FACULTY OF AGRONOMY AND FORESTRY ENGINEERING

EFFECTS OF AFFORDABLE INPUTS PROGRAM ON FOOD POVERTY ALLEVIATION AMONG SMALLHOLDER FARMERS IN MALAWI

BY

REBECCA NKHOMA

SUPERVISED BY

PROFESSOR HELDER ZAVALE

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DECLARATION

I, Rebecca Nkhoma, declare that this dissertation has never been submitted for the purpose of obtaining any degree or in any other field and that it is the result of my individual labor. This dissertation is presented in partial fulfillment of the requirements for obtaining the degree of Master of Science in Agricultural Economics from the University of Eduardo Mondlane.

R. Nkhoma   18/12/2015

Rebecca Nkhoma   Date

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ABSTRACT

Malawi's Affordable Inputs Programme (AIP) aims to enhance smallholder productivity and food security by providing subsidized access to fertilizer and improved seeds, thereby reducing poverty among farming households. Despite its national importance, evidence on its effectiveness in reducing household food poverty remains mixed due to persistent concerns about targeting accuracy, inclusivity, and household vulnerability to climatic shocks. Using nationally representative data of 7,804 agricultural households from the Fifth Integrated Household Survey (IHS5), we apply the control function (CF) approach to address endogeneity in subsidy participation and estimate the programme's causal impact on food poverty. Descriptive results show that AIP beneficiaries are more likely to be female-headed, widowed, and rural households, and tend to have relatively greater access to extension services, land, and livestock assets, with patterns indicating that only the complete AIP package is associated with noticeable improvements in poverty outcomes. The control function estimates reveal that each additional coupon reduces the probability of being food poor by 16.3 percent and lowers the food poverty gap by 6.1 percent, suggesting meaningful but moderate improvements in household food welfare. In addition, factors such as higher education, employment, access to credit, business ownership, livestock holdings, and urban residence significantly improve household welfare. Overall, the study highlights the need to strengthen targeting by also considering the educated and the youth, and complement the AIP with credit access, education, and climate-resilient support to maximize its contribution to sustainable food security in Malawi.

Keywords: Affordable Inputs Programme; Food Poverty Alleviation; Control Function Approach; Smallholder Farmers; Malawi.

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LIST OF ACRONYMS

ACB	Anti-Corruption Bureau
AIP	Affordable Inputs Program
CF	Control Function
CGE	Computable General Equilibrium
CIA	Conditional Independence Assumption
EAs	Enumeration Areas
FAO	Food and Agriculture Organization
FISP	Farm Input Subsidy Program
FGT	Foster-Greer-Thorbecke
GDP	Gross Domestic Product
IHS	Integrated Household Surveys
IV	Instrumental Variable
LSMS	Living Standards Measurement Surveys
MEM	Malawi Economic Monitor
MGDS	Malawi Growth and Development Strategy
MWK	Malawian Kwacha
NSO	National Statistical Office
OLS	Ordinary Least Squares
PAP	Poverty Alleviation Programme
PSM	Propensity Score Matching
PMS	Poverty Monitoring System
PSUs	Primary Sampling Units
SCTP	Social Cash Transfer Programs
SDGs	Sustainable Development Goals
SSA	Sub-Saharan Africa
SSNs	Social Safety Nets
TLU	Tropical Livestock Unit
UN	United Nations
UNICEF	United Nations Children's Fund
USD	United States Dollar

CHAPTER 1:
INTRODUCTION

1.1 Background of the Study

Globally, poverty and extreme poverty remain disproportionately concentrated in rural areas, where the populations are heavily reliant on agriculture for survival (Castañeda et al., 2018). Over the past 35 years, this pattern has remained largely unchanged, and by 2023, approximately 76 percent of the extremely poor lived in rural areas and engaged in low-productivity subsistence farming (FAO, 2019; FAO, 2023).[1] Current estimates from 2024 indicate that nearly 3 billion rural people still depend on subsistence agriculture for their livelihoods. Despite this reliance, many households continue to experience chronic food insecurity due to constrained farm productivity and inadequate access to markets (IFAD, 2024).[2]

Despite sustained economic growth and targeted policy interventions since the early 2000s, extreme poverty remains widespread globally, with about 808 million people projected to live on less than 3.00 United States Dollars (USD) per capita per day in 2025 (Foster et al., 2025).[3] In response to these enduring challenges, African countries have expanded social protection programs, which have contributed to measurable improvements in household welfare, agricultural productivity, and investment (World Bank, 2018; Correa et al., 2023). Agriculture thus remains a crucial pathway out of poverty in the region, providing employment and raising income for smallholder farmers, although its full potential is constrained by low adoption of improved inputs, limited access to credit, inadequate extension services, and weak market linkages (Sithole & Olorunfemi, 2024; Mnukwa et al., 2025; Khan & Kim, 2025).

Given the vital role of agriculture in poverty alleviation across Africa, Malawi's policy responses since the start of the multiparty era in 1994 have focused on reducing poverty and improving access to income, food, and basic social services, as evidenced by the establishment of a Poverty

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[1] FAO stands for Food and Agriculture Organization of the United Nations.

[2] IFAD stands for the International Fund for Agricultural Development.

[3] The international poverty line is expressed in 2021 Purchasing Power Parity (PPP) dollars, which adjusts for differences in the cost of living across countries. This is the updated standard from the World Bank's June 2025 global poverty update.

Monitoring System (PMS) (NSO, 2022).[4] During this period, the Government of Malawi prioritized household welfare by introducing programs to reduce poverty, enhance social protection, and promote rural development (Government of Malawi, 2017). Advancements in governance since then have further supported improvements in human welfare and development outcomes, highlighting the importance of well-being in both governmental and non-governmental efforts (Banik & Chinsinga, 2016; Banda, 2023). This commitment is demonstrated by initiatives such as the Poverty Alleviation Program (PAP) and the Malawi Growth and Development Strategy (MGDS), which focus on reducing poverty, particularly among rural poor communities (Gunnlaugsson & Einarsdóttir, 2018). To support these policy efforts, Malawi also implemented systematic approaches to monitoring living standards, most notably the Integrated Household Surveys (IHS), supported by the World Bank Living Standards Measurement Surveys (LSMS) (Machira et al., 2023).

In spite of the policy reforms initiated in 1994 to address poverty, Malawi's economic growth has remained unstable over the past five years, with average Gross Domestic Product (GDP) growth remaining modest at about 2 to 3 percent annually and leaving the country behind regional peers such as Zambia, Tanzania, and Mozambique (World Bank, 2025). According to the same report, growth slowed from 2.8 percent in 2021 to just 0.9 percent in 2022, resulting in a 1.8 percent decline in per capita GDP. At the same time, persistent poverty remains a challenge, with an estimated 75.4 percent of Malawians, equivalent to about 15.8 million people, living below the updated international poverty line of USD 3.00 per person per day (UNICEF Malawi, 2025).[5]

The high incidence of poverty reflects not only the number of people affected but also the structural constraints that hinder households from escaping it, as nearly 85 percent of the population resides in rural areas and relies primarily on rainfed agriculture, limiting income diversification and perpetuating economic vulnerability (Caruso & Sosa, 2022; FAO, 2023). Similar to other Sub-Saharan African (SSA) countries, Malawi's poverty is heavily influenced by climatic variability (Mgomezulu et al., 2024). In light of this economic instability and Malawi's vulnerability to climate variability, recent studies emphasize the importance of social protection systems that not only redistribute resources but also build household resilience to welfare shocks (Meier, 2024).

[4] NSO stands for National Statistical Office.

[5] UNICEF stands for the United Nations Children's Fund.

Building on a broader poverty reduction and resilience efforts, Malawi has implemented a series of targeted Social Safety Nets (SSNs) programs, the most prominent of which is the Farm Input Subsidy Programme (FISP) (Chibwana et al., 2012; Chirwa & Dorward, 2013; Machira et al., 2023). The program was designed to reduce poverty and enhance long-term food security by improving smallholder farmers' access to modern agricultural inputs such as fertilizer and improved seed (Chibwana et al., 2012; Chirwa & Dorward, 2013). It primarily supports poor farming households through the household head, with the explicit objective of narrowing welfare disparities and promoting shared prosperity (Mwale et al., 2021). To achieve these goals, FISP initially targeted about 1.3 to 1.6 million resource-poor but productive smallholder farmers, providing each beneficiary with fertilizer and hybrid maize seed sufficient to cultivate approximately 0.2 hectares of land (Nyondo et al., 2021). Inputs were distributed through a paper-voucher system redeemable at authorized agro-dealer outlets, although persistent challenges such as poor targeting, favoritism by influential people, and delayed delivery often undermined program effectiveness (Nyondo et al., 2021; Benson et al., 2024). Evidence also indicates that when implemented alongside complementary interventions such as the Social Cash Transfer Programme (SCTP), the subsidy can strengthen both household consumption and productive investment among rural communities (Daidone et al., 2019).

Introduced in the 2005/2006 agricultural season, FISP provided subsidized fertilizer and hybrid seed at less than one-third of the market price, with annual costs ranging between USD 36 million and USD 127 million during its initial years (AGRA, 2017).[6] In 2020/2021, the program was restructured and renamed the Affordable Inputs Programme (AIP), which expanded coverage from approximately 900,000 to 3.7 million smallholder households, effectively reaching almost all farming families across the country (Nyondo et al., 2021). This reform, however, substantially increased fiscal costs, with the program budget surpassing USD 200 million (Mgomezulu et al., 2024). Despite the expansion, only a small proportion of poor farmers benefit directly, as the program's gains are often perceived to accrue to agro-dealers, government officials, and politically connected groups (Alfonso W & Tsoka, 2025; Benson et al., 2024; Nyondo et al., 2021). These persistent challenges continue to raise concerns about the efficiency, equity, and long-term

[6] AGRA stands for Alliance for a Green Revolution in Africa.

sustainability of Malawi's input subsidy programs in achieving inclusive agricultural transformation (Alfonso W & Tsoka, 2025; Benson et al., 2024).

Despite the introduction of the AIP in 2020/2021 to replace FISP, Malawi's input subsidies have achieved limited success in improving food-related outcomes (Nyondo et al., 2023; Benson et al., 2024). Although access to inputs has expanded, evidence shows modest gains in agricultural productivity and food security (Nyondo et al., 2021; Alfonso W & Tsoka, 2025). Studies further reveal that while cash and food transfers improved dietary diversity, input subsidies such as the AIP were less effective and, in some cases, even reduced food consumption and diet quality (Matita et al., 2024; Walls et al., 2023). Moreover, recent assessments warn that poverty and food insecurity remain widespread, with the 2024 Malawi Economic Monitor (MEM) projecting rising poverty rates despite continued public spending on input subsidies (World Bank, 2024; Alfonso & Tsoka, 2025). These concerns highlight the need to assess how the AIP influences food poverty among smallholder households in Malawi.

1.2 Problem Statement

Although there is an expanding body of literature on agricultural input subsidy programmes in sub-Saharan Africa (SSA), most studies have concentrated on input use, crop yields, and production outcomes, with only a limited number examining their effects on household welfare, specifically on food poverty (Mason et al., 2020; Zinnbauer et al., 2018; Ganiyou & Yovo, 2022; Mulula, 2017; Mwale & Kamninga, 2022; Sibande, 2017; Nyirongo & Khataza, 2025; Chakrabarti et al., 2024). Evidence from other countries shows mixed outcomes. In Nigeria, the e-voucher programme significantly increased yields, consumption, and reduced poverty (Wossen et al., 2017), while similar initiatives in Zambia and Togo produced only modest improvements in poverty reduction and food security (Mason et al., 2020; Zinnbauer et al., 2018; Ganiyou & Yovo, 2022).

In Malawi, AIP, formerly FISP, has improved maize yields, fertilizer adoption, and market participation (Sibande, 2017; Nyirongo & Khataza, 2025). However, its overall effect on household food poverty remains inconclusive. Some studies report positive impacts on consumption (Mwale et al., 2021), while others find no significant reduction in food poverty (Pauw et al., 2016; Mulula, 2017; Walls et al., 2023). Many studies relied on data collected before 2017, excluding the period when Malawi experienced major climatic shocks such as floods, droughts, and irregular rains between 2017 and 2020, which significantly influence household welfare. For example, the study by Mulula (2017) precedes these events, offering limited insight into how increased climate variability affects the welfare outcomes of subsidy beneficiaries.

Furthermore, earlier research focused on intermediate outcomes such as productivity, input adoption, market participation, and dietary diversity (Sibande, 2017; Nyirongo & Khataza, 2025; Matita et al., 2024). Although important, these indicators do not necessarily reflect improvements in food poverty incidence or depth. In Malawi's agrarian economy, where seasonal income fluctuations are common, food poverty provides a more direct measure of welfare than general monetary poverty. It captures both the proportion of households unable to meet minimum food requirements and the extent of deprivation among those below the food-poverty line, offering a more policy-relevant reflection of livelihood vulnerability.

In addition, persistent targeting inefficiencies continue to undermine the equity and effectiveness of the programme. Nyondo et al. (2021) reported that an outdated beneficiary database and weak verification systems have allowed exclusion and inclusion errors, while Benson et al. (2024) highlights corruption and favoritism in coupon distribution. Afrobarometer data further show that 71 percent of Malawians believe the AIP favors particular groups or political interests, and only 22 percent think poor farmers are its primary beneficiaries (Alfonso & Tsoka, 2025). Such evidence suggests that the programme's benefits may bypass the poorest households, diluting its poverty-reduction potential.

Building on these gaps, this study provides an updated and comprehensive assessment of AIP's effect on household food welfare in Malawi. It examines differences in socio-economic and institutional characteristics between AIP beneficiaries and non-beneficiaries and estimates how subsidy participation influences food poverty incidence and gap amid recent climatic shocks. By focusing on food poverty rather than general poverty, the study contributes new empirical evidence on the inclusivity, targeting effectiveness, and welfare effects of Malawi's input subsidy policy in a changing climate.

1.3 Contribution of the Study

Poverty among Malawi's smallholder farmers remains persistently high despite decades of agricultural and development interventions. According to UNICEF Malawi (2025), approximately 75.4 percent of Malawians are projected to live below the revised international poverty line of USD 3.00 per capita per day by 2025, indicating a deepening poverty trend over the past decade. The recent revision of the global poverty benchmark (Foster et al., 2025) highlights that poverty in low-income countries across Sub-Saharan Africa is deeper than previously estimated, suggesting that Malawi's poverty situation may be similarly underestimated. Smallholder farmers, who constitute the backbone of the country's food production system, continue to face major constraints such as limited access to fertilizers and improved seed, low agricultural productivity, and recurrent food insecurity (Makate et al., 2024).

In response to these challenges, the Government of Malawi introduced the Affordable Inputs Programme (AIP) to provide subsidized fertilizers and seeds aimed at improving farm productivity and household food security (Government of Malawi, 2022; Chikandanga et al., 2025). The programme aligns with national frameworks such as the National Agriculture Policy (NAP 2024) and the Malawi Vision 2063, both of which prioritize agricultural productivity, commercialization, resilience, and inclusivity as pathways for transforming the agricultural sector into a driver of sustainable economic growth and wealth creation (Government of Malawi, 2024; Kampanje, 2023). At the global level, the AIP supports the aspirations of the Sustainable Development Goals (SDGs 1 and 2), which emphasize eradicating poverty and enhancing food security through sustainable agricultural transformation (United Nations, 2015).

However, the effectiveness of agricultural input subsidy programmes remains contested in Malawi and across the region, with mixed evidence on their impact on income and welfare outcomes. This study, therefore, seeks to assess the effect of the AIP on food poverty among smallholder farmers in Malawi. By generating empirical evidence, the study aims to contribute to policy refinement, enhance the targeting of poverty-reduction interventions, and strengthen the alignment of agricultural support initiatives with the NAP 2024, Malawi Vision 2063, and the SDGs.

1.4 Objective of the Study

The main objective of this study was to assess the effect of Malawi's Affordable Inputs Programme (AIP) on household food welfare among smallholder farmers.

1.4.1 Specific Objectives of the Study

The study aimed to achieve the following specific objectives:

1. To examine differences in demographic, socio-economic, institutional, and environmental characteristics between AIP beneficiaries and non-beneficiaries in Malawi.
2. To estimate the causal effect of AIP participation on the incidence and depth of household food poverty among smallholder farmers in Malawi.

1.4.2 Research Questions

1. How do AIP beneficiaries and non-beneficiaries differ in their demographic, socio-economic, institutional, and environmental characteristics?
2. To what extent does AIP participation reduce the incidence and depth of food poverty among smallholder farmers in Malawi?

CHAPTER 2:
LITERATURE REVIEW

2.1 Theoretical underpinnings: Consumption smoothing theory

Consumption smoothing theory assumes that households seek to maintain stable consumption levels despite facing income fluctuations or shocks, and in line with this theory, risk-averse households protect their consumption through mechanisms such as borrowing or insurance, thereby reducing their vulnerability to unforeseen events (Morduch, 1995). People generally prefer a steady flow of consumption over time rather than experiencing abundance today and scarcity tomorrow (Dornbusch et al., 2015). This preference is closely linked to the concept of resilience, which reflects households' capacity to adapt to changing circumstances (Barrett & Constas, 2014; Béné et al., 2012). Within this framework, programs like AIP provide low-income households with access to essential income resources, enabling them to stabilize their livelihoods (World Bank, 2018). By managing income more effectively, households can maintain a steady flow of consumption even in the face of shocks, using income as a resource for coping strategies and adjusting their means of subsistence as needed (Dercon, 2005).

The theory also suggests that individuals with transient or fluctuating income tend to maintain consumption levels because they perceive income changes as temporary (Friedman, 1957). Rather than reducing spending during low-income periods, they continue to consume steadily, often as a precaution against future uncertainties (Deaton, 1992; Friedman, 1957). Households with greater resilience are therefore better able to manage expenditures and avoid falling into poverty when shocks occur (Townsend, 1994). Programs like AIP can provide additional resources that support consumption-smoothing behavior, helping households withstand economic or food-related shocks more effectively.

2.2 Determinants of AIP Participation

The FISP was designed to target resource-poor smallholder farmers who possess cultivable land and reside within their communities, and it further prioritized vulnerable groups such as female-headed households, child-headed households, orphan-headed households, households caring for physically challenged persons, and those affected by HIV and AIDS (Chirwa et al., 2010). In practice, these criteria proved broad and difficult to apply consistently because the number of households meeting the requirements was much larger than the number of available coupons (Chirwa et al., 2010). Evidence shows that actual beneficiary selection frequently favored households with larger landholdings, more assets, and higher levels of agricultural commercialization, while poorer and vulnerable households, who were the intended priority groups, often received fewer coupons or were excluded entirely (Dorward & Chirwa, 2013). As a result, the programme experienced significant inclusion and exclusion errors, which weakened its ability to achieve pro-poor targeting.

These targeting challenges highlight that access to subsidized agricultural inputs is not random but is shaped by a complex interplay of socio-economic conditions, institutional dynamics, and environmental realities. Understanding which households successfully benefit from the programme is therefore essential for evaluating its fairness, its operational efficiency, and its broader implications for poverty reduction (Benson et al., 2024; Mgomezulu et al., 2024). Moreover, persistent concerns regarding fiscal sustainability and the programme's mixed performance in improving food security outcomes further underscore the importance of examining how effectively targeting is being implemented (Alfonso & Tsoka, 2025; World Bank, 2024).

Building on these targeting challenges, the demographic profile of a household also plays an important role in shaping its interaction with the AIP. Gender dynamics are particularly influential, as female-headed households often face systemic barriers that reduce their likelihood of benefiting from the programme. These barriers include less secure land tenure, limited access to the cash required for co-payments, and weaker connections to the information networks that communicate distribution schedules and locations (ACB, 2022; Walls et al., 2023).[7] In contrast, older household heads tend to be overrepresented among beneficiaries, a pattern attributed to their stronger social capital, established influence within community structures, and longer farming experience, which may make them more visible to those responsible for validating beneficiary lists (Mwale et al., 2021). Marital status further shapes accessibility, as married households can draw on pooled labour and resources, while widowed individuals often experience heightened vulnerability. Their occasional overrepresentation in beneficiary registers may therefore reflect a partial and sometimes

[7] ACB stands for Anti-Corruption Bureau.

inconsistent attempt to prioritize vulnerable groups within the programme's broader targeting approach (Banda et al., 2025; Nyirenda et al., 2021).

These demographic factors work alongside a household's material and economic capital, which also affects subsidy receipt. Land ownership, for instance, remains one of the most consistent determinants of participation. Households cultivating larger plots are systematically more likely to receive inputs, as implementers often perceive them as more productive and capable of generating a meaningful marketable surplus (Mwale & Kamninga, 2022; Nyondo et al., 2021). However, this operational logic introduces a fundamental targeting inconsistency by potentially excluding the land-poor and near-landless, who are often in the greatest need of productivity-enhancing inputs. Similarly, livestock ownership serves as a key proxy for wealth and resilience: households with higher Tropical Livestock Units (TLU) demonstrate a greater likelihood of programme participation, since these assets can be liquidated to cover associated costs (Chirwa & Dorward, 2013). In addition, the ability to diversify income sources through business ownership or to access formal or informal credit provides a critical buffer, enabling households to manage the upfront costs of participating in the subsidy programme, even when inputs are subsidized (Makoza, 2023; Matita et al., 2022).

In addition to household-level characteristics, the institutional and geographic context further shapes access. A household's connectivity to formal and informal institutions plays a key role in mediating its likelihood of receiving inputs. Farmers with regular contact with agricultural extension services are better positioned to benefit, as these channels provide essential information on registration processes and redemption points (Matita et al., 2022; Ragasa et al., 2016). Moreover, there is often significant overlap between AIP beneficiaries and recipients of other social safety nets, such as cash transfer programs, which may indicate either effective targeting of vulnerable households or inefficiencies where multiple forms of assistance fail to reach a broader population (De Weerdt & Duchoslav, 2022).

Spatial factors further influence access to the programme. Although the AIP is explicitly designed for rural households, its implementation is often distorted by political favors and the influence of local power structures, including traditional authorities, resulting in stark regional and even village-level disparities in the quality and quantity of inputs received (ACB, 2022). The programme's targeting intention in climatically vulnerable zones is evident, with households exposed to drought, floods, and irregular rainfall often prioritized on paper. Yet these same households frequently bear the impact of logistical failures, such as late delivery of inputs, which diminishes potential benefits and exacerbates their pre-existing vulnerability (Ajefu et al., 2021; Nyirenda, 2021).

Beyond these core factors, participation is also shaped by more complex social, political, and agro-ecological variables. Social capital and membership in farmer cooperatives or community groups enhance a household's likelihood of receiving inputs, as these networks facilitate information sharing, collective action, and group-based procurement, reducing individual transaction costs (Mgomezulu et al., 2024). Crop choice further influences participation: households focusing on staple cereals, particularly maize, are more likely to be targeted and to self-select into the programme, reflecting a historical emphasis on national food security over crop diversification (Harou, 2018; Chibwana et al., 2012). Political factors also shape the design and continuation of input subsidies, as the programmes attract strong political support due to their appeal to the majority of voters who are smallholder farmers, which reinforces a policy focus on equity over efficiency (Mgomezulu et al., 2024). Finally, geographic accessibility remains a key barrier, with households located far from redemption centers facing higher transport costs and greater opportunity costs, which can effectively exclude the most isolated populations (Ricker-Gilbert & Jayne, 2017).

2.3 Drivers of Poverty and Household Vulnerability

Understanding the drivers of household poverty requires careful attention to demographic dynamics, which frequently shape household welfare outcomes across sub-Saharan Africa (Gross et al., 2021). In Malawi, for example, larger households often struggle with high dependency ratios that dilute available resources, thereby increasing the likelihood of food poverty (Mulula et al., 2017). A similar pattern is observed in Nigeria, where households with more dependents reported significantly higher poverty incidence despite access to fertilizer subsidies (Wossen et al., 2017). Whereas education emerges as a consistent protective factor against poverty risks. Banda et al. (2025) found that educated household heads in Malawi were more capable of adopting technologies and diversifying livelihoods. Comparable evidence from Zambia confirms this association, as Mason et al. (2020) reported that secondary education promoted higher input adoption and better welfare outcomes.

While demographics set important foundations, social dynamics such as gender and marital status further determine how households experience poverty (Boudet et al., 2018). In Malawi, female-headed households are often poorer due to weaker access to land, credit, and labor (Mulula et al. 2017). Comparable gender disparities are reported in Togo, where Ganiyou & Yovo (2022) showed that women's limited access to extension services constrained their ability to benefit from subsidies. Marital status also shapes household welfare since marriage is often assumed to provide resource pooling (Josephson, 2025), yet studies in Rwanda demonstrate that widowed households continue to face significant economic and mental health challenges despite community support (Kayiteshonga et al., 2022).

Beyond demographic and social factors, resource endowments play a crucial role in shaping household poverty outcomes, although their influence varies across contexts (Boudet et al., 2018). In Malawi, larger landholdings are often associated with lower poverty because they enable more effective use of subsidized inputs (Mwale & Kamninga, 2022). However, land size alone is not universally decisive. In Nigeria, Wossen et al. (2017) found that access to credit was a stronger determinant of poverty reduction than land, underscoring how financial resources can sometimes outweigh physical endowments. Evidence from Zambia points in a similar direction: households engaged in small non-farm enterprises were significantly less likely to fall into poverty, even when agricultural returns were modest (Mason et al., 2020). The effectiveness of extension services also shows this variation. In Malawi, their influence remains limited due to irregular coverage (Ragasa et al., 2016), whereas in Rwanda they proved critical in linking input subsidies to productivity gains (Mwesigye et al., 2017). Taken together, these findings highlight that while resource endowments are central to poverty outcomes, their effects are mediated by the broader institutional and market context in which households operate (Boudet et al., 2018).

Alongside demographic, social, and resource-based determinants, environmental factors consistently emerge as cross-cutting drivers of food poverty, often overriding household and structural advantages (Shukla et al., 2019). In Malawi, recurrent floods and irregular rainfall undermine fertilizer responsiveness and worsen vulnerability (Mwale & Kamninga, 2022). Similar patterns are observed in Zambia, where (Hadunka & Janzen, 2023) documented that drought shocks eroded much of the welfare gains achieved through subsidies. The risks are particularly acute in southern Malawi, where land scarcity and climate volatility compound exposure (Walls et al., 2023). A comparable situation is found in northern Nigeria, where erratic rainfall heightened poverty risks despite the presence of subsidy programs (Wossen et al., 2017). Taken together, these examples highlight that food poverty is not only shaped by household resources or institutional arrangements but is also profoundly influenced by environmental shocks that affect entire regions.

2.4 The Role of AIP Participation in Household Poverty Levels

Empirical studies on input subsidies and poverty report mixed results, suggesting that their effectiveness depends heavily on context and program design (Nhlengethwa et al., 2023). Evidence from Togo indicates that targeted fertilizer subsidies contributed to reductions in poverty incidence, depth, and severity, though the magnitude of the impact remained modest (Ganiyou & Yovo, 2022). Mwesigye (2017) similarly found that subsidy programs increased agricultural output and enhanced food security, which translated into higher household incomes and reductions in poverty. However, the strength of these outcomes varied, underscoring that subsidies alone may not be sufficient without complementary measures such as improved markets and extension services. In Zambia, Gasior et al. (2022) used a microsimulation approach to show that subsidies reduced the headcount poverty rate by 3 to 5 percentage points, with the benefits amplified when farmers adjusted their practices in response to input support.

In the Malawian context, the results suggest only modest gains as the FISP/AIP has boosted maize production but has failed to deliver consistent poverty reduction (Matita et al., 2024). Recent studies show that while the program has boosted maize production, its effects on poverty reduction remain limited. Walls et al. (2023) found that although FISP increased maize output, it did not significantly enhance dietary diversity or nutritional outcomes, suggesting little transformative impact on living standards. Likewise, Alfonso & Tsoka (2025) reported that rural food insecurity actually worsened in Malawi during the implementation of AIP, indicating that subsidies alone were insufficient to alleviate the worst forms of deprivation. Furthermore, programme outcomes appear to be shaped by gender and land rights. (Mwale & Kamninga, 2022) demonstrate that subsidies contributed to poverty reduction primarily in patrilineal areas where men hold land rights, while in female landowners, there was essentially no subsidy-driven poverty decline. Their study further highlights that subsidies played a cushioning role during the 2021 drought, mitigating adverse welfare shocks for poor households.

On the other hand, Mason et al. (2020) examine Zambia's input subsidy and report a small reduction in poverty (the poverty headcount fell by about 1.5 percentage points), with the biggest gains among households with small farms (1 to 5 hectares). Similarly, Zinnbauer et al. (2018) found that Zambia's fertilizer subsidy program failed to achieve its goals of poverty reduction and food security enhancement. Despite modest increases in farm incomes, the program's costs outweighed its benefits due to inefficient targeting and resource misallocation. Evidence from Nigeria reinforces this perspective, where Wossen et al. (2017) showed that the e-voucher subsidy program significantly reduced poverty headcount by 17.7 percentage points. By contrast, studies have consistently warned that the poorest farmers often benefit least. In their study, Alavo et al. (2019) in Togo noted that even when subsidies raise incomes, the increases were not substantial enough to lift households above the poverty line, emphasizing the need for additional support.

Furthermore, Camara & Savard (2023) emphasized the need for better targeting mechanisms to include farmers who are typically excluded from markets to enhance economic growth and poverty reduction. On the contrary, older evaluations of Malawi's FISP, for example Sibande et al. (2015) analyzed the effect of FISP and found that while it improved food security, it did not significantly reduce annual per capita consumption expenditure. This suggests that while subsidies may contribute to poverty mitigation, their ability to increase household wealth and lift people out of poverty directly remains limited. Similarly, Mulula et al. (2017) found that FISP did not significantly increase the likelihood of households escaping food poverty, with education playing a more significant role in reducing poverty levels.

2.5 Existing Analytical Approaches for Studying AIP Outcomes

This study employed a quantitative approach to assess the effect of Malawi's AIP on household food welfare, utilizing t-tests for descriptive analysis and the Control Function (CF) approach for causal identification (Wooldridge, 2015; Angrist & Pischke, 2009). This choice is necessitated by the failure of common methods in the literature to fully resolve endogeneity problem. Studies using Propensity Score Matching (PSM), for instance, balance observables like farm size but cannot address unobserved confounders such as farmer ability or political connections, leading to potentially biased estimates (Funsani et al., 2016; Ali et al., 2019; Ganiyou & Yovo, 2022). Similarly, research employing panel data with fixed effects controls only for time-invariant heterogeneity, remaining vulnerable to bias from time-varying factors like annual shifts in local program implementation or household-specific shocks (Mason & Tembo, 2015).

Other studies, such as Alabi & Oshobugie (2020) and Kaiyatsa et al. (2017), have applied the Difference-in-Differences (DID) approach to estimate the causal effects of input subsidy programs. While useful in panel settings, the DID method assumes that both treated and control groups would have followed parallel trends in the absence of treatment, a condition often violated in non-randomized agricultural programs where households experience heterogeneous shocks or regional differences (Angrist & Pischke, 2009; Imbens & Wooldridge, 2009).

Beyond micro-econometric techniques, some analyses utilize Computable General Equilibrium (CGE) models to simulate subsidy impacts (Mkwara, 2013). While valuable for capturing macroeconomic and spillover effects, these models rely on calibration and aggregate data, preventing them from establishing a precise, causal micro-effect at the household level (Dervis et al., 1982; Lofgren et al., 2002). A more direct approach to endogeneity is the Instrumental Variable (IV) method, used in studies like (Ganiyou & Yovo, 2022; Wossen et al., 2017). While IV estimation can address endogeneity, it is generally confined to linear models, making its application challenging for non-linear outcomes such as poverty incidence and poverty gaps. The Control Function (CF) approach, although also requiring a valid instrument, provides greater flexibility by allowing the inclusion of the endogeneity correction term in non-linear models, such as Tobit or Probit, enabling more accurate estimation of causal effects in these contexts (Wooldridge, 2015; Petrin & Train, 2010).

Consequently, the CF approach is adopted as the most methodologically coherent solution (Wooldridge, 2015). By incorporating a control variable derived from the first-stage residuals, the approach accounts for the correlation between unobserved determinants of AIP participation and the outcome equation's error term. This provides a statistically consistent framework for estimating the causal effect of AIP on household food poverty, ensuring robust and reliable inference.

2.6 Delineating the Literature Gap

From the growing body of literature on agricultural input subsidies, many studies have examined welfare outcomes across different contexts, including studies exploring income and production effects of Malawi's AIP, while other evidence examines poverty reduction under subsidy initiatives in other countries. However, despite this expanding evidence base, Malawi-specific findings remain inconclusive, as evidence shows that increased maize production has not consistently translated into improved dietary diversity and nutritional outcomes. This reveals a clear knowledge gap on food specific welfare outcomes, particularly food poverty, and reflects unresolved questions of heterogeneity and causality in determining who ultimately benefits. Therefore, although the literature is growing, robust causal evidence on AIP's effect on food poverty remains limited. This study, therefore, contributes by applying a robust Control Function Approach on national data to isolate this causal effect on food poverty.

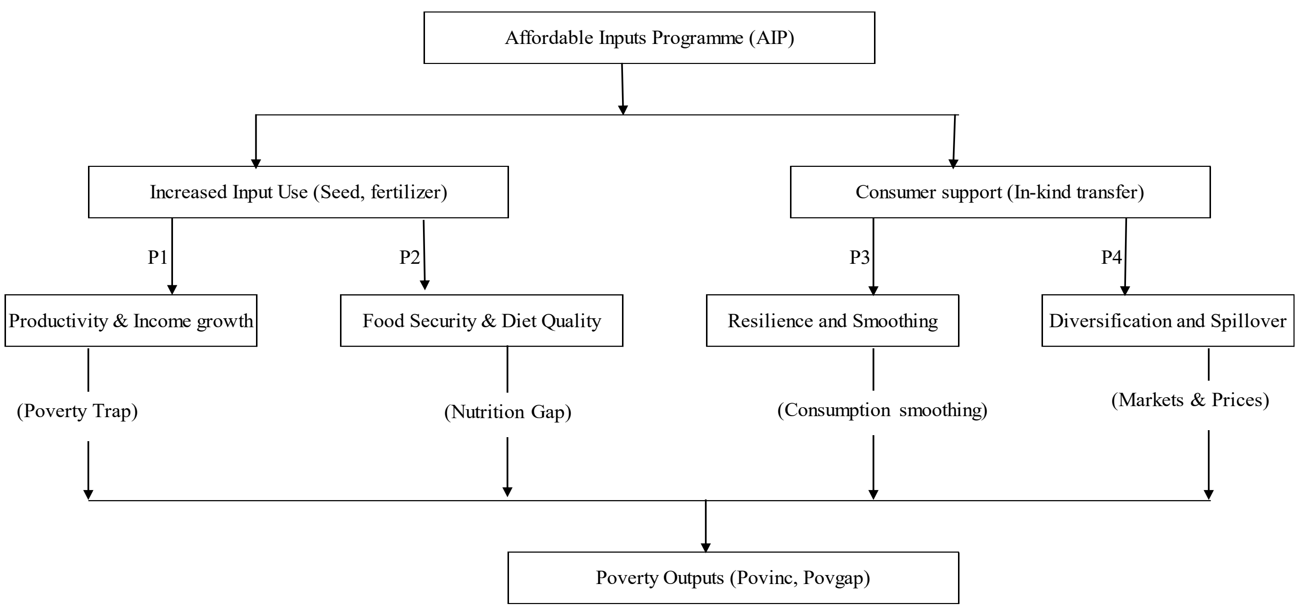
CHAPTER 3:
METHODOLOGY

3.1 Conceptual Framework

Agricultural input subsidy programmes are introduced as policy interventions to drive economic growth that lifts people out of poverty by tackling the structural barriers that trap smallholders in low-productivity cycles, a concept formalized as a poverty trap (Barrett & Carter, 2013). Their ultimate objective is poverty reduction, but they achieve this indirectly by influencing agricultural production and household welfare through a set of intermediate mechanisms (Christiaensen et al., 2011). As Figure 1 illustrates, subsidies work by reducing the cost of fertilizer and seeds, which leads to two entry points, both to greater adoption of modern inputs and to in-kind transfers that ease liquidity constraints at the start of the agricultural season (Chirwa & Dorward, 2013; Osei-akoto et al., 2014). These entry points create the link between subsidy provision and poverty outcomes, forming the basis of Pathway P1 (Productivity and Income Growth) where increased yields enhance food self-sufficiency, lower household food expenditures, and generate surplus income. This pathway reflects the poverty trap theory, which emphasizes the crucial role of external support in moving households toward higher welfare equilibria (Ricker-Gilbert & Jayne, 2011). While the framework depicts the broad pathways, the actual translation of subsidies into welfare gains is mediated by household and contextual characteristics such as landholding size, education, credit access, extension services, gender, marital status, and geographic location (Mason et al., 2020; Correa et al., 2023).

The framework also highlights pathways that extend beyond productivity. Pathway P2 emphasizes food security and diet quality, showing how subsidies can improve household food availability and dietary diversity, particularly when legumes or crop diversification are introduced, thereby generating clear nutritional gains (Sibande et al., 2017; Harou, 2018; Ng'ombe et al., 2025). At the same time, Pathway P3 focuses on resilience and consumption smoothing, which becomes critical when subsidies help stabilize production under shocks such as droughts or floods, thereby protecting households from sharp welfare declines in line with consumption smoothing theory (Ajefu et al., 2021; Kramer et al., 2023). These protective effects are further reinforced when subsidies are complemented by safety nets, access to credit, household savings, or off-farm income opportunities (J-PAL, 2019).[8]

Finally, Pathway P4 emphasizes diversification and spillover effects that operate at the broader economy-wide level. Securing staple production enables households to diversify into higher-value crops and non-farm activities, thereby broadening their income streams. At the same time, increased staple supply contributes to lower food prices, benefiting both subsidy recipients and non-recipients through markets and price effects, while also stimulating rural wages (Ricker-Gilbert et al., 2013; Arndt et al., 2016; Mason et al., 2020). Taken together, the four pathways translate into measurable poverty reductions, reflected in lower food poverty (povinc) and narrower poverty gaps (povgap). This integrated framework underscores the role played by input subsidies as multidimensional tools, combining productivity, nutrition, risk protection, and market effects into an integrated strategy for reducing poverty.



Source: Author's construction, adapted from (Mkupete, 2025)and informed by (Ricker-Gilbert et al., 2013; Arndt et al., 2016; Mason et al., 2020; Sibande et al., 2017; Harou, 2018; Ng'ombe et al., 2025; Ajefu et al., 2021; Kramer et al., 2023; Correa et al., 2023)

Figure 1: Conceptual framework illustrating AIP poverty-reduction pathways

8 J-PAL refers to the Abdul Latif Jameel Poverty Action Lab

3.2 Empirical Strategy

To address the study's objectives, different empirical methods were employed, each aligned with a specific research question. Objective 1, which examines differences in demographic, socio-economic, institutional, and environmental characteristics between AIP beneficiaries and non-beneficiaries, was assessed using t-tests for mean comparisons. Food poverty measures, capturing incidence and depth, were derived using the Foster–Greer–Thorbecke (FGT) indices. To estimate the causal effect of AIP on household food poverty, the Control Function (CF) approach was applied, as it corrects for potential endogeneity in program participation and ensures consistent estimates. These methods were selected not only because they are widely used in the poverty and subsidy evaluation literature but also because they are well-suited to the data structure and the specific objectives of this study.

3.3 Measurement of Food Expenditure and Poverty

We measured household food poverty using per-capita food expenditure, which reflects the amount of food resources available for each household member. Food expenditure refers to the total amount spent or estimated for food consumed by a household over a given period. In this study, total household food expenditure is defined as the sum of the monetary value of food obtained from own production, expenditures on purchased food, and the monetary value of food received as gifts or remittances, consistent with standard consumption measurement guidelines (Deaton & Zaidi, 2002, Kennedy et al., 2011). Per capita food expenditure is calculated by dividing total household food expenditure by the number of household members. This adjustment accounts for household size and composition and allows for comparable measurement of food consumption across households of different sizes. In addition, the food consumption data enabled us to categorize consumption into specific food groups, namely: cereals, roots and tubers, nuts and pulses, vegetables, meat and fish, fruits, milk products, sugar and fats, beverages, and spices/miscellaneous products, following common food classification approaches used in household consumption surveys (NSO, 2020).These food groups were constructed based on the nature of food items consumed.

In line with established approaches in the poverty literature (Foster et al., 1984; Haughton & Khandker, 2009), the analysis employed the FGT class of poverty indices, which are widely used because they are decomposable, sensitive to the distribution of welfare among the poor, and capable of capturing both the incidence and intensity of poverty. The FGT index is expressed as:

$$FGT_\alpha = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{Z-Y_i}{Z}\right)^\alpha \tag{1}$$

where Z represents the food poverty line (Malawian Kwacha (MWK) 101,293.4 per person per year, as defined by the 2019/20 Malawi IHS). The food poverty line (Z) indicates the minimum per-capita food expenditure required to meet basic food needs and maintain minimum dietary energy requirements. Households with per-capita food expenditure below this level are classified as food poor; in other words, food poverty describes the condition in which the household's per-capita food expenditure is insufficient to afford the basic minimum food basket (quantity and quality) necessary for adequate nutrition (O'Connor et al., 2016). Meanwhile, Y_i denotes the per-capita food expenditure of a household i, N is the total number of households in the sample, and H is the number of households whose per-capita food expenditure is below the food poverty line.

The parameter α serves to distinguish different poverty dimensions (Foster et al., 1984; Haughton & Khandker, 2009). When $\alpha = 0$, the index yields the food poverty headcount ratio, i.e. the proportion of households whose per-capita food expenditure falls below Z (food poverty incidence). When $\alpha = 1$, the index gives the food poverty gap, indicating the average shortfall of the poor's expenditure relative to the food poverty line (depth of food poverty). When $\alpha = 2$, the index provides the squared food poverty gap, which places more weight on households whose expenditure is far below the poverty line, thus capturing severity of food poverty and inequality among the food poor.

Although the FGT framework allows for all three measures, this study only focused on the headcount and gap indices, as these are the most policy-relevant. They directly show the proportion of households living below the poverty line and the average shortfall from it, providing clear insights for evaluating the effects of AIP (Haughton & Khandker, 2009; Ravallion, 1994).

3.4 Differences Between AIP Beneficiaries and Non-Beneficiaries

The first objective examined whether there are significant differences in socio-economic, institutional, food consumption, climatic, and poverty characteristics between households that benefited from the Affordable Inputs Programme (AIP) and those that did not. Beneficiaries are households that received subsidized inputs under AIP, while non-beneficiaries did not. This analysis provides insight into whether the programme effectively reaches its target group of smallholder farmers and whether participation is associated with differences in household characteristics and food consumption patterns.

To examine these differences, independent-samples t-tests were used to compare mean values between the two groups, as they are separate and unrelated. The t-test determines whether the mean values of two groups differ significantly (Gujarati & Porter, 2009; Wooldridge, 2016). Hence, mean comparisons were conducted for all continuous and binary variables, and statistical significance was determined based on the corresponding p-values at the 1%, 5%, and 10% levels.

The variables included in this analysis capture household socio-demographic and institutional characteristics, food consumption patterns, climatic shocks, and poverty indicators (Table 1). These include sex, age, education, land size, livestock ownership, access to credit and extension services. While the t-test results highlight differences between AIP beneficiaries and non-beneficiaries, they reflect descriptive associations rather than causal effects of programme participation. This does not establish causal relationships, which are addressed under the second objective through econometric analysis.

Table 1: Variable Description

VARIABLE	TYPE	DESCRIPTION
Sex	Binary	Sex of household head (1 = male; 0 = otherwise)
Age	Continuous	Age of the household head in years
Education		
None	Binary	Household head with no education = 1; otherwise = 0
Primary	Binary	Household head completed primary education = 1; otherwise = 0
Secondary	Binary	Household head completed secondary education = 1; otherwise = 0
Tertiary	Binary	Household head completed tertiary education = 1; otherwise = 0
Marital Status		
Married	Binary	Household head married = 1; otherwise = 0
Separated	Binary	Household head separated = 1; otherwise = 0
Widowed	Binary	Household head widowed = 1; otherwise = 0
Not married	Binary	Household head never married = 1; otherwise = 0
Geo-area	Binary	Residence location (1 = urban; 0 = rural)
Credit	Binary	Household had access to credit = 1; otherwise = 0
Extension services	Binary	Household had contact with extension services = 1; otherwise = 0
Business	Binary	Household operates a non-farm enterprise = 1; otherwise = 0
Safety nets	Binary	Household benefited from any safety net program (cash transfers or food aid) = 1; otherwise = 0
Tropical Livestock Unit	Continuous	Total livestock owned, in Tropical Livestock Units (TLU)
Land	Continuous	Size of land cultivated or owned by household (hectares)
Drought	Binary	Household was affected by drought = 1; otherwise = 0
Floods	Binary	Household was affected by flooding = 1; otherwise = 0
Irregular rains	Binary	Household experienced irregular rainfall = 1; otherwise = 0
Employment	Binary	Household employment status = 1; otherwise = 0

3.5 Estimating the Effect of AIP on Household Food Poverty: Control Function Approach

The main objective of this study is to assess the effect of AIP on household welfare, a broad concept that refers to a household's overall well-being, including income, consumption, assets, and living standards (Deaton, 1997; Ravallion, 2001). For this study, we narrowed household welfare to food-related measures, focusing on per-capita food expenditure and FGT-based indicators of poverty incidence and gap, which are directly measurable. This focus aligns with the first specific objective, which examines differences in demographic, socio-economic, institutional, and climatic characteristics between AIP beneficiaries and non-beneficiaries. Together, these two objectives provide a baseline understanding and a measurable assessment of the programme's impact on household food welfare.

To estimate the causal influence of AIP on household food poverty, the study was supposed to employ a regression framework consistent with (Chibwana et al., 2014). The following model was specified:

$$y_i = \beta_0 + \beta_1 AIP_i + \beta_2 X_i + \varepsilon_i \tag{2}$$

where y_i is the food poverty for the household (i). AIP is the number of subsidies received by the household (i). X_i denotes a vector of covariates that includes household characteristics such as sex, age, education, and marital status, along with employment status, geographical location, participation in non-farm enterprises, land size, livestock ownership, access to credit and extension services, and exposure to climatic shocks, including droughts, floods, and irregular rainfall. ε_i is an error term. The main coefficient of interest in equation (2) is β_1, which measures the effect of AIP on food poverty. We expect a negative coefficient β_1 . In other words, AIP is expected to have a food poverty decrement effect.

However, participation in AIP is endogenous because the decision to participate in the subsidy program is influenced by factors that also affect household food poverty, creating a correlation between AIP_i and the error term ε_i. This endogeneity arises from non-random program selection, unobserved household characteristics such as farmer ability or social networks, and policy targeting. If not addressed, these sources of endogeneity can lead to biased and inconsistent estimates of the effect of AIP participation. To overcome this challenge, we applied the two-step CF approach, following (Mason & Tembo 2015b; Sibande et al., 2017; Wossen et al., 2017), which explicitly models the selection process and allows for consistent estimation of the causal effect of AIP on household food poverty in the following steps.

Step 1:

Factors affecting the number of subsidies received were determined using Ordinary Least Square (OLS). Different variables were used as independent variables in the model, consistent with literature on participation in subsidy programs (Chibwana et al., 2012; Chirwa & Dorward, 2013; Matita et al., 2022). Furthermore, the CF approach requires the inclusion of instrumental variables (IV) in the first stage. These are variables that influence access to AIP but affect food poverty only indirectly. In this study, two potential instruments were initially considered in line with the literature (Sibande et al., 2017; Wossen et al., 2017; Alavo et al., 2019; Mason et al., 2020). The first was the length of residence, capturing how long a household has been established in a village or community. While this variable has been validated in other contexts as influencing access to agricultural inputs, it did not fit our model. Diagnostic tests revealed a weak instrument problem, as the first-stage F-statistic was below the conventional threshold of 10, a benchmark widely used to indicate instrument strength (Staiger & Stock, 1997). The second instrument, village population size, proved more robust. Village population was used as an instrumental variable because allocation of subsidized inputs in Malawi has historically been proportional to village size, with larger established villages receiving more coupons. The emergence of numerous smaller breakaway villages since the inception of FISP in 2005 has further reinforced population size as a key determinant of subsidy distribution (Chibwana et al., 2012). In this study, this instrument passed the relevance test, with an F-statistic greater than 10, confirming its strength. Accordingly, village population size was retained as the valid instrument for AIP participation in the control function approach.

The first-stage model was specified as:

$$AIP_i = \beta_0 + \beta_1 Z_i + \beta_2 X_i + u_i \qquad (3)$$

Where AIP_i is the number of subsidized inputs received by household i, Z_i is the instrumental variable (village population size), X_i is a vector of household and institutional characteristics (Number of coupons received, region, flood exposure, land size, sex, age, education level, marital status, geo-area), and u_i is the error term. From equation (3), the fitted residuals $\hat{u}_i$ are obtained. These residuals capture the endogenous component of AIP participation that is correlated with unobserved factors affecting food poverty. By including $\hat{u}_i$ in the second stage, the CF approach corrects for endogeneity and produces consistent estimates.

Step 2:

Predicted residuals obtained from the first-stage regression were included in the second-stage model to correct for potential endogeneity in AIP participation. Because the dependent variable, food poverty, is binary, the second stage was estimated using a Probit model. The Probit model assumes the existence of an unobserved latent variable representing the household's underlying propensity to experience food poverty, which is observed only when it exceeds a certain threshold (Greene, 2012; Cameron & Trivedi, 2005). In this context, the observed outcome takes the value of 1 if the household is food poor and 0 otherwise, depending on whether the latent food poverty index crosses that threshold. A statistically significant coefficient on the generalized residual term indicates that the decision to participate in AIP is endogenous.

The predicted residuals $\hat{u}_i$, obtained from equation (3), capture the endogenous component of AIP participation correlated with unobserved factors influencing food poverty. Including $\hat{u}_i$ in the second-stage equation corrects for endogeneity, ensuring consistent parameter estimates. The second-stage Probit specification is given as:

$$P(poor = 1) = \beta_0 + \beta_1 AIP_i + \beta_2 X_i + \delta \hat{u}_i + \epsilon \tag{4}$$

In this context, the coefficient δ captures the presence and magnitude of endogeneity in programme participation. A statistically significant δ indicates that unobserved factors correlated with both participation and outcomes bias the baseline estimates, thus validating the control function correction (Cameron & Trivedi, 2005; Wooldridge, 2015). The corrected coefficient β_1 then consistently estimates the causal effect of AIP on household food poverty.

In addition to poverty incidence, the analysis also extended to the poverty gap, which captures the depth of poverty among affected households. Unlike poverty incidence, which is a binary measure, the poverty gap is a continuous variable censored at zero, since non-poor households have no measurable shortfall, while poor households exhibit a positive poverty gap. This censoring makes the Ordinary Least Squares (OLS) estimator inappropriate, as it violates the assumption of a continuous dependent variable, leading to biased and inconsistent estimates (Wooldridge, 2010; Greene, 2018).

To account for this limitation, the study adopts the Tobit modeling framework, originally proposed by Tobin (1958), which estimates underlying poverty levels while accounting for both the likelihood of being poor and the depth of poverty among poor households. The model provides consistent and efficient maximum likelihood estimates under the assumptions of normality and homoskedasticity of the error term (Amemiya, 1984; Gujarati & Porter, 2009). This approach has been widely used in poverty and welfare studies where measures such as consumption shortfalls or poverty gaps are censored at zero (McDonald & Moffitt, 1980; Foster et al., 1984).

Formally, the Tobit model can be expressed as:

$$PovertyGap_i^* = \beta_0 + \beta_1 AIP_i + \beta_2 X_i + \delta \hat{u}_i + \epsilon \tag{5}$$

$$PovertyGap_i = \begin{cases} 0, & if\ PovertyGap_i^* \leq 0 \\ PovertyGap_i^*, & if\ PovertyGap_i^* > 0 \end{cases}$$

Here, PovertyGap_i^* represents the latent, unobserved poverty gap for the household i, while PovertyGap_i is the observed poverty gap, which is censored at zero for non-poor households. As in the incidence model, the predicted residual term $\hat{u}_i$is included to correct for endogeneity in AIP participation. A statistically significant coefficient δ indicates that AIP allocation is endogenous. After correcting for endogeneity, the coefficient β_1 provides a consistent estimate of the causal effect of subsidy access on the depth of poverty, capturing how AIP participation affects the latent poverty gap.

3.5.1 Variable description and expected results

This study employs household-level socio-economic, demographic, and environmental factors as the determinants of food poverty incidence and poverty gap. The sex of the household head (male = 1) is expected to reduce poverty because male-headed households generally have better access to resources and income-generating opportunities (Gross et al., 2021; Mulula et al., 2017). Similarly, the age of the household head is expected to have a negative effect on poverty, as older heads tend to accumulate assets, skills, and experience, though very old age may increase vulnerability due to declining labor capacity (Duhon et al., 2025).

Education is measured at primary, secondary, and tertiary levels, with no education as the base category. Higher education levels are expected to reduce poverty by enhancing human capital and income-generating capacity (Mason et al., 2020; Banda et al., 2025). Marital status, categorized as separated, widowed, or never married (base = married), is also expected to reduce poverty since smaller households face lower dependency burdens, and widowed or vulnerable households often benefit from targeted social programs (Mason et al., 2020; Beegle et al., 2018; Ajefu et al., 2021; Gross et al., 2021; Josephson, 2025).

Households in urban areas (geo-area) are expected to be less poor due to better access to markets, infrastructure, and services (Caruso & Sosa, 2022). Access to credit and extension services is anticipated to reduce poverty by facilitating productive investments and enhancing agricultural productivity (Gasior et al., 2022; Ragasa et al., 2018). Likewise, non-farm business operations help reduce poverty by diversifying income sources (Josephson, 2025).

Household livestock holdings were converted into Total Livestock Units (TLU) using FAO-converted factors for different species, such as cattle, goats, and poultry, creating a continuous measure that captures the overall magnitude of livestock wealth. This measure is crucial for rural livelihoods, as sustainable livestock systems enhance food security and promote inclusive economic growth (FAO, 2011). Empirical studies further indicate that households with higher TLU tend to have increased income and reduced poverty levels, highlighting the importance of livestock assets in alleviating poverty (Acosta, 2024; Zegeye, 2022).

Environmental shocks, including droughts, floods, and irregular rainfall, are expected to increase poverty by negatively affecting agricultural production and household income (Ajefu et al., 2021; Shukla et al., 2019). On the other hand, land ownership and household employment provide productive assets and income streams that help reduce poverty (Mwale & Tembo, 2022; Caruso & Sosa, 2022). Overall, these explanatory variables inform the analysis of the dependent variables: food poverty incidence and the poverty gap. For clarity and ease of reference, Table 2 summarizes all variables, their definitions, and their expected signs.

Table 2: Variable description and their expected signs

Variable	Description	Sign
Sex	Gender of household head (male = 1; otherwise = 0)	–
Age	Age of household head (years)	–
No education (base)		
Primary	Household head completed primary education = 1; otherwise = 0	–
Secondary	Household head completed secondary education = 1; otherwise = 0	–
Tertiary	Household head completed tertiary education = 1; otherwise = 0	–
Married (base)		
Separated	Household head separated = 1; otherwise = 0	–
Widowed	Household head widowed = 1; otherwise = 0	–
Not married	Household head never married = 1; otherwise = 0	–
Geo-area	Household located in urban area = 1; otherwise = 0	–
Credit	Household had access to credit = 1; otherwise = 0	–
Extension services	Household accessed extension services = 1; otherwise = 0	–
Business	Household operates a non-farm business = 1; otherwise = 0	–
Tropical Livestock Unit	Total livestock owned, in Tropical Livestock Units (TLU)	–
Drought	Household affected by drought = 1; otherwise = 0	+
Floods	Household affected by flooding = 1; otherwise = 0	+
Irregular rains	Household experienced irregular rainfall = 1; otherwise = 0	+
Land	Size of land cultivated/owned (hectare)	–
Employment	Household head employed (formal/informal) = 1; otherwise = 0	–
Poverty incidence	Household food poverty status (1= poor; otherwise = 0)	Dependent
Poverty gap	Food poverty gap index	Dependent

3.5.2 Model Diagnostic

In the first stage of the analysis, Ordinary Least Squares (OLS) was applied, and diagnostic tests were conducted to verify the validity of its underlying assumptions. The Breusch–Pagan test was employed to detect heteroscedasticity, since the OLS framework assumes homoscedastic error terms, and violation of this assumption leads to inefficient estimators and biased inference (Breusch & Pagan, 1979; Wooldridge, 2016). To assess the presence of multicollinearity among the explanatory variables, Variance Inflation Factors (VIFs) were calculated, as high collinearity inflates the variance of coefficient estimates and undermines statistical precision (Gujarati & Porter, 2009). A link test was performed to identify potential model specification errors, including omitted variables or inappropriate functional form, which are known to compromise the reliability of regression estimates (Pregibon, 1980; Cameron & Trivedi, 2005). Finally, the Jarque–Bera test was used to assess normality of residuals (Jarque & Bera, 1980). While normality was desirable for efficiency, it was not required for unbiased and consistent estimation in large samples (Wooldridge, 2010).

The main focus of the first stage was to verify the strength and relevance of the instrument. An F-statistic exceeding 10, following Staiger and Stock (1997), indicated that the instrument was sufficiently strong, allowing us to proceed confidently to the second stage of the control function estimation.

For the probit model, several diagnostic tests were conducted to ensure the validity of the estimates. First, the significance of the residual from the first-stage regression was checked to confirm the presence of endogeneity, which validates the use of the control function approach. Second, the link test was performed to assess model specification; a non-significant squared predicted term (_hatsq) is expected, indicating correct specification (Pregibon, 1980). Finally, the Hosmer–Lemeshow goodness-of-fit test was applied to evaluate how well the model predicts observed outcomes, with a non-significant result expected, showing that the model fits the data adequately. These diagnostics collectively ensure that the estimated effects of subsidy participation on food poverty incidence are reliable and interpretable (Hosmer & Lemeshow, 2000; Cameron & Trivedi, 2005).

Finally, for the Tobit model, diagnostic checks were conducted to ensure the robustness of the results. The dependent variable, Poverty gap, is censored at zero for households that are not poor; hence, its distribution will be examined to justify the presence of censoring and the appropriateness of the Tobit model (Tobin, 1958; Wooldridge, 2010). The normality of residuals was assessed using the Shapiro–Wilk test and visual inspection through histograms and normal probability plots (Shapiro & Wilk, 1965). Where residuals deviate from normality, robust standard errors will be applied to ensure valid statistical inference (Gujarati & Porter, 2009; Cameron & Trivedi, 2010).

3.6 Study Area and Data Description

The study area is Malawi, a landlocked country in southeastern Africa, divided into three administrative regions (Northern, Central, and Southern) and 32 districts. According to the 2018 Population and Housing Census, the country had a population of nearly 18 million, with about 84 percent residing in rural areas where agriculture is the main source of livelihood (NSO, 2019).

Since AIP is designed to support farming households, this study focuses on Malawi's agricultural population.

The analysis uses data from IHS5 collected in 2019/20 by the National Statistical Office (NSO) of Malawi with technical support from the World Bank under the LSMS-ISA initiative (NSO, 2020). The survey was conducted between April 2019 and March 2020, covering all districts of the country and producing estimates representative at the national, regional, and district levels, as well as for urban and rural domains. Out of the 11,434 households successfully interviewed, this study restricts the sample to 8,798 households engaged in agricultural activities.

After cleaning the data to exclude incomplete and inconsistent cases, the final analytical sample comprises 7,804 agricultural households distributed across the three regions and both geographical areas of Malawi. As shown in Table 3, most households are located in rural areas, which aligns with the country's population distribution. Out of the total sample, 991 households benefited from the Affordable Inputs Programme (AIP), while 6,813 were non-beneficiaries.

The IHS5 followed a multistage sampling design. In the first stage, Enumeration Areas (EAs) were selected from the 2018 Population and Housing Census using probability proportional to size (PPS), stratified by district and implicitly stratified by rural/urban location, Traditional Authority, and EA codes. In the second stage, a systematic random sample of 16 households was drawn from each EA after an updated household listing (NSO, 2020). This design ensured representativeness and allowed the survey to capture both seasonal and regional variations in household welfare.

Table 3: Sample distribution by AIP participation, region, and geographical area

Category	Beneficiaries	Non-Beneficiaries	Total
		Urban	
North	12	145	157
Central	14	168	182
South	30	209	239
Total	56	522	578
		Rural	
North	143	1,012	1,155
Central	252	2,306	2,558
South	540	2,973	3,513
Total	935	6,291	7,226
		Overall	
North	155	1,157	1,312
Central	266	2,474	2,740
South	570	3,182	3,752
Total	991	6,813	7,804

CHAPTER 4:
RESULTS AND DISCUSSION

This section presents the empirical results, including descriptive statistics of key demographic, socio-economic, institutional, and climatic variables, followed by the results of the Control Function approach estimating the effect of AIP participation on household food poverty. The findings are discussed in light of existing literature on agricultural input subsidies.

4.1 Differences Between AIP Beneficiaries and Non-Beneficiaries

Table 4 presents the demographic characteristics of AIP beneficiaries and non-beneficiaries, showing differences that reflect both program targeting and underlying social patterns. A higher proportion of male-headed households was found among non-beneficiaries (69 percent) compared to beneficiaries (64 percent), meaning the programme reached relatively more female-headed households. The significantly lower proportion of male-headed households among beneficiaries suggests some success in gender-sensitive targeting, potentially addressing historical biases in agricultural input distribution (Banda et al., 2025; Walls et al., 2023). This targeting reflects efforts to prioritize socially vulnerable groups, as female-headed households often face greater economic constraints due to limited access to land, credit, and labor (Mulula et al., 2017).

Age differences between the two groups further highlight programmatic patterns. Beneficiaries were older on average (47 years) than non-beneficiaries (45 years), signifying that relatively older household heads were more likely to participate. Older farmers may have greater influence in community networks and are often perceived as more experienced, which can increase their likelihood of accessing scarce resources (Mwale & Kamninga, 2022; Gasior et al., 2022). At the same time, this may disadvantage younger farmers who face higher barriers to entry into agriculture and are in greater need of input support to establish productive livelihoods. This finding agrees with earlier evaluations of subsidy programmes in sub-Saharan Africa, which noted that younger farmers are often excluded due to weaker social ties and limited land ownership (Koira, 2015; Nyondo et al., 2023).

Marital status also differentiates participants, with widowed household heads more likely to be beneficiaries (16 percent) compared to non-beneficiaries (13 percent). Widowhood is strongly associated with vulnerability, as it often leads to reduced labor availability, loss of spousal income, and greater dependency burdens (Kayiteshonga et al., 2022). The higher inclusion of widowed households indicates that AIP reached socially disadvantaged groups, reinforcing its role as a pro-poor social protection tool (Gross et al., 2021). Conversely, married households were more prevalent among non-beneficiaries (72 percent compared to 69 percent), which may reflect the relative resource pooling advantage of married couples, reducing their prioritization for subsidy allocation (Josephson, 2025). Only 6 percent of beneficiaries reside in urban areas compared to 8 percent of non-beneficiaries, reinforcing AIP's focus on rural households, consistent with Malawi's Vision 2063 emphasis on rural development (Kampanje, 2023). These differences highlight non-random participation, emphasizing the need for ongoing monitoring to ensure inclusivity for all vulnerable groups, particularly those with limited social capital (Banda et al., 2025).

Table 4: Mean differences in demographic characteristics by AIP participation

Variable	Beneficiaries (A)	Non-Beneficiaries (B)	Total	P-value for the difference (B-A)
Sex (Male = 1)	0.641	0.690	0.684	0.002
Age	47.414	44.520	44.888	0.000
Geo-Area (Urban = 1)	0.057	0.077	0.074	0.024
Education				
No education	0.888	0.891	0.890	0.813
Primary	0.055	0.052	0.053	0.684
Secondary	0.052	0.053	0.053	0.931
Tertiary	0.004	0.004	0.004	0.973
Marital Status				
Married	0.685	0.719	0.715	0.026
Separated	0.142	0.135	0.136	0.534
Widowed	0.162	0.130	0.134	0.005
Non-married	0.010	0.015	0.015	0.194
Observations	991	6,813	7,804	

Table 5 reveals significant differences in socio-economic, institutional support, and climatic shock exposure between AIP beneficiaries and non-beneficiaries, further explaining the programme's targeting patterns. Beneficiaries exhibit greater access to institutional resources, which likely enhances their ability to participate in and benefit from the programme. For instance, 58.4 percent of beneficiaries access agricultural extension services compared to 54.7 percent of non-beneficiaries, suggesting that extension officers may play an important role in linking farmers to the program or that households already engaging with extension services are more likely to benefit (Matita et al., 2024). This also aligns with findings from Zambia, where access to extension services significantly increased subsidy participation (Gasior et al., 2022). Furthermore, a larger share of beneficiaries also reported receiving other safety nets (23.6 percent vs 15.5), pointing to an overlap between AIP and existing social protection initiatives. While this overlap can strengthen resilience for the most vulnerable households, it also risks inefficiencies if programme resources are concentrated on households already supported by other interventions, leaving out equally poor but less connected groups (Beegle et al., 2018; Mgomezulu et al., 2024). Beneficiaries also hold more livestock assets, with an average Total Livestock Unit (TLU) of 40.9 percent compared to 34.7 percent for non-beneficiaries, indicating a stronger resource base that supports agricultural productivity and resilience to shocks (Acosta et al., 2024; Zegeye, 2022). Larger landholdings among beneficiaries (1.62 hectares vs 1.50 hectares) further suggest that AIP reaches households with slightly greater productive capacity, enabling more effective use of subsidized inputs (Mwale & Kamninga, 2022). This pattern raises concerns about potential exclusion of the most resource-constrained households, as noted in similar subsidy programmes in Togo (Ganiyou & Yovo, 2022).

However, beneficiaries also face greater climatic exposure, with 41.9 percent reporting drought compared to 35.7 percent of non-beneficiaries. Beneficiaries also report slightly higher exposure to irregular rains (56.1 percent vs 53.3 percent). This indicates that AIP targets areas with significant environmental risks, aligning with vulnerability-based targeting strategies emphasized by Shukla et al. (2019) and Mgomezulu et al. (2024). The higher drought and irregular rains exposure among beneficiaries suggests that the programme prioritizes households in climatically vulnerable regions, where agricultural support is critical for mitigating production losses (Walls et al., 2023). These findings imply that AIP balances targeting productive farmers with reaching vulnerable households, but the reliance on institutional linkages and resource endowments may inadvertently exclude the poorest, as highlighted by Alfonso & Tsoka (2025). To enhance inclusivity, programme design should strengthen outreach to resource-poor households with limited access to extension services or livestock assets (Chikandanga et al., 2025).

Table 5: Socio-economic, institutional & climatic mean differences by AIP participation

Variable	Beneficiaries (A)	Non-Beneficiaries (B)	Total	P-value for the difference (B-A)
	Panel A: Socio-economic & Institutional Factors			
Business Ownership	0.067	0.072	0.071	0.565
Access to Credit	0.319	0.302	0.304	0.279
Employment Status	0.116	0.123	0.122	0.541
Access to Extension	0.584	0.547	0.552	0.029
Access to Safety Nets	0.236	0.155	0.165	0.000
Tropical Livestock Unit	0.409	0.347	0.355	0.099
Land size	1.622	1.504	1.519	0.032
	Panel B: Climatic Shocks			
Drought	0.419	0.357	0.365	0.000
Floods	0.315	0.322	0.321	0.657
Irregular rain	0.561	0.533	0.537	0.099
Observations	991	6813	7804	

4.2 Effect of AIP on Food Poverty: Control Function Approach Results

To account for potential endogeneity, a control function approach was implemented. In the first stage, an OLS regression was estimated to generate residuals for use in the second-stage models. Initial diagnostics indicated heteroscedasticity (Breusch–Pagan $\chi^2 = 695.58$, $p < 0.001$), meaning that the error variances were not constant across observations. This was corrected using robust standard errors (robust variance-covariance estimator, VCE-robust), ensuring valid inference (Breusch & Pagan, 1979; Wooldridge, 2016). Multicollinearity was not a concern, as the mean VIF was 1.53 and the maximum VIF was 2.73, both well below the conventional threshold of 10, suggesting that independent variables were not highly correlated (Gujarati & Porter, 2009). Model specification was also satisfactory (link test: __hat p = 0.000, _hatsq p = 0.262), indicating no major omitted variable bias. The Jarque–Bera test showed that the residuals were not normally distributed; however, this does not compromise the consistency of OLS estimates, as normality is not a necessary condition for valid inference in large samples (Wooldridge, 2010; Cameron & Trivedi, 2005). Finally, the first-stage regression was jointly significant ($p < 0.001$), with an F-statistic of $F = 11.00$, showing that the instruments were strong predictors of the endogenous variable (see Appendix A for supporting diagnostics).

In the second stage, a probit regression was used to estimate the effect of subsidy participation (number of coupons) on food poverty incidence. The residual from the first stage was included as an endogenous regressor, and its coefficient was positive and significant (dy/dx = 0.147, p = 0.002), confirming endogeneity and validating the control function approach. Model specification (link test: _hat p = 0.000, _hatsq p = 0.152) and goodness-of-fit (Hosmer–Lemeshow $\chi^2 = 9.30$, p = 0.318) confirmed that the probit model fit the data well, since a high p-value in the Hosmer–Lemeshow test indicates no significant deviation between predicted and actual outcomes (Hosmer & Lemeshow, 2000; Cameron & Trivedi, 2005) (see Appendix B1 for full second-stage probit diagnostics).

Following the estimation of the Tobit model, diagnostic checks were conducted to verify the validity of the model assumptions. The normality of residuals was evaluated using the Shapiro–Wilk test developed by Shapiro & Wilk (1965) and visual inspection. The test (W = 0.769, $p < 0.001$) rejected normality, and the histogram indicated a left-skewed, leptokurtic pattern with most residuals around –0.2 and a long right tail. Such deviations are common in Tobit models because censoring of the dependent variable restricts the observed distribution, and the residuals represent only the portion of the latent variable above or below the censoring point (Wooldridge, 2010). Therefore, non-normality may partly arise from the latent variable formulation itself rather than a model misspecification. Given the large sample (n = 7,804), the Shapiro–Wilk test may also detect minor deviations as significant (Gujarati & Porter, 2009; Cameron & Trivedi, 2010). The non-normality was not severe enough to bias results, as Tobit maximum likelihood estimators remain consistent under mild violations (Greene, 2018). Robust standard errors were used to ensure reliable inference. The residual from the first stage was included as an endogenous regressor, and its coefficient was positive and significant (dy/dx = 0.056, p = 0.000), confirming endogeneity and validating the control function approach (see Appendix B2 for full second-stage Tobit diagnostics).

With these tests confirming model validity, the following results demonstrate how AIP participation affects the incidence and depth of food poverty among smallholder households. Detailed coefficient estimates for the Probit and Tobit models are provided in Appendices A and B for reference. In Table 6, the Pseudo R^2 values of 0.035 in the probit model and 0.052 in the Tobit model both indicate the proportion of variation in the dependent variable explained by the respective models. Similarly, the log pseudolikelihood values of -4926.2457 in the probit model and -3660.8284 in the Tobit model both reflect the overall fit of each model to the data. The Wald chi-square ($\chi^2 = 317.87$, $p < 0.01$) in both models indicates that the explanatory variables are jointly significant in explaining the outcome.

Table 6: Average marginal effects from the control function approach

Variable	Poverty Incidence		Poverty Gap	
	Marginal Effects	P-value	Marginal Effects	P-value
Number of coupons	-0.163 (0.047)	0.001	-0.061 (0.015)	0.000
Sex (male=1)	-0.069 (0.018)	0.000	-0.020 (0.006)	0.001
Age	-0.000 (0.000)	0.210	-0.000 (0.000)	0.209
No education (base)				
Primary education	-0.100 (0.023)	0.000	-0.033 (0.007)	0.000
Secondary education	-0.142 (0.022)	0.000	-0.045 (0.006)	0.000
Tertiary education	-0.164 (0.076)	0.032	-0.054 (0.018)	0.003
Married (base)				
Separated	-0.045 (0.020)	0.026	-0.013 (0.006)	0.036
Widow	-0.100 (0.021)	0.000	-0.027 (0.006)	0.000
Not married	-0.163 (0.038)	0.000	-0.043 (0.012)	0.000
Credit access	-0.026 (0.012)	0.028	-0.009 (0.004)	0.019
Extension access	-0.014 (0.011)	0.213	-0.006 (0.003)	0.091
Land size	0.002 (0.004)	0.683	0.000 (0.001)	0.830
Business ownership	-0.088 (0.022)	0.000	-0.028 (0.007)	0.000
Drought shock	0.019 (0.012)	0.114	0.008 (0.004)	0.041
Flood shock	0.040 (0.012)	0.001	0.014 (0.004)	0.000
Irregular rainfall	0.029 (0.011)	0.010	0.009 (0.004)	0.016
Geo-area (urban=1)	-0.162 (0.023)	0.000	-0.059 (0.008)	0.000
Tropical Livestock Unit	-0.043 (0.007)	0.000	-0.016 (0.002)	0.000
Employment	-0.078 (0.018)	0.000	-0.026 (0.006)	0.000
Residual	0.147 (0.048)	0.002	0.056 (0.015)	0.000
Observations	7,804		7,804	
Wald Chi^2	317.87			
Pseudo R^2	0.035		0.052	
Log pseudolikelihood	-4926.2457		-3660.8284	

Note: Standard errors are in parentheses

Table 7: Differences in Poverty Incidence and Gap Across Subsidy Packages

	Poverty Incidence		Poverty Gap	
AIP Package	Coefficient	P-value	Coefficient	P-value
No subsidy (base)				
Fertilizer only	-0.020 (0.024)	0.395	-0.009 (0.008)	0.247
Maize + Fertilizer	-0.035 (0.040)	0.379	-0.021 (0.013)	0.108
Maize + Fertilizer + Cash crops	-0.068 (0.025)	0.007	-0.023 (0.008)	0.004
Constant	0.366 (0.006)	0.000	0.098 (0.002)	0.000

Note: Standard errors are in parentheses

Table 6 presents the average marginal effects from the CF approach, providing robust evidence of AIP's impact on food poverty among smallholder households in Malawi. Each additional coupon reduces the probability of being food poor by 16.3 percent and decreases the poverty gap by 6.1 percent, holding demographic characteristics (sex, age, education, marital status), institutional and livelihood factors (credit access, extension access, TLU, landholding, business ownership, employment, geographical area) and exposure to environmental shocks (drought, floods, irregular rainfall) constant. These findings indicate that AIP significantly mitigates both the incidence and depth of food poverty, particularly by reducing the severity of deprivation among the poorest households. This aligns with prior studies, such as Ganiyou & Yovo (2022), who found that targeted fertilizer subsidies in Togo reduced poverty incidence and depth, though with modest overall effects. Similarly, Mason and Tembo (2015) reported that Zambia's input subsidies lowered poverty but were more effective at mitigating deprivation than eliminating it. The significant reduction in the poverty gap underscores AIP's role as a protective mechanism, enabling households to maintain consumption levels during agricultural seasons, consistent with consumption smoothing theory (Morduch, 1995; Dercon, 2005).

To further contextualize this effect, a descriptive comparison across subsidy packages (Table 7) shows that partial packages, such as fertilizer-only or maize seed combined with fertilizer, are not associated with significant reductions in poverty relative to non-beneficiaries. In contrast, households receiving a complete AIP package, comprising fertilizer, maize seed, and cash crops, experience noticeably lower poverty incidence and a smaller poverty gap. This pattern reinforces the coupon-based evidence by suggesting that welfare gains are strongest when households receive a comprehensive bundle of inputs rather than partial support. It is essential to note that this package analysis is descriptive in nature and does not account for other household, institutional, or climatic factors; therefore, it serves to complement the control function results rather than provide additional causal estimates.

In the context of Malawi's structural constraints, the effect of AIP is particularly evident, given the reliance of rainfed agriculture and climatic variability add to vulnerability (Caruso & Sosa, 2022). Unlike Nigeria's e-voucher programme, which reduced poverty headcount by 17.7 percent (Wossen et al., 2017), AIP's effects are tempered by inefficiencies in targeting and delivery, as noted by Alfonso & Tsoka (2025). For instance, the programme's benefits are often diluted by favoritism and delayed input distribution (Benson et al., 2024). Nevertheless, the significant negative effect on food poverty suggests that access to subsidized inputs enhances maize yields and food self-sufficiency, reducing reliance on market purchases and stabilizing household consumption (Sibande et al., 2017; Nyirongo & Khataza, 2025).

Building on this comprehensive programme effect, demographic characteristics strongly shape household vulnerability to food poverty. Male-headed households are 6.9 percent less likely to be food poor and experience a 2 percent smaller poverty gap than female-headed households, holding other factors constant. This finding aligns with evidence that women, despite higher participation rates in agricultural programmes, often face systemic barriers in translating access into productivity due to unequal control over land, limited access to labour, and financial constraints (Doss, 2018; Chirwa & Dorward, 2013). Consequently, male-headed households may be better positioned to convert input subsidies into food security gains through more flexible resource allocation and market engagement (Mason et al., 2020).

Education is also a critical protective factor against food poverty. Compared to households with no formal education, those with primary, secondary, and tertiary education experience lower probabilities of being food poor (10, 14.2, and 16.4 percent, respectively) and smaller poverty gaps (3.3, 4.5, and 5.4 percent, respectively), holding all other factors constant. This pattern is consistent with earlier findings that education enhances households' capacity to adopt improved technologies, manage inputs efficiently, and respond adaptively to market and climatic shocks (Mason et al., 2020; Banda et al., 2025). Educated farmers also tend to have greater awareness of agronomic practices, improved record-keeping, and stronger connections to extension services, which jointly enhance food security outcomes. These results support broader literature underscoring the transformative role of human capital in sustaining long-term poverty reduction (Ganiyou & Yovo, 2022; Josephson, 2025).

Marital status also plays a significant role in shaping food poverty outcomes. Compared to married households, separated, widowed, and never-married household heads face lower probabilities of being food poor by 4.5 percent, 10 percent, and 16.3 percent, respectively, and experience smaller poverty gaps by 1.3 percent, 2.7 percent, and 4.3 percent, holding other factors constant. This aligns with descriptive results showing that widows are more represented among beneficiaries, suggesting the programme helps reduce poverty among vulnerable households. Although somewhat surprising result may be attributed to differences in dependency burdens, as married households often support larger family sizes, which dilutes income and increases consumption needs, thus elevating the risk of food poverty (Josephson, 2025; Beegle et al., 2018).

Beyond demographic characteristics, institutional and livelihood factors are equally vital in influencing household welfare. Credit access reduces the probability of being food poor by 2.6 percent and the poverty gap by 0.9 percent, holding all other factors constant. This finding aligns with previous evidence that access to credit empowers smallholders to purchase complementary inputs, invest in productive assets, and smooth consumption during lean seasons, thereby strengthening resilience to food insecurity (Gasior et al., 2022).

Livestock ownership, measured in tropical livestock units (TLU), reduces the probability of being food poor by 4.3 percent and the poverty gap by 1.6 percent, holding other factors constant. Consistent with descriptive results showing higher livestock ownership among beneficiaries, highlighting the importance of productive assets in mitigating poverty. This effect reflects the multifaceted role of livestock as a source of food, draught power, manure, and liquid capital that can be converted into cash during distress periods. Such functions enhance households' ability to withstand shocks and maintain consumption, explaining the significant reduction in both poverty incidence and depth (Acosta et al., 2024; Zegeye, 2022).

Similarly, non-farm business ownership reduces the probability of being food poor by 8.8 percent and the poverty gap by 2.8 percent, holding all other factors constant. The result corroborates earlier studies emphasizing income diversification as a crucial pathway out of rural poverty (Josephson, 2025). Engagement in off-farm enterprises provides an additional revenue stream that cushions households from agricultural volatility and strengthens overall welfare stability.

Access to agricultural extension services decreases the poverty gap by 0.6 percent, although its effect on poverty incidence is not statistically significant, holding all other factors constant. This suggests that extension interventions are particularly beneficial for already poor households, improving productivity and consumption smoothing rather than preventing initial poverty entry. This is consistent with Ragasa et al. (2016), who found that technical advice and farmer training tend to improve welfare outcomes primarily among resource-constrained farmers.

In addition to institutional and livelihood characteristics, spatial location, employment, and exposure to environmental shocks also influence household food poverty outcomes. Urban households are 16.2 percent less likely to be food poor and experience a 5.9 percent smaller poverty gap, holding all other factors constant. This pattern mirrors findings from Caruso & Sosa (2022), who attribute urban welfare advantages to better access to markets, infrastructure, and diversified income opportunities. Employment, likewise, reduces the probability of being food poor by 7.8 percent and the poverty gap by 2.6 percent, holding other variables constant, confirming that stable income sources shield households from transitory shocks and improve their capacity to purchase inputs and food (Mason et al., 2020) .

Environmental shocks, however, counteract many of these gains. Floods increase the probability of being food poor by 4 percent and the poverty gap by 1.4 percent; irregular rainfall raises them by 2.9 and 0.9 percent, respectively; and drought increases the poverty gap by 0.8 percent without significantly affecting incidence, holding all other factors constant. These findings echo earlier work demonstrating that climatic shocks undermine productivity and household income, thus intensifying food poverty (Shukla et al., 2019; Mngomezulu et al., 2024; Meier, 2024). Such results underscore the importance of complementary climate-resilient strategies such as irrigation, drought-tolerant crops, and agricultural insurance to safeguard gains from social protection programmes.

Finally, the positive and significant residual term validates the control function approach, confirming that unobserved characteristics such as farmer ability, risk preferences, or social networks affect both AIP participation and food poverty outcomes. This supports the robustness and consistency of the estimated effects (Cameron & Trivedi, 2005; Wooldridge, 2015).

In summary, AIP significantly reduces food poverty incidence and depth, but its impact is moderated by demographic, institutional, and environmental factors. The programme's success in targeting vulnerable yet productive households is evident, but challenges such as climatic shocks and gender disparities limit its transformative potential. These findings underscore the need for integrated strategies combining subsidies with education, financial inclusion, and climate adaptation to achieve sustainable poverty reduction, aligning with Malawi's Vision 2063 and SDG objectives (United Nations, 2015; Kampanje, 2023).

CHAPTER 5:
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study assessed the effects of the Agricultural Input Programme (AIP) on household food welfare in Malawi, guided by two specific objectives: (1) To examine differences in demographic socio-economic, institutional and environmental characteristics between AIP beneficiaries and non-beneficiaries using t-tests, and (2) to estimate the causal effect of AIP participation on household food poverty using the Control Function (CF) approach.

Results revealed significant demographic, socio-economic, institutional and environmental characteristics differences between beneficiaries and non-beneficiaries, indicating non-random programme participation. Beneficiaries were more likely to be female-headed, older, and widowed, reflecting partial success in reaching socially vulnerable groups. They also owned slightly larger landholdings, more livestock, and had greater access to extension services and other safety nets, suggesting that the programme favors households with moderate productive capacity. This pattern implies that while AIP achieves some degree of pro-poor targeting, it may still exclude the most resource-poor farmers who lack land, credit, or social networks.

Results from the Control Function approach confirmed that AIP participation significantly reduces both the probability and depth of food poverty, even after correcting for endogeneity in coupon allocation. Each additional coupon received reduced the likelihood of being food poor by about 16.3 percent and the poverty gap by 6.1 percent. The results also underscored the importance of complementary factors such as education, credit access, employment, livestock ownership, and off-farm income in amplifying the welfare effects of AIP. Conversely, environmental shocks such as floods and irregular rainfall increased poverty risk, highlighting the vulnerability of rural households to climate variability.

In conclusion, the study demonstrates that AIP remains an important policy tool for reducing food poverty among smallholder farmers in Malawi. However, its overall impact is moderated by targeting inefficiencies, gender disparities, and environmental risks. Sustainable poverty reduction, therefore requires strengthening programme inclusivity, and resilience to climate-related shocks.

5.2 Recommendations

The findings indicate that relatively better-off households are more likely to benefit from the AIP, highlighting the need to improve targeting so that support reaches those who can use it most effectively, including the youth. Education should also be considered as a targeting criterion, as households with higher levels of education may be better able to apply inputs efficiently, adopt improved farming practices, and achieve greater gains from the programme. In addition, regular monitoring should track whether the intended poverty-reduction objectives are being achieved, helping to identify and correct any targeting gaps. Since the subsidy programme alone may not substantially reduce poverty, combining it with complementary support such as extension services and access to credit could enhance its effectiveness. Furthermore, future research should examine the impact of the AIP on poverty transitions, particularly using panel data from recent household surveys, to understand how the programme influences households' movement into and out of poverty over time.

As Malawi advances toward Vision 2063 and the Sustainable Development Goals, AIP should remain part of a broader agricultural transformation strategy. Aligning the programme with national priorities on productivity and resilience will maximize its developmental impact. Finally, further research is needed to assess the programme's long-term impacts, particularly whether it enables permanent exits from poverty and its fiscal sustainability.

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APPENDIX

Appendix A First Stage – Robustness Checks (Control Function Approach)

A1. Validation of OLS for Control Function

A1.1. Heteroscedasticity Test

```
. hettest

Breusch-Pagan/Cook-Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of number_coupons

H0: Constant variance

    chi2(1) = 695.58

Prob > chi2 = 0.0000
```

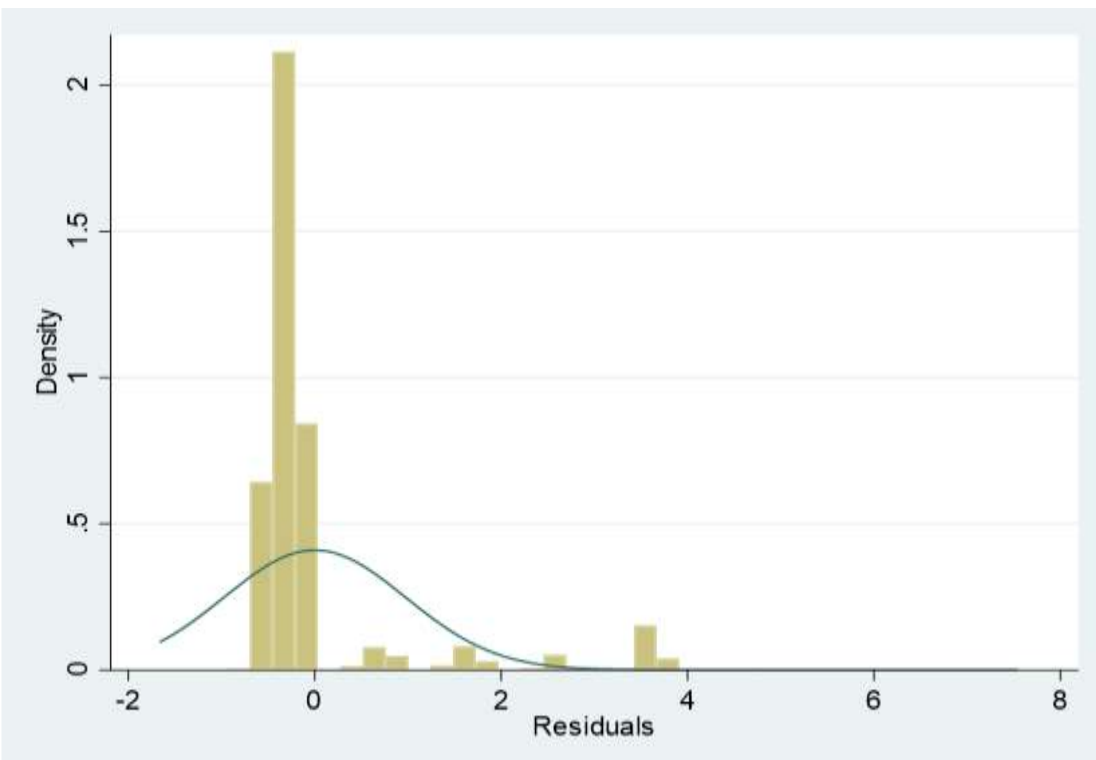
A1.2. Multicollinearity Check

```
. vif

    Variable |       VIF       1/VIF
-------------+----------------------
   lnvillage |      1.30    0.771082
      region |
     Central |      2.26    0.443356
       South |      2.73    0.366626
      floods |      1.10    0.911606
        land |      1.11    0.898936
         sex |      2.46    0.407305
         age |      1.25    0.800058
        educ |
     Primary |      1.03    0.968040
   Secondary |      1.04    0.962828
    Tertiary |      1.01    0.993810
     marital |
   Separated |      1.84    0.543017
       Widow |      2.16    0.462907
 Non-married |      1.03    0.970257
     geoarea |      1.07    0.937260
-------------+----------------------
    Mean VIF |      1.53
```

A1.3. Model Specification Check

```
. linktest

Source |       SS           df       MS      Number of obs   =     7,804
-------------+---------------------------------- F (2, 7801)      =     69.05
       Model |130.858014      2     65.4290069    Prob > F        =    0.0000
    Residual |7392.25219    7,801  .947603152    R-squared       =    0.0174
-------------+----------------------------------Adj R-squared   =    0.0171
       Total |7523.1102     7,803  .964130488    Root MSE        =    .97345
------------------------------------------------------------------------------
number_couponns | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
        _hat |   1.301638   .2822406     4.61   0.000     .7483711    1.854905
      _hatsq | -.4559572   .4065951    -1.12   0.262    -1.252993    .3410781
       _cons | -.0423074   .0485637    -0.87   0.384    -.1375053    .0528905
------------------------------------------------------------------------------
```

A1.4 Jarque–Bera Normality Test



Appendix B: Second-Stage Control Function Diagnostics

B1. Poverty Incidence (Binary Outcome, Probit with Control Function)

B1.1. Probit Model Coefficients for the Effect of the AIP on Household Food Poverty Incidence

foodpov	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
number_coupons	-.4518244	.1318087	-3.43	0.001	-.7101647	-.1934842
sex	-.1921187	.0499197	-3.85	0.000	-.2899595	-.0942779
age	-.0013287	.0010603	-1.25	0.210	-.0034068	.0007495
educ (no-education (base))						
Primary education	-.288815	.0701451	-4.12	0.000	-.4262968	-.1513332
Secondary education	-.4214593	.0719892	-5.85	0.000	-.5625554	-.2803631
Tertiary education	-.4974229	.2703856	-1.84	0.066	-1.027369	.032523
Marital (married (base))						
Separated	-.1245482	.0567243	-2.20	0.028	-.2357258	-.0133707
Widow	-.2873713	.0635989	-4.52	0.000	-.4120228	-.1627198
Not married	-.4915233	.1309552	-3.75	0.000	-.7481909	-.2348558
credit	-.072288	.0328453	-2.20	0.028	-.1366636	-.0079124
extension_acc	-.0375903	.03022	-1.24	0.214	-.0968205	.0216399
land	.0041825	.0102369	0.41	0.683	-.0158816	.0242465
business	-.2429978	.0604517	-4.02	0.000	-.3614808	-.1245147
drought	.0526134	.0333044	1.58	0.114	-.012662	.1178887
floods	.110816	.0324207	3.42	0.001	.0472727	.1743593
irr_rain	.081126	.0314713	2.58	0.010	.0194435	.1428086
geoarea	-.4476477	.0650254	-6.88	0.000	-.5750952	-.3202002
tlu	-.1204707	.01904	-6.33	0.000	-.1577885	-.083153
employment	-.2166944	.0487065	-4.45	0.000	-.3121574	-.1212314
residuals	.4084711	.1325338	3.08	0.002	.1487095	.6682327
_cons	.1271914	.0755327	1.68	0.092	-.02085	.2752328

B1.2. Model Specification (Link Test)

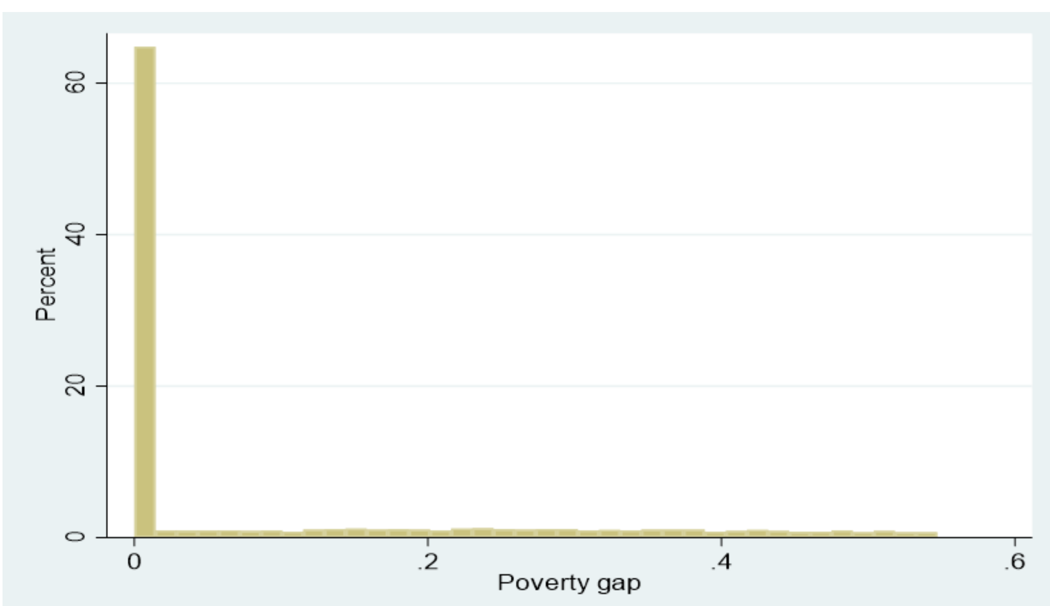
```
Probit regression                                       Number of obs =  7,804
                                                        LR chi2(2)     = 356.74
                                                        Prob > chi2    = 0.0000
Log likelihood = -4925.2398                             Pseudo R2      = 0.0349
------------------------------------------------------------------------------
     foodpov | Coefficient Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        _hat |   1.177096   .1360297     8.65   0.000     .9104822    1.443709
      _hatsq |   .1738009   .1212799     1.43   0.152    -.0639033    .4115051
       _cons |   .0278961   .0310364     0.90   0.369     -.032934    .0887263
```

B1.2. Goodness-of-Fit (Hosmer–Lemeshow Test)

```
Variable: foodpov
 Number of observations = 7,804
       Number of groups = 10
Hosmer–Lemeshow chi2(8) = 9.30
            Prob > chi2 = 0.3178
```

B2. Poverty Gap (Tobit Model)

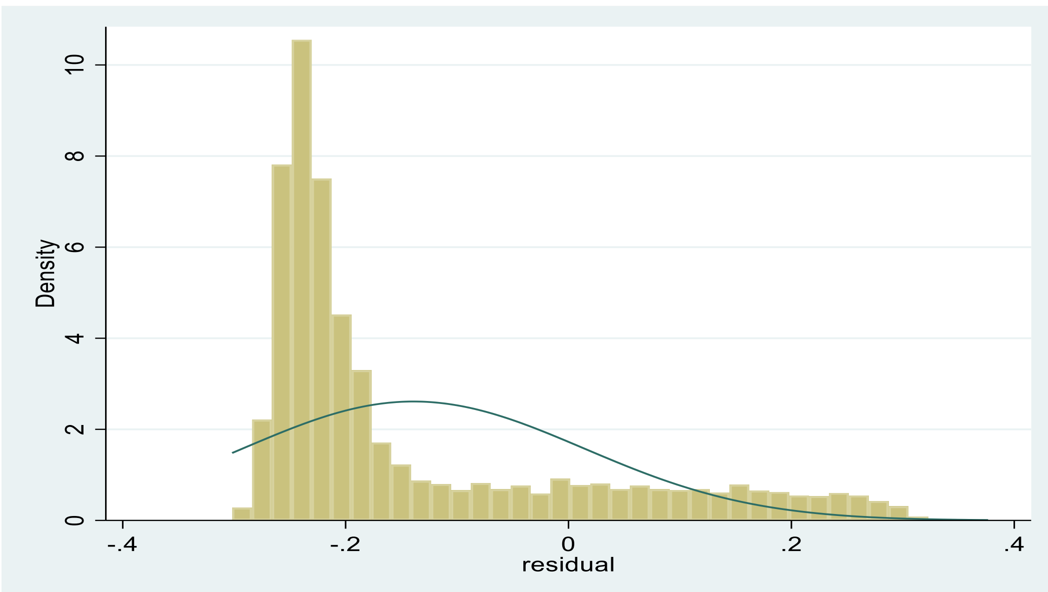
B2.1 Histogram of the Poverty Gap among Sample Households



B2.2 Non-Normality of Residuals (based on Shapiro–Wilk test)

```
. swilk resid

                   Shapiro-Wilk W test for normal data

    Variable |        Obs       W           V         z       Prob>z
-------------+------------------------------------------------------
       resid |      7,804    0.76948    925.338    18.160    0.00000

Note: The normal approximation to the sampling distribution of W'
      is valid for 4<=n<=2000.
```

B2.3 Non-Normal Distribution of Residuals



B2.4. Tobit Model Coefficients for the Effect of the AIP on Household Food Poverty Gap

povgap	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
number_coupons	-.1628404	.0403098	-4.04	0.000	-.2418585	-.0838224
sex	-.0520666	.01512	-3.44	0.001	-.0817058	-.0224274
age	-.0004132	.0003291	-1.26	0.209	-.0010583	.0002319
educ (No-education (base))						
Primary education	-.0969351	.0224337	-4.32	0.000	-.1409111	-.052959
Secondary education	-.1427346	.0231992	-6.15	0.000	-.1882113	-.0972579
Tertiary education	-.1811695	.0859482	-2.11	0.035	-.3496511	-.012688
marital (married (base))						
Separated	-.0351911	.0172578	-2.04	0.041	-.069021	-.0013612
Widow	-.0778211	.0197046	-3.95	0.000	-.1164475	-.0391948
Not married	-.1336756	.0446059	-3.00	0.003	-.2211152	-.046236
credit	-.0238464	.0101844	-2.34	0.019	-.0438105	-.0038822
extension_acc	-.0157139	.0093021	-1.69	0.091	-.0339486	.0025208
land	.0006767	.0031568	0.21	0.830	-.0055115	.0068649
business	-.0748048	.0195015	-3.84	0.000	-.113033	-.0365766
drought	.0209468	.0102413	2.05	0.041	.0008711	.0410224
floods	.0366296	.0098518	3.72	0.000	.0173174	.0559419
irr_rain	.0234513	.0097478	2.41	0.016	.004343	.0425597
geoarea	-.1567164	.021143	-7.41	0.000	-.1981623	-.1152705
tlu	-.0438777	.0063	-6.96	0.000	-.0562274	-.031528
employment	-.0700453	.0156388	-4.48	0.000	-.1007015	-.0393891
residuals	.1477734	.0405065	3.65	0.000	.0683698	.2271769
_cons	.0502322	.0230703	2.18	0.029	.0050081	.0954563
var(e.povgap)	.1138273	.0024934			.109043	.1188215