrate that asymmetric information may not necessarily be the key feature in explaining consumption insurance. It is thus imperative to acknowledge the limitation that risk cannot be eradicated in its entirety. Alot of work has examined the role of asymmetric information, moral hazard and heterogeneity, among others, to ascertain whether the complete markets model can be amended to include some form of imperfect insurance (Blundell et al., 2008). It is, therefore, important to understand the role that various sources of insurance play in order to draw precise policy inferences.

Chapter 2 not only investigates the effect of the *Mtukula Pakhomo* social insurance program on household consumption but it goes further to estimate the marginal gains on welfare. The results are based on an approach (sufficient statistic) that combines the advantages of the reduced form approach (a transparent and credible identification strategy) and the structural approach (policy relevance for welfare analysis).

Evidence from the analysis demonstrates that the program is estimated to have not only increased consumption for beneficiary households but these households also experienced significant benefits in welfare relative to non-beneficiaries of the program. These results also varied by gender with the estimated gain being amplified in female headed households as compared to male headed households.

World Bank (2018b) asserts that social safety nets help people escape extreme poverty, close the poverty gap, and reduce inequality as well as build household resilience to respond to shocks across the life cycle, all which are key to building human capital. They further recognize that the extent to which these transfers have an impact on poverty and inequality depends on factors such as program coverage, transfer level, and the beneficiary or benefit incidence. It is worth exploring further the findings from this thesis as reallocation of resources to more effective social insurance may likely lead to a policy shift. Redesigning social insurance policies to be optimal is thus key as it will protect vulnerable households from shocks, enhance their welfare and promote equality across the population. Recognizing the role of safety nets, in part, helps address inter-generational cycle of poverty.

Chapter 3 moves away from household consumption to aggregate government consumption and it's implications for health.The approach taken is to use a panel VAR with endogenous variables except for an external financial risk. The results reveal that public health spending leads to improved health outcomes. This is proxied by child mortality which lowers with a positive shock to government spending in health. However, as can be expected, increased health spending crowds out other components of government spending. This indicates a rivalling for fiscal capacity reflecting the limited fiscal capacities of most governments particularly in low and low-middle income countries. Interms of the fiscal multiplier, traditional multipliers are shown to be $\simeq 1$ but even lower in the short-run. In this thesis the estimated multiplier is roughly equal to 0.28. This creates a political economy trap for myopic policy makers. Short term horizon of politicians neglect long run benefits in health for investment in tangibles such as infrastructure. Finally, the external premium is estimated to be detrimental for health spending. This is evident during global crises such as the global financial crisis and the COVID 19 pandemic.

Health spending should thus be viewed as an economic investment rather than a cost. It is recognised that the short run economic multiplier effect of health spending is not as large as some other forms of public spending. Nonetheless, the long run implications cannot be ignored. Spending public resources on health leads to improved population health and associated economic returns. An examination of how health expenditure can achieve even greater economic returns and facilitate greater public investments into the sector is key. Research is still in its infancy, but spending on healthcare inputs that have higher multipliers and aligning health sector and industrial policy objectives could be possible ways. Further research on how to increase the multiplier effects of health spending is desperately sought. Needless to say, a holistic approach is key in the balance between increased resources for health alongside efficient, effective, and equitable use of those resources to achieve health sector objectives.

Appendix: Chapter 1

Figure A.1: Assessing Matching Quality - Employment Group

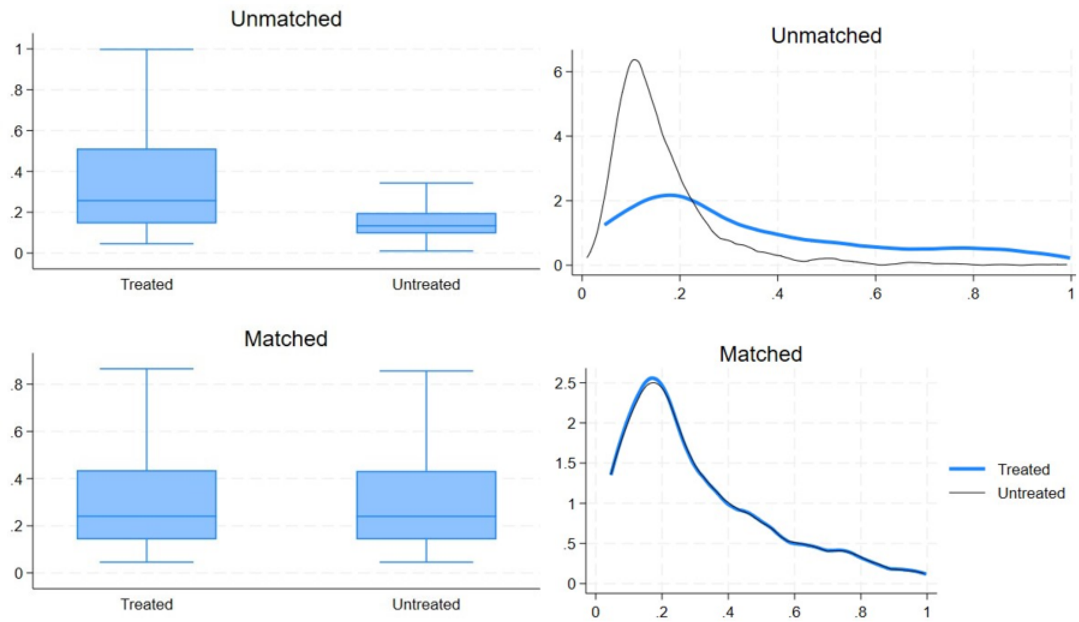
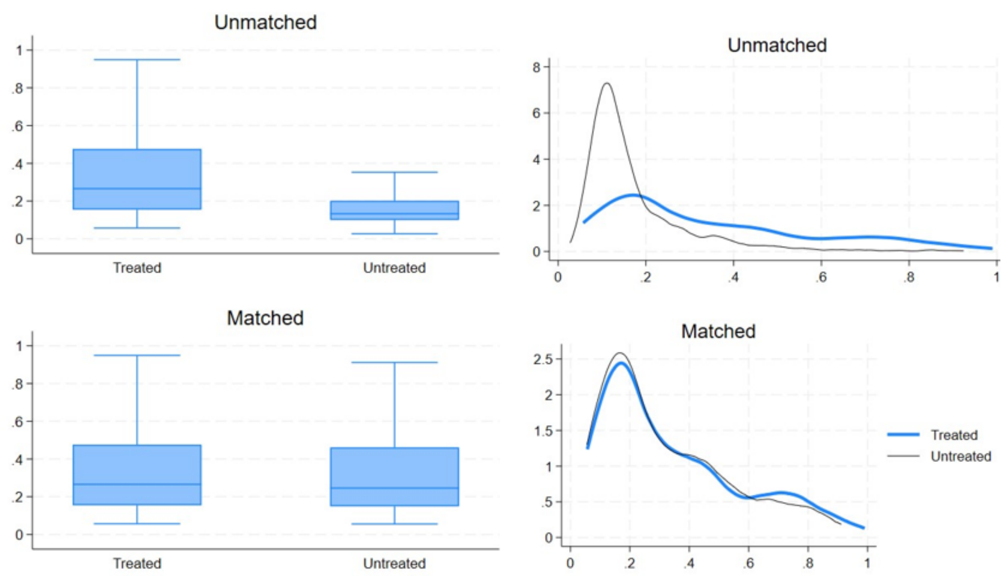


Figure A.2: Assessing Matching Quality - Residence Group



Appendix: Chapter 2

A.2.1 Detailed Proof of Equation 2.6

The agent chooses e to maximize expected utility:

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

$$v(c_1) - u(c_0) = \psi'(e) \tag{A.1}$$

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

$$\begin{aligned} &\max_b W(b) = ev(A + w_1 - \tau(b)) + (1-e)u(A + w_0 + b) - \psi(e) \\ &\text{s.t. } e = e(b) \end{aligned} \tag{A.2}$$

Differentiating (A.2) and using the FOC for e in (A.1) yields:

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

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

$$
= (1-e) \left[u'(c_0) - \big(\frac{\varepsilon_{1-e,b}}{e} + 1 \big) v'(c_1) \right] = 0 \tag{A.3}
$$

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.

A.2.2 Change in Ultra Poverty Incidence

Table A.1: Change in Ultra Poverty Incidence

VARIABLES	All	Female	Male
Beneficiary District	0.0565***	0.0540***	0.0596***
	(0.0165)	(0.0167)	(0.0164)
Central	0.170***	0.166***	0.173***
	(0.0272)	(0.0273)	(0.0274)
South	0.0772**	0.0725**	0.0825**
	(0.0318)	(0.0327)	(0.0312)
Log Population	0.0289**	0.0293**	0.0296**
	(0.0110)	(0.0111)	(0.0110)
Employment	-0.0136**	-0.0234**	-0.0310**
	(0.00600)	(0.0109)	(0.0130)
Constant	-0.279**	-0.261*	-0.271**
	(0.133)	(0.128)	(0.125)
Observations	28	28	28
R-squared	0.785	0.782	0.788

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

Notes: Ethnicity or tribe controlled for but results not shown for brevity.

Appendix: Chapter 3

A3.1 Eswatini

Between 2010 and 2020, there has been a significant slowdown in Eswatini's real gross domestic product (GDP) averaging 2.2 percent, largely due to poor performance of exports and investment (Figure A.3.1). About 85 percent of its imports and about 60 percent of exports are from South Africa. Following the decline and relocation of foreign private investment to South Africa, the World Bank (2022a) indicates that the economy has largely relied on government investment and consumption to drive growth since the end of apartheid in South Africa. It further reports that private investment remains constrained by an unfavourable investment climate and governance challenges. Poverty and inequality remain widespread and a rural phenomenon. The World Bank (2022b) reported a poverty headcount at 58.9 percent at the national poverty line in 2016. It further estimated that 28.6 percent of the population lived below the international poverty line of US$1.90 per day in 2020.

Eswatini is part of the Common Monetary Area (CMA) of the South Africa Customs Union (SACU)[6], with South Africa, Lesotho and Namibia. The Lilangeni is pegged to the South African Rand and that is key to anchoring the policy framework and containing inflation which has remained in single digits in the past decade (Figure A.3.2). The CMA membership consequently limits the independent use of monetary and exchange rate policy instruments.

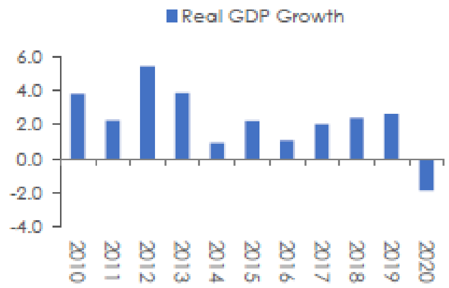
The global financial crisis in 2010 saw a sharp decline in SACU revenues triggering a fiscal crisis and a fall in international reserves. The Government implemented significant fiscal adjustment coupled and with a recovery in SACU revenues there was an improvement in both fiscal and external balances in 2012 and 2013 (International Monetary Fund, 2020). Since then, the fiscal balance has remained in deficit as SACU revenues have been on a downward trajectory coupled with declining growth trends (Figure A.3.3). As SACU revenues continued to fall this led to a narrowing of the current account surplus. It fluctuated from about 13 percent in 2015 to around 1.3 percent in 2018, with a subsequent recovery to 6.7 percent in 2020 (Figure A.3.4).

The country has made some progress in reducing mortality rates albeit at a slow pace (Figure A.3.5). Child mortality has fallen from 54.7 children per 1,000 live births to 37.4 children per 1,000 live births in 2020. Kingdom of Eswatini (2019) attributed this to the

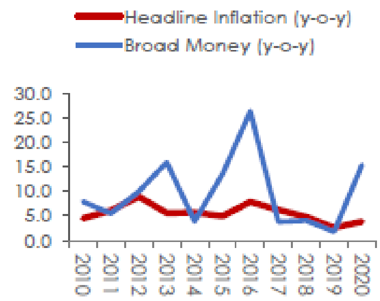
[6]Botswana left the CMA but is still part of the SACU

Figure A.3: Eswatini Key Macroeconomic and Social Indicators: 2010-2020

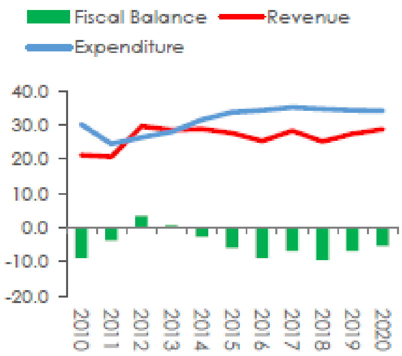
A.1.1: Real GDP Growth
Percent



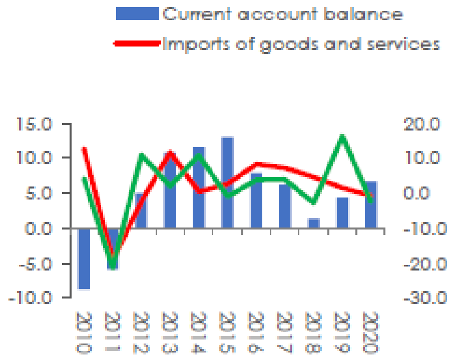
A.1.2: Inflation and Broad Money Growth
Percent



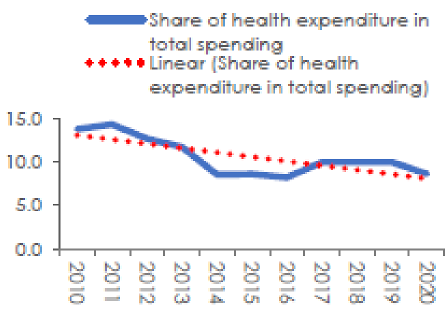
A.1.3: Revenue, Expenditure and Fiscal Balance
Percent of GDP



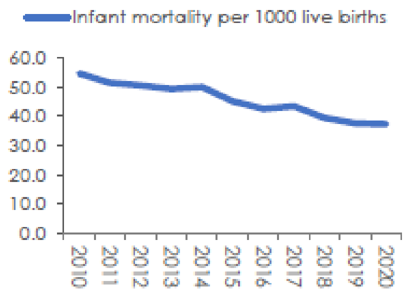
A.1.4: Imports, Exports and CA Balance
Percent of GDP (LHS) Current Account Balance
Percent change (RHS) Imports and Exports



A.1.5: Domestic Health Expenditure
Percent of general government expenditure



A.1.6: Infant Mortality
Per 1,000 live births



Source: Authors based on World Development Indicators and World Economic Outlook data introduction of new vaccines and increasing immunization coverage as well as stabilization in prevalence of HIV/AIDS, incidence of malaria and tuberculosis. However, the country continues to experience an increase in noncommunicable diseases. An analysis of the share of health expenditure as a proportion of total expenditure shows that it has been volatile but stagnating at around 10 percent (Figure A.3.6), below the Abuja declaration[7] target of 15 percent.

A3.2 Malawi

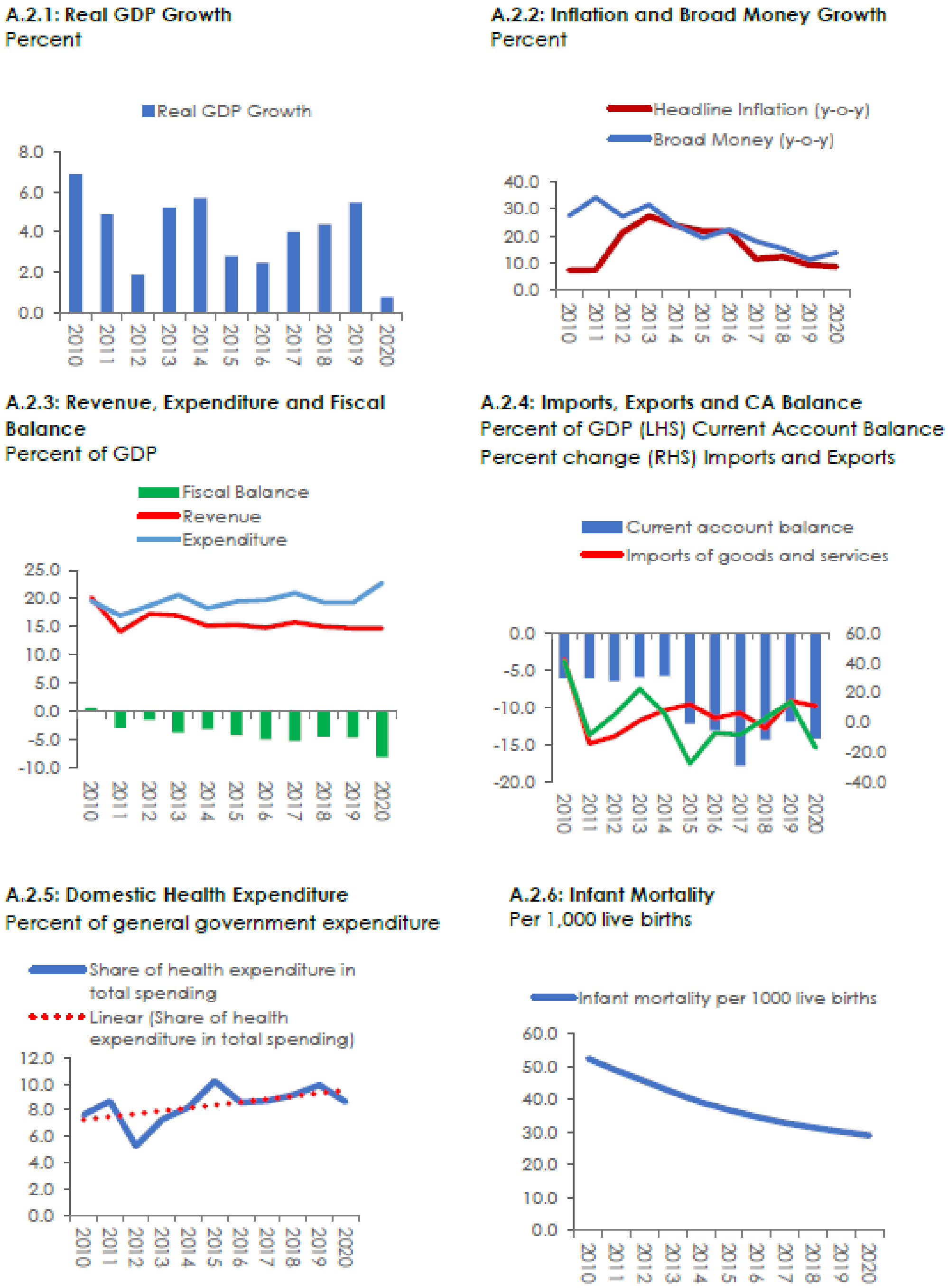
Malawi's economy grew by an annual average of 4.0 percent over the last decade marked by high volatility in real GDP growth due to limited buffers against shocks (Figure A.4.1). Macroeconomic instability has been attributed to vulnerabilities to weather related shocks and weak public finance management. Most of the population, especially the poor, are involved in subsistence and rain-fed agriculture which is riddled with low productivity. As a result, poverty levels have remained high with limited improvement in per capita incomes. The World Bank (2022b) reported that the poverty headcount at the national poverty line stagnated at 50.7 percent in 2019/2020. It further estimated that the international poverty line of US$1.90 per day classified 74.3 percent of the population as being poor in 2020.

Although the country recorded single digit inflation for much of the 2000s, a devaluation of the local currency by 49 percent in 2012 saw inflation spike to over 20 percent. Containing inflation remained a challenge for at least 5 years, compounded by rising food and fuel prices and previous monetary accommodation of fiscal indiscipline. A tight monetary stance ensued which contributed to a fall in inflation below double digits (Figure A.4.2). Consumer prices have since been on an upward trajectory due to the impact of the COVID 19 pandemic with a rise in money supply as authorities loosened monetary policy in response to the crisis.

As Record et al. (2018) report, fiscal outturns and performance have been masked with significant volatility. Fiscal indiscipline has led to large domestic borrowing requirements, crowding out private sector lending, and stoking non-food inflation. This has also undermined the effectiveness of monetary policy by restraining credit growth but with rising inflation. Financing such persistent fiscal deficits has also led to a growing share of public expenditure going towards servicing domestic debt at the expense of service

[7] A pledge made by African Union (AU) countries in 2001 to allocate at least 15 percent of the national annual budget towards the health sector

Figure A.4: Malawi Key Macroeconomic and Social Indicators: 2010-2020



Source: Authors based on World Development Indicators and World Economic Outlook data delivery and public investment. The fiscal balance has continued to widen from a surplus of 0.6 percent in 2010 to around 8.1 percent in 2020 (Figure A.4.3).

Current account deficits stood at around 14 percent of GDP in 2020 (Figure A.4.4) with a continued increase in imports (including fuel, medical drugs and fertilizer) as proceeds from tobacco exports dwindled. The International Monetary Fund (2021) noted that the Malawi Kwacha appreciated substantially in real effective terms owing to limited nominal exchange rate adjustment further contributing to high current account deficits and a loss of foreign exchange reserves.

The country has made impressive strides in reducing child mortality from 2000 with the chance of survival tripling by 2020 (Figure A.4.5). The Government of Malawi (2022) has attributed this to child health interventions which have had a significant impact on child health outcomes. These include an increase in births attended by skilled health staff from about half to over 90 percent and a reduction in the incidence of malaria which is a leading cause of morbidity and mortality in children and pregnant women, among others. This corresponds to an increase in health expenditure (as a share of the national budget) from around 5 percent in 2010 to around 9 percent to date (Figure A.4.6). The overall spending to the health sector, however, remains low and below the Abuja target of 15 percent.

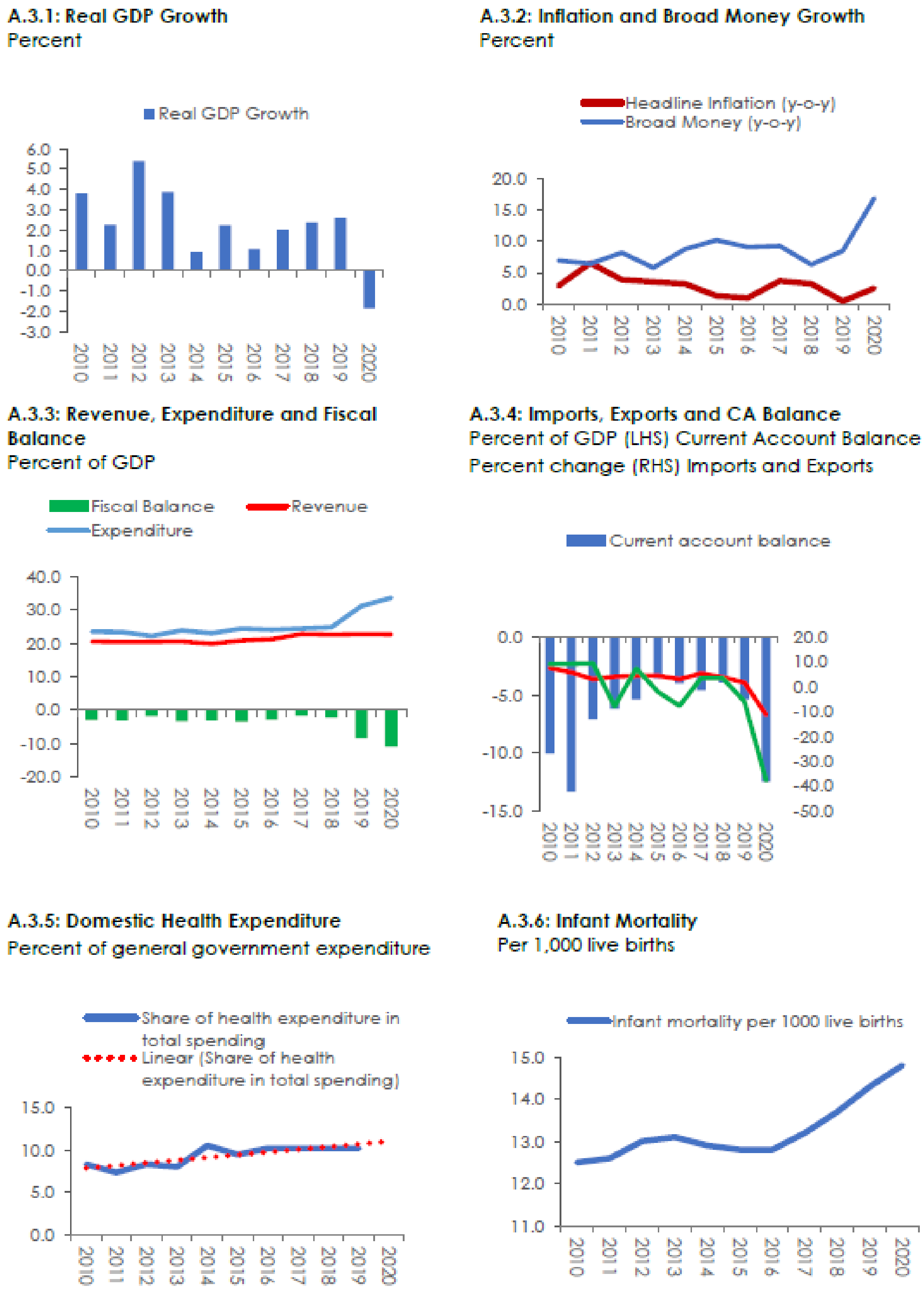
A3.3 Mauritius

Mauritius has been on a steady growth path averaging about 3.7 percent from 2010 to 2019, driven by the service sector in particular tourism, finance and Information Communications and Technology (ICT). In 2020, however, the economy contracted by about 14.9 percent bringing the average since 2010 to around 2.2 percent (Figure A.5.1). This was attributed to the COVID 19 pandemic which led to a sharp decline in services, particularly tourism (over a fifth of the economic activity). The country has witnessed steady, strong, and inclusive growth which has seen poverty levels based on the national poverty line stand at 10.3 percent in 2017. Extreme poverty is almost eliminated with 0.2 percent of the population living below the international poverty line of US$1.90 per day in 2017 (World Bank, 2022b).

Low inflation has been sustained over the past decade remaining in single digits. Recent years have seen a rise in inflation owing to external supply shocks related to increased energy and food prices as well as higher freight prices (Figure A.5.2).

In the past decade, Mauritius has been struggling with reining in public expenditure

Figure A.5: Mauritius Key Macroeconomic and Social Indicators: 2010-2020



Source: Authors based on World Development Indicators and World Economic Outlook data which has seen the fiscal deficit widen, standing at 10.9 percent in 2020 (Figure A.5.3). The World Bank (2022a) notes that the emergency response to the pandemic was effective at protecting livelihoods but it came at a high fiscal cost with a spike in public debt. This was despite a 12.6 percent of GDP nonrefundable transfer from the Bank of Mauritius to the Government in FY2020/2021. It followed another 3.9 percent of GDP transfer in the budget of the preceding fiscal year.

The economy has run a structural current account deficit which narrowed to below 5 percent of GDP between since 2015, driven mainly by the down cycle in investment (World Bank, 2017). The sharp deterioration in tourism saw the current account deficit widen from 2019 reaching 12.5 percent in 2020 (Figure A.5.4).

An analysis of the share of health expenditure as a proportion of total expenditure shows that it has increased from 8.3 percent in 2010 but has stagnated at around 10.2 percent since 2016 (Figure A.5.5). This is below the Abuja target of 15 percent.

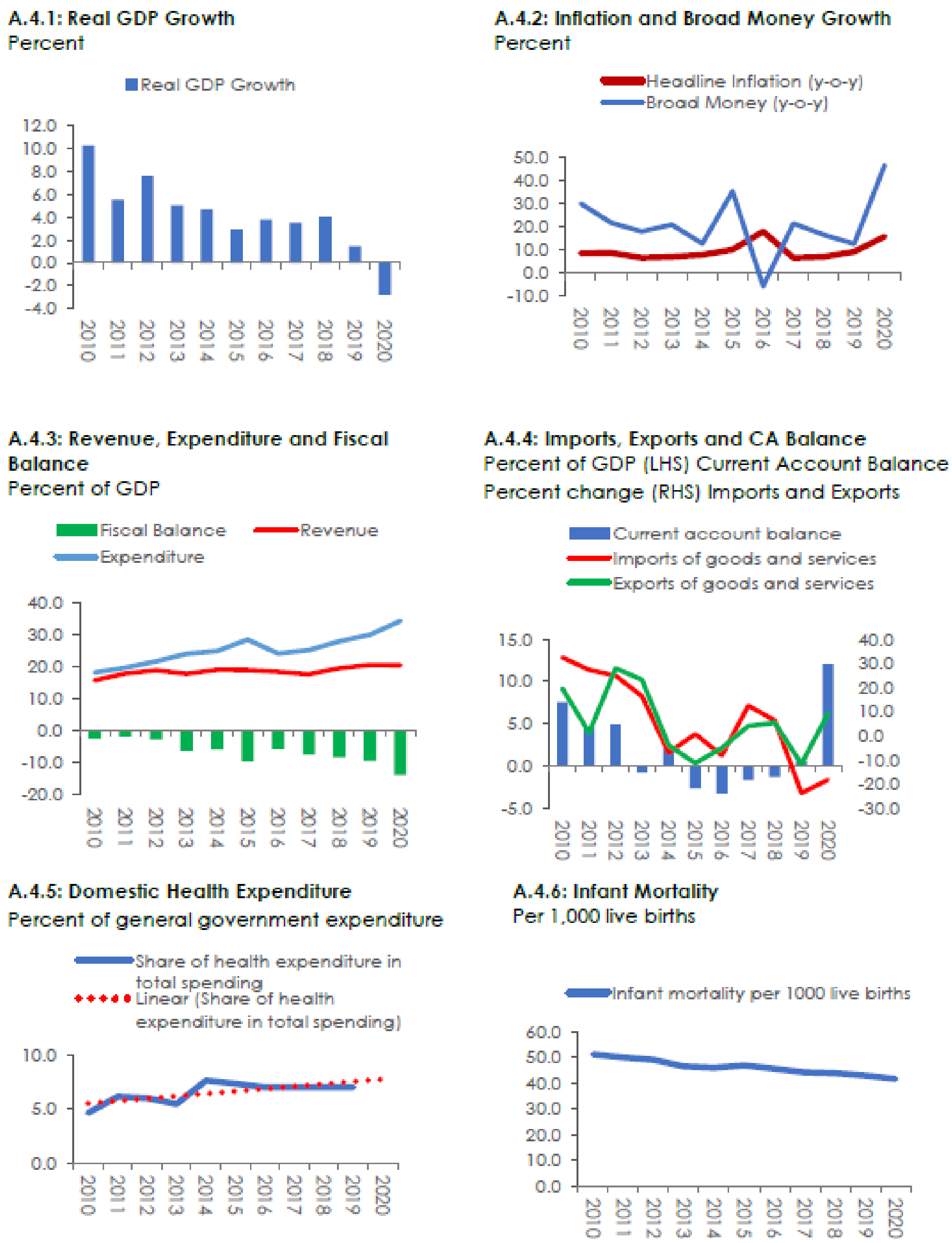
From a rate of 16.6 deaths per 1,000 live births, Mauritius experienced a decline in child deaths reaching a record low of 12.5 deaths per 1,000 live births in 2009. Over the years, the rate has fluctuated between 12 – 14 deaths recording 14.8 deaths per 1,000 live births in 2020 (Figure A.5.6). The Government of Mauritius (2022) identified the main causes as congenital anomalies, septicemia and infections specific to perinatal period.

A3.4 Zambia

Zambia registered an average real GDP growth rate of 4.2 percent between 2010 and 2020. Growth was bolstered by high copper prices and production as well as expansion in construction and services. Declining copper prices compounded by macro-fiscal vulnerabilities saw a declining growth trend. In 2020, the economy contracted by 2.8 percent with the onset of the Covid 19 pandemic (Figure A.6.1). Consequently, poverty and inequality remain high. The World Bank (2022b) reported a poverty headcount of 54.4 percent at the national poverty line in 2015. It further estimated that 60.1 percent of the population is living below the international poverty line of US$1.90 per day in 2020.

Inflation remained in single digits between 2010 and 2014. In 2015 and 2016 there was an upward pressure on prices. As the global demand for copper fell, low commodity prices ensued. This was exacerbated by a drought which also led to a fall in hydropower generation. Mining production was affected leading to a depreciation of the Zambia Kwacha and fueling inflationary pressure. Although inflation returned to single digits between 2017 and 2019, the COVID 19 pandemic led to an increase in the inflation rate

Figure A.6: Zambia Key Macroeconomic and Social Indicators: 2010-2020



Source: Authors based on World Development Indicators and World Economic Outlook data to 15.7 percent in 2020 (Figure A.6.2).

The fiscal deficit widened from 2.4 percent of GDP in 2010 to 13.8 percent of GDP in 2020 (Figure A.6.3). It was financed by a mounting stock of domestic arrears and accumulation of non-concessional public debt. Although revenues generally improved, the deficit continued to rise following faster-than-budgeted execution of foreign-financed capital spending (International Monetary Fund, 2019).

The current account balance has largely been in surplus, albeit modest deficits in some years. In 2020, the economy registered a current account surplus of 12 percent of GDP owing to a strong recovery in exports that outpaced imports (Figure A.6.4).

Whilst the share of health spending relative to total expenditure has increased from 4.7 percent in 2010 to 7.0 percent in 2020 (Figure A.6.5), it remains below the Abuja target of 15 percent.

Child mortality has substantially fallen since 2000 from 90.2 deaths per 1,000 live births, reaching 51.2 deaths per 1,000 live births in 2010. By 2020, the country recorded 41.7 deaths per 1,000 live births (Figure A.6.6). The Government of the Republic of Zambia (2022) attributed this to interventions such as Safe Motherhood Action Groups, community-based distributors, procurement of emergency obstetric and neonatal care, and in-service training of skilled workers. A fall in the incidence of malaria (major cause of morbidity and mortality) also contributed to the success.

References

Abadie, A. and Imbens, G. W. (2016). Matching on the Estimated Propensity Score. *Econometrica*, 84(2):781–807.

Abdoulayi, S., Angeles, G., Barrington, C., Brugh, K., Handa, S., Hill, M. J., Kilburn, K., Otchere, F., Mvula, P., Tsoka, M., et al. (2014). Malawi Social Cash Transfer Program Baseline Evaluation Report. *The Transfer Project, University of North Carolina at Chapel Hill.*

Abdoulayi, S., Angeles, G., Barrington, C., Brugh, K., Handa, S., Kilburn, K., and Zietz, S. (2016). Malawi Social Cash Transfer Programme Endline Impact Evaluation Report. *Chapel Hill, Zomba: The University of North Carolina, University of Malawi.*

Abrigo, M. R. and Love, I. (2016). Estimation of Panel Vector Autoregression in Stata. *The Stata Journal*, 16(3):778–804.

Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, 84(3):488–500.

Amare, M., Jensen, N. D., Shiferaw, B., and Cissé, J. D. (2018). Rainfall Shocks and Agricultural Productivity: Implication for Rural Household Consumption. *Agricultural systems*, 166:79–89.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton university press.

Ashenfelter, O. (1978). Estimating the Effect of Training Programs on Earnings. *The Review of Economics and Statistics*, pages 47–57.

Ashenfelter, O. and Card, D. (1985). Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs. *The Review of Economics and Statistics*, 67(4):648–60.

Attanasio, O. P. and Rios-Rull, J. V. (2003). Consumption smoothing and extended families. *Econometric Society Monographs*, 37:209–242.

Austin, P. C. (2009). Balance Diagnostics for Comparing the Distribution of Baseline Covariates Between Treatment Groups in Propensity-Score Matched Samples. *Statistics in medicine*, 28(25):3083–3107.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American economic review*, 103(6):2121–2168.

Autor, D. H., Dorn, D., Hanson, G. H., and Song, J. (2014). Trade adjustment: Worker-level evidence. *The Quarterly Journal of Economics*, 129(4):1799–1860.

Baily, M. N. (1978). Some Aspects of Optimal Unemployment Insurance. *Journal of public Economics*, 10(3):379–402.

Baird, S., McIntosh, C., and Özler, B. (2011). Cash or Condition? Evidence from a Cash Transfer Experiment. *The Quarterly journal of economics*, 126(4):1709–1753.

Barro, R. and Sala-i Martin, X. (2004). Economic Growth Second Edition.

Barro, R. J. (1981). Output Effects of Government Purchases. *Journal of political Economy*, 89(6):1086–1121.

Bastagli, F., Hagen-Zanker, J., Harman, L., Barca, V., Sturge, G., and Schmidt, T. (2019). The Impact of Cash Transfers: A Review of the Evidence from Low-and Middle-Income Countries. *Journal of Social Policy*, 48(3):569–594.

Batini, N., Eyraud, L., Forni, L., and Weber, A. (2014). *Fiscal Multipliers: Size, Determinants, and Use in Macroeconomic Projections*. International Monetary Fund.

Becker, S. O. and Hvide, H. K. (2013). Do Entrepreneurs Matter?

Bernanke, B. S. and Mihov, I. (1998). Measuring monetary policy. *The quarterly journal of economics*, 113(3):869–902.

Blanchard, O. and Perotti, R. (2002). An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output. *the Quarterly Journal of Economics*, 117(4):1329–1368.

Bloom, D. E., Canning, D., and Sevilla, J. (2001). The Effect of Health on Economic Growth: Theory and Evidence.

Blundell, R., Pistaferri, L., and Preston, I. (2008). Consumption Inequality and Partial Insurance. *American Economic Review*, 98(5):1887–1921.

Brugh, K., Angeles, G., Mvula, P., Tsoka, M., and Handa, S. (2018). Impacts of the Malawi Social Cash Transfer Program on Household Food and Nutrition Security. *Food Policy*, 76:19–32.

Caliendo, M. and Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of economic surveys*, 22(1):31–72.

Cameron, A. C. and Trivedi, P. K. (2013). *Regression Analysis of Count Data*, volume 53. Cambridge university press.

Card, D. and Krueger, A. B. (1993). Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania. Working Paper 4509, National Bureau of Economic Research.

Chenery, H. B. and Syrquin, M. (1975). *Patterns of Development, 1950-1970.* Published for the World Bank by Oxford University Press.

Chetty, R. (2006). A General Formula for the Optimal Level of Social Insurance. *Journal of Public Economics*, 90(10-11):1879–1901.

Chetty, R. (2008a). Moral Hazard Versus Liquidity and Optimal Unemployment Insurance. *Journal of political Economy*, 116(2):173–234.

Chetty, R. (2008b). Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods.

Chetty, R. and Finkelstein, A. (2013). Social Insurance: Connecting Theory to Data. In *Handbook of public economics*, volume 5, pages 111–193. Elsevier.

Chetty, R. and Looney, A. (2006). Consumption Smoothing and the Welfare Consequences of Social Insurance in Developing Economies. *Journal of public economics*, 90(12):2351–2356.

Chinsinga, B. (2009). Political Economy of Cash Transfers in Malawi.

Clark, C. (1940). The Morphology of Economic Growth. *The Conditions of Economic Progress (Macmillan, London)*, pages 337–373.

Cochrane, J. H. (1991). A Simple Test of Consumption Insurance. *Journal of political economy*, 99(5):957–976.

Crump, R. K., Hotz, V. J., Imbens, G. W., and Mitnik, O. A. (2009). Dealing With Limited Overlap in Estimation of Average Treatment Effects. *Biometrika*, 96(1):187–199.

Cunningham, S. (2021). *Causal Inference: The Mixtape.* Yale university press.

Deaton, A. (1992). *Understanding Consumption.* Oxford University Press.

Dehejia, R. H. and Wahba, S. (1999). Causal Effects in Non-Experimental Studies: Reevaluating the Evaluation of Training Programs. *Journal of the American statistical Association*, 94(448):1053–1062.

Dercon, S. (2002). Income Risk, Coping Strategies, and Safety Nets. *The World Bank Research Observer*, 17(2):141–166.

Easterly, W. and Levine, R. (1997). Africa's Growth Tragedy: Policies and Ethnic Divisions. *The Quarterly Journal of Economics*, pages 1203–1250.

Federal Reserve Economic Data (2022). Emerging Markets Corporate Plus Index Option-Adjusted Spread. Accessed: 2022-08-18.

Feldstein, M. (1978). The Effect of Unemployment Insurance on Temporary Layoff Unemployment. *The American Economic Review*, 68(5):834–846.

Garrido, M. M., Kelley, A. S., Paris, J., Roza, K., Meier, D. E., Morrison, R. S., and Aldridge, M. D. (2014). Methods for Constructing and Assessing Propensity Scores. *Health services research*, 49(5):1701–1720.

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., and Vermeersch, C. M. (2016). *Impact Evaluation in Practice.* World Bank Publications.

Gollin, D., Lagakos, D., Waugh, M. E., et al. (2011). *The Agricultural Productivity Gap in Developing Countries.* Leonard N. Stern School of Business, Department of Economics.

Gordon, D. B. and Leeper, E. M. (1994). The Dynamic Impacts of Monetary Policy: An Exercise in Tentative Identification. *Journal of Political economy*, 102(6):1228–1247.

Government of Malawi (2020a). *Malawi Social Cash Transfer Programme - Mtukula Pakhomo, Technical Annex K: Manual for Retargeting of SCTP Beneficiaries.* Government of Malawi.

Government of Malawi (2020b). The Malawi National Social Support Programme, Working Paper, Review of the Proxy means Test (PMT) for Social protection beneficiaries using IHS4 Data. *Government of Malawi.*

Government of Malawi (2022). Malawi 2022 Voluntary National Review Report for Sustainable Development Goals.

Government of Mauritius (2022). Voluntary National Review Report of Mauritius 2019.

Government of the Republic of Zambia (2022). Zambia Sustainable Development Goals Voluntary National Review 2020.

Grimard, F. and Hamilton, B. (1999). Estimating the Elderly's Returns on the Farm: Evidence from Cote d'Ivoire. *Journal of Development Economics*, 58(2):513–531.

Gruber, J. (1997). The Consumption Smoothing Benefits of Unemployment Insurance. *The American Economic Review*, 87(1):192–205.

Handa, S., Angeles, G., Abdoulayi, S., Mvula, P., Tsoka, M., et al. (2015). Malawi Social Cash Transfer Programme: Midline Impact Evaluation Report. *Chapel Hill, Zomba: The University of North Carolina, University of Malawi.*

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The review of economic studies*, 64(4):605–654.

Heckman, J. J. and Robb Jr, R. (1985). Alternative Methods for Evaluating the Impact of Interventions: An Overview. *Journal of econometrics*, 30(1-2):239–267.

Holtz-Eakin, D., Newey, W., and Rosen, H. S. (1988). Estimating Vector Autoregressions with Panel Data. *Econometrica: Journal of the econometric society*, pages 1371–1395.

Hsiao, W. C. and Heller, P. S. (2000). What Should Macroeconomists Know About Health Care Policy: A Primer. *IMF working papers*, 2000(136).

Ichino, A., Schwerdt, G., Winter-Ebmer, R., and Zweimüller, J. (2007). Too old to work, too young to retire?

Ilzetzki, E., Mendoza, E. G., and Végh, C. A. (2013). How Big (Small?) are Fiscal Multipliers? *Journal of monetary economics*, 60(2):239–254.

Imai, K., King, G., and Stuart, E. A. (2008). Misunderstandings Between Experimentalists and Observationalists About Causal Inference. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 171(2):481–502.

Imbens, G. W. (2015). Matching Methods in Practice: Three Examples. *The Journal of Human Resources*, 50(2):373–419.

International Monetary Fund (2019). IMF 2019 Article IV Consultation - Press Release; Staff Report; and Statement by the Executive Director for Zambia.

International Monetary Fund (2020). IMF 2019 Article IV Consultation - Press Release; Staff Report; and Statement by the Executive Director for the Kingdom of Eswatini.

International Monetary Fund (2021). IMF 2021 Article IV Consultation - Press Release; Staff Report; and Statement by the Executive Director for Malawi.

Jensen, R. (2000). Agricultural Volatility and Investments in Children. *American Economic Review*, 90(2):399–404.

Kalebe-Nyamongo, C. and Marquette, H. (2014). Elite Attitudes Towards Cash Transfers and the Poor in Malawi.

Kaplan, G., Moll, B., and Violante, G. L. (2018). Monetary Policy According to HANK. *American Economic Review*, 108(3):697–743.

Kaplan, G. and Violante, G. L. (2018). Microeconomic Heterogeneity and Macroeconomic Shocks. *Journal of Economic Perspectives*, 32(3):167–194.

Kingdom of Eswatini (2019). The Kingdom of Eswatini Voluntary National Review 2019 Review.

Kraay, A. (2012). How Large is the Government Spending Multiplier? Evidence from World Bank lending. *The Quarterly Journal of Economics*, 127(2):829–887.

Kuznets, S. and Murphy, J. T. (1966). *Modern economic growth: Rate, structure, and spread*, volume 2. Yale University Press New Haven.

Leuven, E. and Sianesi, B. (2018). PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing.

Lindert, K., Andrews, C., Msowoya, C., Paul, B. V., Chirwa, E., and Mittal, A. (2018). Rapid Social Registry Assessment: Malawi's Unified Beneficiary Registry (UBR). *World Bank*.

Lunt, M. (2014). Guide to Propensity Analysis. Available at https://personalpages.manchester.ac.uk/staff/mark.lunt/propensity_guide.pdf, Last accessed on 2023-xx-xx.

Mace, B. J. (1991). Full Insurance in the Presence of Aggregate Uncertainty. *Journal of Political Economy*, 99(5):928–956.

Maddala, G. S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics*. Number 3. Cambridge university press.

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A Contribution to the Empirics of Economic Growth. *The quarterly journal of economics*, 107(2):407–437.

Mcintyre, D., Meheus, F., and Røttingen, J.-A. (2017). What level of domestic government health expenditure should we aspire to for universal health coverage? *Health Economics, Policy and Law*, 12(2):125–137.

Mckenzie, D. (2023). What To Do About Parallel Trends When You Only Have Baseline Data. Available at https://blogs.worldbank.org/impactevaluations/what-do-about-parallel-trends-when-you-only-have-baseline-data, Accessed on: June 4, 2023.

Miller, C. M., Tsoka, M., and Reichert, K. (2011). The Impact of the Social Cash Transfer Scheme on Food Security in Malawi. *Food policy*, 36(2):230–238.

Morduch, J. (1995). Income Smoothing and Consumption Smoothing. *Journal of economic perspectives*, 9(3):103–114.

Mussa, R. (2017). Early-Life Rainfall Shocks and Intergenerational Education Mobility in Malawi.

National Statistical Office (2014). *Malawi Labour Force Survey 2013*. Government of Malawi.

National Statistical Office (2017). *Integrated Household Panel Survey (IHPS) 2010-2016*. Government of Malawi.

Ngongondo, C., Xu, C.-Y., Gottschalk, L., and Alemaw, B. (2011). Evaluation of Spatial and Temporal Characteristics of Rainfall in Malawi: A Case of Data Scarce Region. *Theoretical and applied climatology*, 106:79–93.

NSO (2020). Malawi Poverty Report. *Government of Malawi*.

Ralston, L., Andrews, C., and Hsiao, A. J.-Y. (2017). The Impacts of Safety Nets in Africa: What Are We Learning? *World Bank Policy Research Working Paper*, (8255).

Ramey, V. A. and Zubairy, S. (2018). Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data. *Journal of Political Economy*, 126(2):850–901.

Ravn, M. O., Schmitt-Grohé, S., and Uribe, M. (2012). Consumption, Government Spending, and the Real Exchange Rate. *Journal of Monetary Economics*, 59(3):215–234.

Record, R., Kumar, P., and Kandoole, P. (2018). *From Falling Behind to Catching Up: a Country Economic Memorandum for Malawi*. World Bank.

Riley, E. (2018). Mobile Money and Risk Sharing Against Village Shocks. *Journal of Development Economics*, 135:43–58.

Romer, C. D. and Romer, D. H. (2010). The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks. *American Economic Review*, 100(3):763–801.

Rosenbaum, P. R. and Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70(1):41–55.

Rothschild, M. and Stiglitz, J. (1976). Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information. *The Quarterly Journal of Economics*, 90(4):629–649.

Rubin, D. B. (1990). Formal Mode of Statistical Inference for Causal Effects. *Journal of Statistical Planning and Inference*, 25(3):279–292.

Sachs, J. D. and Warner, A. (1995). Economic Convergence and Economic Policies.

Shimer, R. and Werning, I. (2007). Reservation Wages and Unemployment Insurance. *The Quarterly Journal of Economics*, 122(3):1145–1185.

Sianesi, B. (2004). An Evaluation of the Swedish System of Active Labor Market Programs in the 1990s. *Review of Economics and statistics*, 86(1):133–155.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica: journal of the Econometric Society*, pages 1–48.

Spilimbergo, A., Schindler, M., and Symansky, S. A. (2009). Fiscal Multipliers. *IMF Staff Position Notes*, 2009(011).

Stock, J. H. and Watson, M. W. (2001). Vector Autoregressions. *Journal of Economic Perspectives*, 15(4):101–115.

Townsend, R. M. (1994). Risk and Insurance in Village India. *Econometrica: journal of the Econometric Society*, pages 539–591.

Townsend, R. M. (1995). Consumption Insurance: An Evaluation of Risk-Bearing Systems in Low-Income Economies. *Journal of Economic perspectives*, 9(3):83–102.

World Bank (2004). *Health Financing for Poor People: Resource Mobilization and Risk Sharing*, volume 434. World Bank Publications.

World Bank (2016). Malawi Economic Monitor: Absorbing Shocks, Building Resilience. Technical report, The World Bank.

World Bank (2017). Country Partnership Framework for Mauritius for the Period FY17-FY21.

World Bank (2018a). *Malawi Economic Monitor: Realizing Safety Nets' Potential.* The World Bank.

World Bank (2018b). *The State of Social Safety Nets 2018.* The World Bank.

World Bank (2019). *Malawi: Jobs-Poverty Diagnostics.* World Bank.

World Bank (2022a). *Macro Poverty Outlook, Spring Meetings 2022: Country-by-Country Analysis and Projections for the Developing World.* World Bank.

World Bank (2022b). World Development Indicators. Accessed: 2022-08-18.

World Health Organization (1978). *Poverty, Development, and Health Policy.* World Health Organization.

World Health Organization (2001). *Macroeconomics and Health: Investing in Health for Economic Development.* World Health Organization.

World Health Organization (2010). The World Health Report: Health Systems Financing: the Path to Universal Coverage.